Wintering Ground Habitat Selection by the Eastern Whip-poor-will

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Abstract

Aerial insectivore populations have been suffering steep declines, with habitat loss due to expanding human activities being a prominent contributing factor (Nebel et al., 2010). The Eastern Whip-poor-will (*Antrostomus vociferus*) is of particular concern in New England, where populations have been declining at a rate of 4.4% per year. While conservation efforts in states including Massachusetts are expanding, little is known about the species' behavior on the non-breeding grounds. Without full annual-cycle research, coherent conservation goals and plans are difficult to establish. This gap in knowledge motivated us to seek to characterize the wintering habitat used by whip-poor-wills. Specifically, we were interested in what landscape features may influence habitat selection, because as landscapes change due to human expansion, preferred habitat may not correlate with available habitat. In 2018, we deployed 21 GPS tags on males breeding in Massachusetts, and recaptured 12 in 2019 (for a 57% recapture rate). These tags collected location data for both fall and spring migration, as well as the wintering period. Tagged males wintered primarily in Mexico and Central America, with only one bird remaining in the United States. We constructed winter territory locations using MCPs, then compared habitat used on the wintering locations to habitat available at random locations by characterizing land cover types (e.g. mature forest, young forest, agriculture, and development) at three spatial scales: the territory, local (2-km), and landscape (5-km) scales. Most territories were less than 2.5 hectares and contained a mixture of young forest, mature forest, and some also included agricultural land. At the 2-km scale, actual wintering locations contained 31% more forest cover and 43% less agricultural land compared to random locations. Given that life-history information for this species is lacking, the results from this study will help inform full annual-cycle conservation efforts.

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Chapter 1: Literature Review

Decline of Aerial Insectivores

Trends in ecology indicate that a great number of passerine species are suffering long-term population declines. Of these, aerial insectivores are thought to be particularly vulnerable (Nebel et al., 2010). Habitat loss due to development, agriculture, and other human related activities are considered prominent causes of population reduction, although a number of other factors must be acknowledged as well. Pesticides and climate change are among the human-based issues that avian species face, in addition to interspecific factors such as increased predation and brood parasitism (Hunt, 2012; Nebel et al., 2010; Smith et al., 2015). For migratory species, habitat loss is not limited to their breeding grounds; increased agricultural expansion in South and Central America affects the availability of suitable wintering habitat (Hunt, 2012).

In North America, aerial insectivores are declining at rates similar to or greater than other groups (Smith et al., 2015). This decline is identified as beginning after 1980, with a negative change point for swifts, swallows, and nightjars (SSNs) arising in the mid-to-late 1980s (Smith et al., 2015). When factoring in change points prior to 1980, geographic trends emerge. In the west and northeast, initial trends were moderately positive and then began steeply declining up through present day. In contrast, populations tracked in the south showed a steep increase at first, followed by a decrease or stable trend through present day. Flycatchers, another subgroup, had similar population trajectories to SSNs in the northeast, while across the rest of the continent they were quite different (Smith et al., 2015). These multi-group change points in the northeast (Figure 1) may help identify the cause(s) of the respective population declines. It is possible that the groups were affected by the same environmental factors in this region, or that separate factors affecting the individual groups occurred at similar time points (Smith et al., 2015).

Several hypotheses have been proposed to explain these observed geographic gradients. There is a greater degree of industrialization and population density associated with the northeast United States, so human actions and influences may contribute to the declines seen trending towards this region (Nebel et al., 2010). However, the decline becomes increasingly severe with movement into Canada, where industrialized areas are fewer. Atmospheric pollutants do travel along this gradient, though, so this could account for the way human activity produces these patterns of decline. Specifically, pollutants affect soil and water quality, which is correlated with negative effects on insect abundance and diversity (Nebel et al., 2010). Aerial insectivores rely on insect populations as a sufficient food source, so declines in insect populations may be an influence on aerial insectivore populations. If the breeding season does not align with the greatest abundancy of food, this may be especially true, as was the case with the Pied Flycatcher (Nebel et al., 2010).

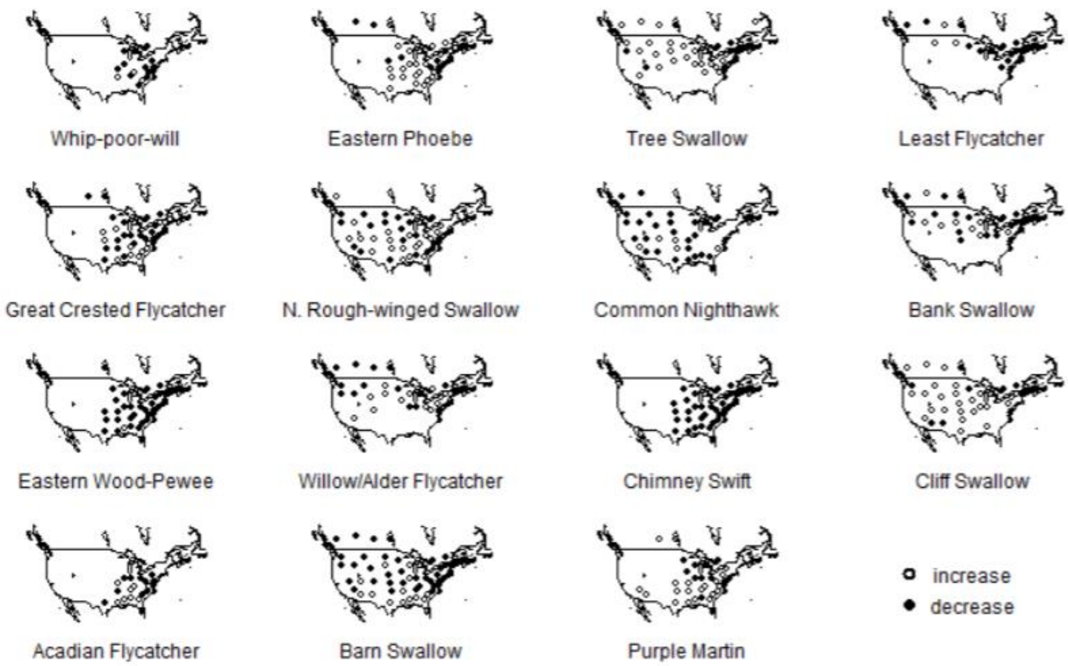

Figure 1. Population trends for fifteen species of aerial insectivores based on Breeding Bird Survey data from 1966 to 2006 (Nebel et al., 2010).

Migration is another time of high mortality for birds. Longer migration distances are associated with a greater degree of population decline (Nebel et al., 2010). Certain stressors may also be more prevalent on wintering than breeding grounds. For example, specific pesticides that are used in Central and South America (the wintering location of many North American aerial insectivores) are associated with decreases in insect abundance, which as stated before could easily contribute to avian population declines (Nebel et al., 2010). Species that migrate greater distances have increased energetic demands as well, so if the habitat quality on the wintering grounds is reduced in any way, they suffer a greater cost compared to shorter-distance migrants (Nebel et al., 2010).

Eastern Whip-poor-wills in New England

Whip-poor-will Background

The Eastern Whip-poor-will (*Antrostomus vociferus*) belongs to the nightjar family of birds, part of the larger group of aerial insectivores (Smith et al., 2015). Both males and females range in size from 22 to 26 cm, with a wingspan of 45-48 cm. An average adult typically weighs between 43 and 64 grams (Cink et al., 2017). A whip-poor-will's plumage (Figure 2) is designed to match its habitat; their feathers are mottled gray and brown, which allows them to blend in with the leaves among the forest floor used for nesting (Cink et al., 2017; Mass Audubon, 2019). Males have white corners on their feathers that extend to their tails (Cink et al., 2017; Mass Audubon, 2019). Whip-poor-wills are very similar in appearance to Chuck-will's-widows

(*Antrostomus carolinensis*), but are 6-10cm smaller and may only weigh one-third as much (Cink et al., 2017).

Figure 2. An adult male whip-poor-will after being captured at night (Photo: Burgos)

Whip-poor-wills are most active at night, beginning their foraging behavior after dusk, feeding by the light of the moon, and retreating into the forest soon before sunrise (National Audubon Society, n.d.). Feeding behaviors include two main methods. They may fly low, slowly, and silently along the tree line, catching insects in their especially wide mouths (National Audubon Society, n.d.). Alternatively, they may lie in wait on a perch, then fly out from a branch to capture moths and beetles (Mass Audubon, 2019).

Breeding is initiated by a male calling out in order to attract potential mates (National Audubon Society, n.d.). Males are highly territorial, and will often respond aggressively to the calls of other males. They defend their territories by hissing at and chasing off intruders, with their beaks open wide and wings aloft (Cink et al. 2017). While not much is known about their courtship behavior, the male does typically approach the female on the ground, bobbing and bowing his head (National Audubon Society, n.d.). Once breeding has occurred, females lay their two eggs directly on the ground (most often the forest floor); no nest is made (Cink et al. 2017; Mass Audubon, 2019; National Audubon Society, n.d.). The eggs are patterned brown and gray against a cream/white background, closely resembling the leaf litter typically found in the woods (Mass Audubon, 2019). Eggs are incubated for 19 to 21 days, at which point downy hatchlings emerge with their eyes closed Cink et al. 2017; National Audubon Society, n.d.). They are fed by both parents via regurgitated insects, and may have their first flight after about three weeks (National Audubon Society, n.d.). Females may have one or two broods per season, as a second clutch can be laid while the male continues caring for the first offspring (Cink et al. 2017; National Audubon Society, n.d.). Compared to other species, relatively little is known about the breeding and rearing behavior of whip-poor-wills, which means there are gaps in understanding the life history of these birds.

Another area of their life history for which information is lacking is the time spent during migration and on wintering grounds. Whip-poor-wills spend the breeding season in the northeast United States with extension into Canada, while their winter range covers the southernmost U.S., and the eastern regions of Mexico and Central America (Figure 3, BirdLife International, 2018). They are thought to migrate over land surrounding the Gulf of Mexico rather than over the open water (BirdLife International, 2018; Cink et al., 2017). However, the exact habitat types used on the wintering grounds remains mostly unknown.

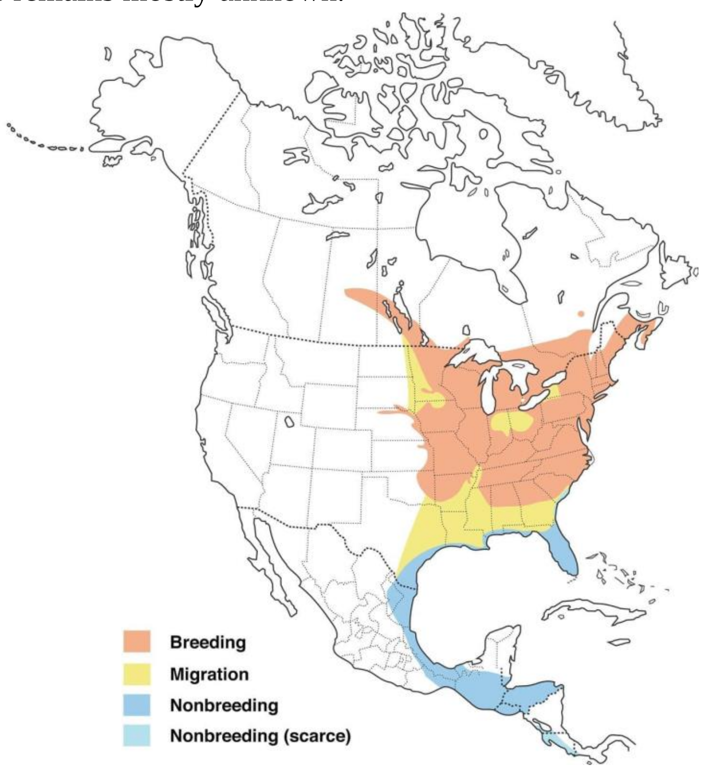

Figure 3. Whip-poor-will range map (Cink et al., 2017)

Without detailed knowledge of migration and wintering ground habitats, it is difficult to establish conservation goals. Interestingly, just last year (2018) IUCN uplisted this species to the "Near Threatened" status, demonstrating current concern of the conservation of the species, and their population status is declining, most notably in northeastern North America. In 2016, there were an estimated 1.8 million individuals worldwide, but this represents what may be a 70% decrease since 1966 (BirdLife International, 2018; Kusmer, 2019).

Population Decline

Of the aerial insectivores present in New England, whip-poor-wills have been designated as a "Species of Special Concern" (Dorsey, 2018). Since 1966, the whip-poor-will population in New England has been declining at a rate of 4.4% per year, and 6.6% per year in Massachusetts specifically (Sauer et al., 2017; Walsh et al., 2013). As is the case with many avian species, limited habitat is thought to be a significant factor in this decline. Whip-poor-wills have been known to breed on fire-adapted pine-oak habitats, but as urban development and fire suppression increases, there are fewer optimal breeding locations available in New England (Vitz, 2019). A reduction in food sources, namely large moth and beetle populations, may also be reflective of the decrease in whip-poor-will numbers (National Audubon Society, n.d.). It is also possible that increased mortality during migration or on the wintering grounds is contributing to the overall population decline (Cink et al., 2017). There is not much known about the life history of whip-poor-wills during this period of time, which makes it difficult to determine how this part of their breeding cycle influences population dynamics.

Breeding Grounds in Massachusetts

In Massachusetts, six locations have been identified as being home to twenty or more breeding whip-poor-will pairs (Dorsey, 2018). Of these six, two were selected for study in this report. These were Montague Plains Wildlife Management Area (WMA) and Joint Base Cape Cod. A third site, Bolton Flats WMA, was also chosen, even though it is home to less than twenty breeding whip-poor-will pairs. Familiarity with the site and its relative ease of access made it a convenient study location. These sites are characterized by low-nutrient, acidic, sandy soils and are predominated by oak and pitch pine understories. In addition, all sites have a rich history of land management via controlled burns.

There have been some efforts to create new habitats for whip-poor-wills, by initiating disturbances via logging and controlled fires, but without more detailed knowledge regarding the reproductive success and habitat preferences of these birds, protecting and managing populations is particularly difficult (Vitz, 2019).

Annual Life Cycle Research

Animal ecology research is biased towards the breeding season (Marra et al., 2015). The fact that the majority of research on several vertebrate taxa is conducted during breeding means that crucial life history information is missing (Marra et al., 2015). While they may be temporally or geographically separate, periods of the annual cycle are inextricably linked, and so an understanding of a species' full annual life cycle is critical for "interpreting potential effects of major stressors like climate change" (Marra et al., 2015). The term "seasonal interactions", while relatively new in the literature, describes the long-observed phenomenon that events that occur during one period of the annual cycle can influence both individuals and populations in later periods (Marra et al., 2015). Poor physical condition in one season (e.g. wintering) may influence reproductive success or survival in the next season (e.g., breeding) (Marra et al., 2015). Darwin himself recognized that "events prior to breeding can influence female fecundity in migratory birds” (Marra et al., 2015). Unfortunately, there is a severe lack of research that investigates which phases of the annual cycle of such migrants are highly correlated with population limitations (Klaassen et al., 2014).

Recent advances in technology allow for new approaches and increased opportunities for annual life cycle research. Some of the smallest available tracking devices are light-level geolocators (Bridge et al., 2011). These tags record numerous light-level data points, and combined with the real-time clock also employed by the device, the times of sunrise and sunset can be identified (Bridge et al., 2011). Based on this information, latitude is determined by the length of day or night, and longitude is related to the time of high noon (Bridge et al., 2011. However, these calculations do require specialized software, and a number of factors can obscure the data. Something as simple as excess cloud cover or a bird remaining in a covered area can result in noticeable uncertainties or seemingly anomalous location coordinates (Bridge et al., 2011). Previous Eastern Whip-poor-will research in Massachusetts used geolocators for their small size and relative affordability, but shifted to using GPS tags as they have become more miniaturized and cost-effective. GPS tags are advantageous because they “can provide extremely accurate location data” (Bridge et al., 2011). Location coordinates are directly collected and stored; these readings do require a considerable amount of power, which can be an issue and cause batteries to die early, limiting the amount of data points that can be collected (Bridge et al., 2011). Both geolocators and GPS tags require less power than other methods, because they store the collected data rather than transmitting it in real-time. As a result, these devices do require tagged individuals to be recaptured so that the data can be obtained. Other options for tracking technology do not involve recapture. These methods include satellite tracking, ground-based receivers, and radar systems (Bridge et al., 2011).

Life History and Events Around the Wintering Grounds

Marra et al. (2011) reviewed a number of high impact research articles and found that across all taxa reviewed, 61% of studies focused only on the breeding season. This was further emphasized in birds as close to 70% of all research done was focused on the breeding grounds (Marra et al., 2015). Despite the fact that millions of birds have been banded with USGS number bands, the life history and migratory ecology of many bird species remains unknown. This is due to the fact that the populations of study and the geographical areas they utilize are massive, but the individuals themselves are small. New developments in technology including smaller, lighter, and less expensive tracking units have made research in this area easier, but there is still much to be learned about the life history of migratory species.

Understanding an individual’s behavior on the wintering grounds, breeding grounds, and during migrations is important as these three periods are often drastically distinct from one another. The breeding season and migration periods are typically much shorter compared to the wintering season and are often much more physically demanding. During the breeding season, individuals are often engaged in reproductive behaviors and rearing offspring, and during migration they are almost constantly on the move. In contrast, behavior on the wintering grounds is typically much more stationary, as individuals’ main concerns are foraging and survival

(Marra et al., 2015). These differences in behavior are often linked by differences in habitat. Even on the breeding grounds, organisms use different habitats for different purposes. One of the reasons edge habitat is favored by whip-poor-wills is because they tend to breed and nest in the scrub-oak understory forest and forage for insects in more open clearings (MassAudubon, 2019). Researching and recognizing these habitat distinctions, in addition to the migration routes and wintering grounds of a species "enables evaluation of those geographical areas, including ecologic analysis and research, identification of potential habitat threats, and development of conservation strategies" (Beason et al., 2012).While understanding an organism's behavior on breeding grounds is important, without considering the other aspects of its life cycle, it is only a small part of a much larger picture.

Habitat Distinctions

When considering habitat management plans for species of concern, identifying exactly which habitat to prioritize can be of critical importance. However, different terms describing the existence and utility of habitat must first be distinguished. Habitat that is preferred may not be present, and that which is present may not be accessible.

In general, the term "***habitat***" may be used to describe an area that promotes the occupancy of a given species, including the resources and conditions that allow for survival and reproduction (Krausman, 1999). These resources are food, water, shelter, and anything else a species requires for success (survival and reproductive). Any area that has these necessary resources has the potential to be a habitat for the species in question. To designate an area as habitat is not an indicator of the permanency of the occupancy; land used for migration and dispersal also qualifies as habitat even though its usage may be temporary (Krausman, 1999).

Habitat usage refers specifically to how an organism uses the resources available to them in a given habitat (Krausman, 1999). The use of resources is divided into categories based on the function of said usage, with behaviors including nesting, feeding/foraging, and denning (Krausman,1999). An area of habitat may be used for more than one function, and the same characteristics may define habitat used for multiple functions. Depending on the season (temporal or breeding vs. wintering), different habitats may be needed or of particular use (Krausman, 1999). For example, during nesting, whip-poor-wills utilize mature forest–typically with little understory–as the location to lay their eggs, while clearings surrounded by the treeline are better suited for foraging (Mass Audubon, 2019).

The process of choosing which habitat to use is known as ***habitat selection***. This is based on a complex series of behaviors, both innate and learned, that enable an animal to make decisions about the habitat it would use in different environmental conditions (Krausman, 1999). These decisions involve a number of factors, including the various desired functions of the habitat. The proximate and ultimate utility of the habitat is also considered: how does the habitat in question promote long-term vs. short-term success (Krausman, 1999). Influences beyond the individual that affect habitat selection include competition (both intra- and interspecific) and predation pressures (Krausman, 1999). ***Habitat preference*** is thus a consequence of habitat selection, wherein certain resources are used disproportionately to others (Krausman, 1999).

Habitat quality involves how well the environment provides the resources necessary for survival and reproduction (Krausman, 1999). Quality may be ranked as low, medium, or high, depending on if the resources allow for individual survival, reproduction, or the persistence of a population (Krausman, 1999). These classifications are based more on the ability of the habitat to maintain a population than the specific vegetative features of the area (Krausman, 1999).

Habitat decisions also depend on what habitat is physically available to an animal. Resources may not be truly accessible, even if they are abundant, if an animal cannot be present in the habitat containing said resources (Krausman, 1999). However, true availability is hard to quantify, so abundance is often used as a substitute measure (Krausman, 1999).

ArcGIS and Conservation Efforts

ArcGIS (GIS = geographic information system) is a software that allows for the management and analysis of geographically-referenced information through a number of programs and tools. These tools are often useful in research that aims to establish conservation goals. The Environmental Systems Research Institute (ESRI) offers several examples of the ways in which the monitoring of wildlife habitats via ArcGIS aids conservation activities. At Garamba National Park in the Democratic Republic of the Congo, many elephants wear tracking collars so that their movements can be visualized in real time (Gadsden, 2019). Using GIS, when a large group is seen to be huddled together in a small area, this unusual behavior alerts the staff that something is happening in the park to frighten the animals; it often indicates that poachers are nearby (Gadsden, 2019). Having this information readily available improves the ability of the wildlife staff to reduce poaching and maintain their elephant population.

GPS data can also be combined with habitat mapping to examine the changing interactions species have with their environment. Dian Fossey Gorilla Fund International (DFGFI) undertook a project in which they wanted to know how the behavior of the mountain gorillas (*Gorilla beringei beringei*) living in the Virunga volcanic region was related to the alterations in their habitat over time. This team considered ESRI programs including ArcView and ArcGIS as ideal tools, because they "allow[ed] researchers to merge data from many different sources, scales, and dates and recombine them in a powerful display and analytical environment" (Steklis et al, 2007). By digitizing existing maps all into one place, they were able to create a three-dimensional model of the elevation of the region (Steklis et al., 2007). This information was combined with satellite radar data used for vegetation classification, and GPS units were used to track the gorillas' movements, as well as other key features of the national parks in which they resided (Steklis et al., 2007). To examine how these movement patterns had changed over time, they used the GIS to compare the GPS data with information from decades past (Steklis et al., 2007). A database of field notes, photographs, and maps was compiled, which included digitizing hand-drawn maps of daily gorilla movements from the 1970s and 80s (Steklis et al., 2007). With the aid of ArcGIS, the DFGFI continues to work towards its goal of "understand[ing] the changing patterns of gorilla behavior and the gorillas' relationship to their environment and to quantify and understand the impacts of poaching and encroachment" (Steklis et al., 2007).

The ArcGIS platform can also be used to identify habitats that are critical for target species, so that these land types can be classified and prioritized for conservation. The National Audubon Society's Washington chapter, in conjunction with the Washington Department of Fish and Wildlife, used ArcGIS to study songbird populations that rely on dry sagebrush habitat (Langston, 2016). These organizations had previously been using separate, fragmented data, which made it difficult to identify issues and establish unified goals (Langston, 2016). By collaborating within ArcGIS, the groups were able to record more comprehensive data regarding disturbances of the sagebrush, and the locations and numbers of birds in these habitats (Langston, 2016). Knowing which areas of this ecosystem are most at risk, and therefore which songbird populations are most vulnerable, allows conservation efforts to become more focused (Langston, 2016).

ArcMap, one of the specific applications available through ArcGIS, is especially useful for managing layers of geographic data. Data layers may include land cover types, road maps, and aerial photographs, which can all be organized and analyzed with a number of geoprocessing tools. For example, a report on kestrels studied the landscape features that promoted the occupancy of nest boxes across Massachusetts. Using ArcMap, this team was able to overlay land cover maps with land use data layers from a government database (Berner et al., 2015). This allowed them to quantify land types in regions of interest, and in turn draw conclusions about how land usage in areas near nest boxes contributes to whether or not these boxes are occupied (Berner et al., 2015). However, land cover and land use data is not readily available for the entire globe. In these cases, land cover can be digitized and classified manually in ArcMap. Geoprocessing tools can then be used for a number of statistical analyses.

Chapter 2: Habitat Selection by Eastern Whip-poor-wills

Abstract

Full annual-cycle conservation is critical for the Eastern Whip-poor-will (*Antrostomus vociferus*), as this species has declined 69% across its range since 1970. Using GPS data loggers, we characterized wintering habitat used by whip-poor-wills. In 2018, we placed GPS tags (Lotek Pinpoint-10) on twenty-one males breeding in Massachusetts and recaptured 57% (12 males) in summer 2019. GPS tags collected data during fall and spring migration and the wintering period. Data from tags indicated that these males wintered primarily in Mexico and Central America. To compare habitat in whip-poor-will territories versus random locations, we quantified land cover (e.g., forest cover, agriculture, development, and young forest) from aerial photos at three distinct spatial scales, including the territory, local (2-km), and landscape (5-km) scales. Most territories were small (less than 2.5 hectares) and contained a mixture of mature forest, young forest, and some included agricultural land. Habitat differences were apparent, with 43% less agriculture and 31% more forest in actual compared to random locations at the 2 km spatial scale. As basic natural history and ecological information is lacking for this species, results from this study will support the development of full annual-cycle conservation efforts.

Introduction

In Massachusetts, Eastern Whip-poor-will (*Antrostomus vociferus*) populations have been experiencing an annual decline of 6.6% since 1966 (Sauer et al., 2017). While they are known to breed throughout the eastern United States, they are not found ubiquitously across the landscape. Instead they are found in localized breeding populations that are closely associated with pine-oak forests with occasional clearings and small amounts of underbrush (Wilson & Watts, 2008; Cink et al., 2017). The recent declines of whip-poor-will populations are likely caused in part by loss of this type of habitat (Akresh & King, 2016). While habitat loss is likely a factor, many ornithologists believe that not all available habitat is occupied during the breeding season, leading researchers to speculate on additional causes of population decline. This species also exhibits cryptic behavior, making it difficult to study them and thereby establish full life-cycle conservation efforts. Automated tracking devices, however, allow the opportunity to fill in some of these data gaps for this species (Wilmers et al., 2015).

Whip-poor-wills are of particular interest in Massachusetts where they are listed as a “Species of Special Concern” under the Massachusetts Endangered Species Act. This species is considered a “Species of Greatest Conservation Need” by Migratory Bird Joint Ventures (http://mbjv.org/) and the North American Bird Conservation Initiative has stated that it is a species at risk of extinction without significant action (2016) throughout its breeding range. Fortunately, there have been multiple efforts from both state and local agencies that aim to promote conservation of the species. While this will help to improve populations, this is only on the breeding grounds. Little information is known about the migration and wintering ecology of the whip-poor-will and therefore land management for the species during its migration and wintering periods is impossible. Information from this project will make this possible. Increasing conservation efforts directed toward whip-poor-wills and their habitats will also benefit an entire suite of wildlife that depend on similar habitat and increase biodiversity across the landscape, which is critical to building healthy ecosystems.

This study sought to identify and characterize habitat used by Eastern Whip-poor-will populations in order to designate priority habitats and staging areas. Specifically, we used land cover data to examine the habitat selected by whip-poor-wills on their wintering grounds. We hypothesized that habitat used by whip-poor-wills differs from random sites available to birds. In particular, we examined land cover types (forest, agriculture, residential, etc.) at the local (e.g., 2km) and landscape (e.g., 5 km) scales. A pair of recent studies on the migration patterns and wintering locations of the whip-poor-will were conducted by English et al. (2017) in Canada and Tonra et al. (2018) in Ohio. These groups used geolocators and GPS tags, respectively, to track individuals and found that their birds were wintering in locations along the Gulf of Mexico and through Central America as far as Costa Rica. Our study used GPS tags to examine the wintering grounds of whip-poor-wills from Massachusetts and these GPS tags provided specific location coordinates, allowing for precise tracking of the movements of the birds. We were able to define a wintering territory for each bird, and analyze which features of this territory promoted habitat selection.

Methods

In summer 2018, we affixed 27 GPS tags (PinPoint 10 GPS tag, Lotek Wireless Inc.; IACUC #17-88) on birds and focused our 2019 target netting efforts on recapturing these individuals at Bolton Flats Wildlife Management Area (WMA), Montague Plains WMA, and Joint Base Cape Cod in 2019 (Figure 4). We sampled birds on 17 nights from May 6th – June 24th 2019. We used playback recordings to lure territorial whip-poor-wills into a mist-net set up that consisted of two adjacent 12 m x 3 m nets. Net lanes were chosen based on the habitat characteristics and locations of uncaught males. We prioritized small conifers when searching for net lanes but if there were none where we had previously heard a male, we placed a net along the forest edge or through a corridor in the shrubs. We finished setting up nets 30 minutes before sunset. Once the first male was heard, we turned on the call playback and placed it under each setup. Captured birds were brought to a banding station, where we attached a USGS number band and recorded the bird's age and morphological characteristics (e.g. weight, wingspan). Next, we placed new GPS tags on each bird's back using a leg-loop harness (Rappole and Tipton, 1991), at which point the birds were released from the station.

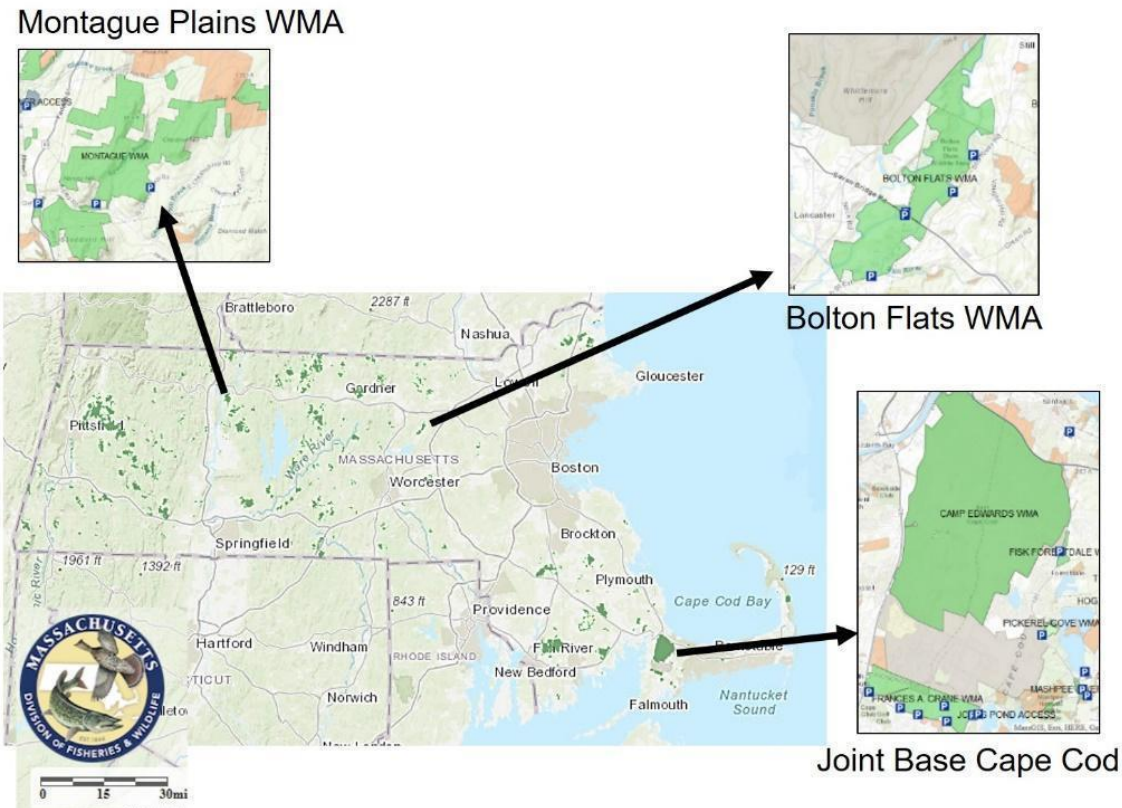

Figure 4. Study sites where whip-poor-wills were targeted for recapture in 2019

GPS tags were programmed to take 62 points over the course of a year, on the following schedule: one point collected at the night of deployment, one point every seven days from September 2nd until September 19th, one point every 3 days from September 22nd to November 27th , one point every 7 days from December 4th to February 28th , and one point every 3 days from March 4th to May 6th . Times of data collection were based on potential time periods for fall migration, wintering period, and spring migration (English et al. 2017, Matthews, personal communication).

We checked and retained data from each returned GPS tag that had GPS fixes with duration of precision value <5. Next, we generated minimum convex polygons (MCPs) to represent winter territories using the adehabitatHR package (Calenge, 2006) in R (v. 3.5.2; R Core Development Team 2019). An MCP is "the smallest polygon around points with all interior angles less than 180 degrees" (Paterson, 2018). While we also defined wintering territories using the kernel method, we used MCPs for our analyses because they typically incorporate a larger area. Given our low sample size and that data points were not collected every day, we wanted to include as much land cover as possible that the whip-poor-wills may have been using for habitat.

We imported shapefiles containing the winter territory MCP for each bird into ArcMap 10.7 (ESRI, Redlands, California), on top of a World Imagery Basemap layer. Using the aerial photography of the basemap layer, we identified and characterized land cover types of interest: agriculture, bare, forest, open water, plantation, developed, wetland, and young forest (Appendix 1). We digitized land cover types within a 5-km radius circle around a point centered on the winter territory and a point centered on a “random” polygon within 35 km of the actual territory location (Figure 5). We used the 35 km measurement because this was the shortest distance between primary and secondary wintering territories for birds that relocated during the wintering season. The primary wintering territory was always the first territory that the bird arrived at and the territory in which the bird stayed the longest. Picking a random location within 35 km allowed us to choose a “random” location that was within the same landscape as the actual winter territory (Appendix 2). The “random” location was used as a point of comparison. If the land covers of an actual, selected location differ from the random, this demonstrated an individual’s selection of specific habitat features.

Figure 5. A screenshot of the 35 km clip with the 2 km and 5 km radii at an actual location in the center and the 2 km and 5 km radii for a random location on the left.

On the wintering grounds, we characterized habitat types by looking at prior and current aerial photographs from Google Earth Pro 7.3.2 (Google, Mountain View, California). After digitizing, we used the geoprocessing features of ArcMap to calculate the areas of all of the polygons representing each land cover type. We tested for differences between actual and random locations in four of the most relevant land types (mature forest, agriculture, developed land, and young forest) using paired t-tests (Appendix 3). Each land cover was analyzed for differences at the territory, 2 km, and 5 km scales. Next, we ran a multiple correlation of all land cover types in order to determine if any were significantly correlated. Finally, we had three birds that relocated from their first winter territory to a second. In order to identify possible causes for this relocation, we ran a t-test on percent forest cover of the one territory birds as compared to the two territory birds.

Results

Field Results

In the summer of 2018, we deployed 27 GPS tags, 21 of which were onto males. We recaptured 12 of these tagged birds, giving us a 57% recapture rate for males. We were unsuccessful at recapturing any tagged female individuals. We have attributed this to the fact that females are less likely to be responsive to the territorial call that was played from the playback recorders. We did not attempt to spotlight females on nest in order to increase female recapture rates.

GPS Data

The birds we recaptured wintered in a variety of locations and countries. Six of the birds wintered in Mexico, 1 in Belize, 2 in Guatemala, 2 in Honduras, and 1 in South Carolina (Figure 6). Overall there were 305 total GPS points taken across all 12 birds, with 90% of those being usable (n = 275). The birds arrived at the wintering grounds at different times over a two-month period from October 1st to December 4th. The difference in arrival times influenced the number of data points on each winter territory and the mean number of data points that were used to estimate territory size was 23 (range 9-35) per territory. The mean MCP territory size was 3.2 ha (2.3 SE).

Figure 6. The wintering locations of all 12 individuals, as indicated by the yellow dots.

Habitat Selection

Given our low sample size, for all statistical tests, we used a threshold of $P = 0.10$ rather than 0.05 in order to determine significance. There was 43% less agriculture at the actual locations than the random at the 2 km scale ($t = -1.81$, $P = 0.098$) and 21% less at the 5 km scale ($t = -1.83$, $P = 0.094$, Figure 7). With forest cover the reverse is true as there is marginally more forest cover at the territory scale ($t = 1.74$, $P = 0.109$, Figure 8). At the 2 km scale, there was

31% more forest cover (t = 3.00, P = 0.012) and at the 5 km scale there was 19% more (t = 2.70, P = 0.021) as compared to the random locations (Figure 8). There were no statistically significant differences between the amount of developed land on the actual vs. random locations (all P > 0.100), however on average there was less developed land around actual locations than random (Figure 9). For young forest, there was marginally more cover at the 2 km scale (t = -1.75, P = 0.108) and significantly more cover at the 5 km scale (t= -1.82, P = 0.096, Figure 10) around random locations.

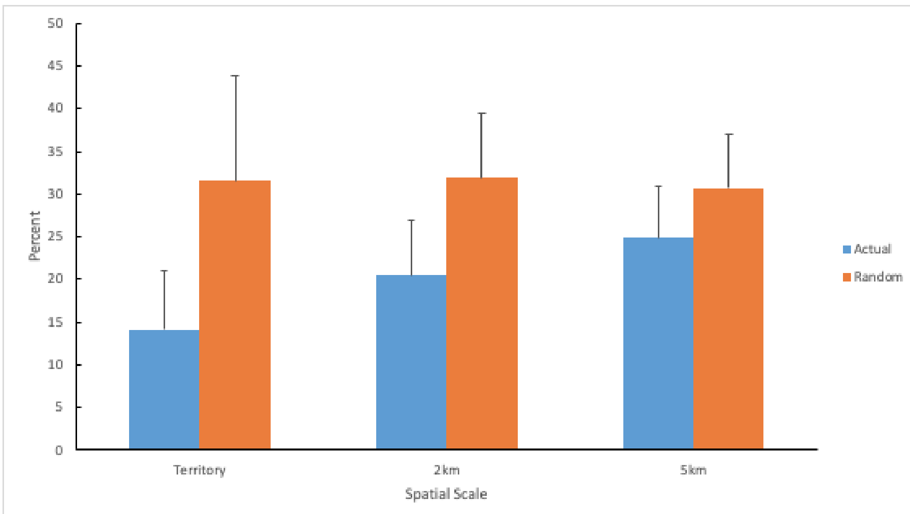

Figure 7. Mean percent agriculture (+SE) on the actual and random locations at the territory, 2 km, and 5 km scales.

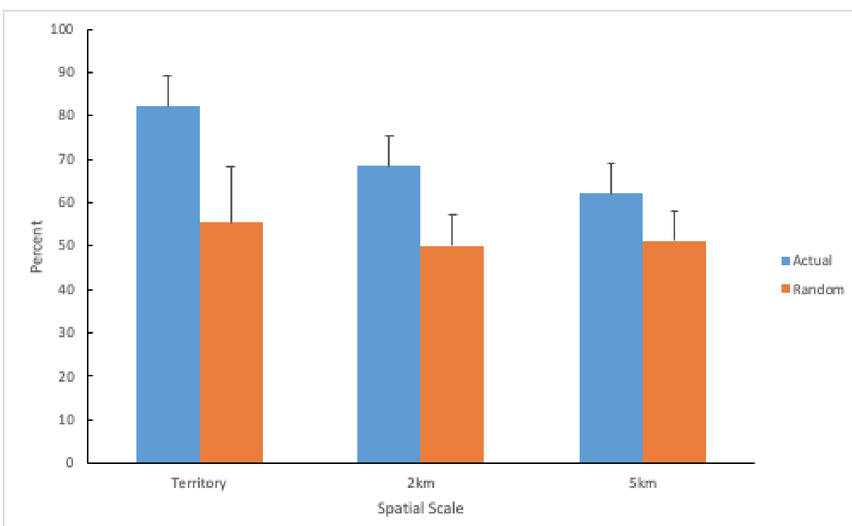

Figure 8. Mean percent forest cover (+SE) on the actual and random locations at the territory, 2 km, and 5 km scales.

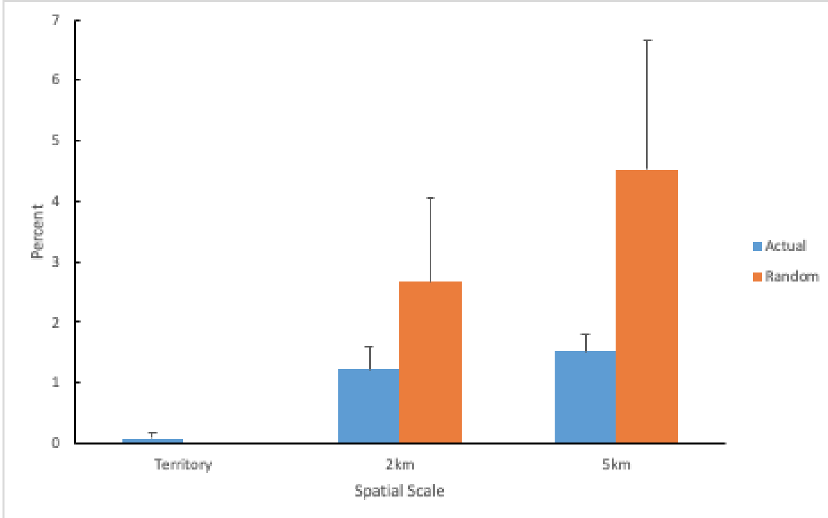

Figure 9. Mean percent developed land cover (+SE) on the actual and random locations at the territory, 2 km, and 5 km scales.

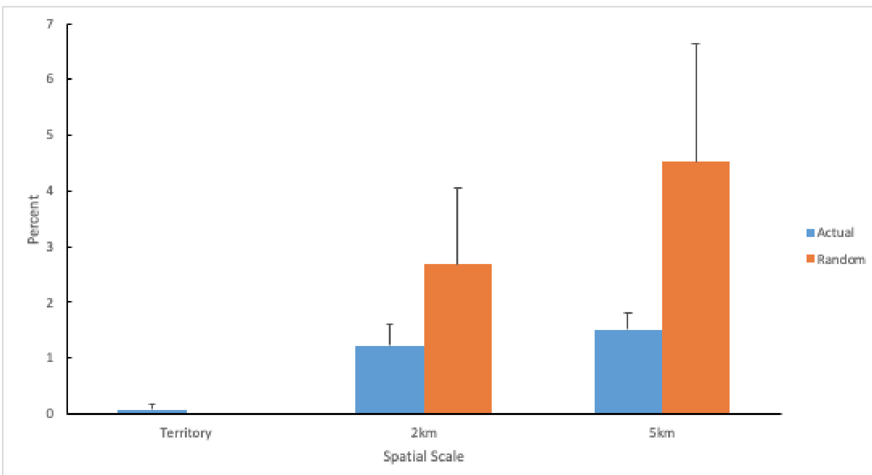

Figure 10. Mean percent young forest cover (+SE) on the actual and random locations at the territory, 2 km, and 5 km scales.

There was a significant negative correlation at every scale between agriculture and forest (Terr: $r = -0.78$, $P < 0.01$, 2km: $r = -0.78$, $P < 0.01$, 5km: $r = -0.71$, $P < 0.01$). Additionally, there was a significant negative correlation between forest and young forest at the 2 km ($r = -0.36$, $P = 0.09$) and 5 km scale ($r = -0.38$, $P = 0.07$). There were no correlations among developed land cover and forest, agriculture, or young forest (all $P > 0.10$). In addition, for primary territories, one-territory birds had, on average, 67% more forest cover on their wintering territory than two-territory birds ($t = 5.296$, $P < 0.001$, Figure 11).

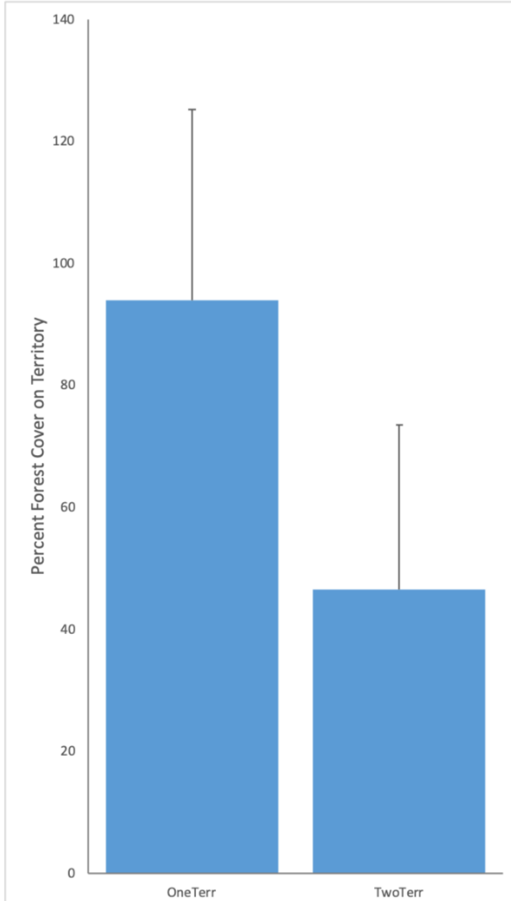

Figure 11. Average forest cover (+SE) of primary territories for one-territory and two-territory birds.

Discussion

The whip-poor-wills in this study were wintering on highly active and heavily worked landscapes. Agricultural land was quite prevalent on the landscapes, which changed rapidly from year to year. Below (Figure 12) is a comparison of agricultural development near the winter territory of bird 2110 in Oaxaca, Mexico. From 2014 to 2019, there was a notable increase in agricultural development moving east towards the territory. Mature forest was frequently being replaced by agriculture, and this is supported by the strong inverse correlation between the two land types at every scale. This is significant as our land cover analysis revealed that whip-poor-wills are selecting for heavily forested landscapes and avoiding agricultural disturbance. On the breeding grounds, whip-poor-wills are known to utilize forest without dense understory and are closely associated with edge habitat (Wilson & Watts, 2008). In Massachusetts specifically, whip-poor-wills are associated more often with open canopy early successional forest (Akresh & King, 2016). Analogous conclusions about the specifics of the forest used on the wintering grounds (where foraging is the highest priority rather than raising offspring) have yet to be drawn, which invites opportunities for further research. Given the trend of agricultural expansion replacing the mature forest that the birds are selecting, future landscape changes will most likely play a role in further population declines.

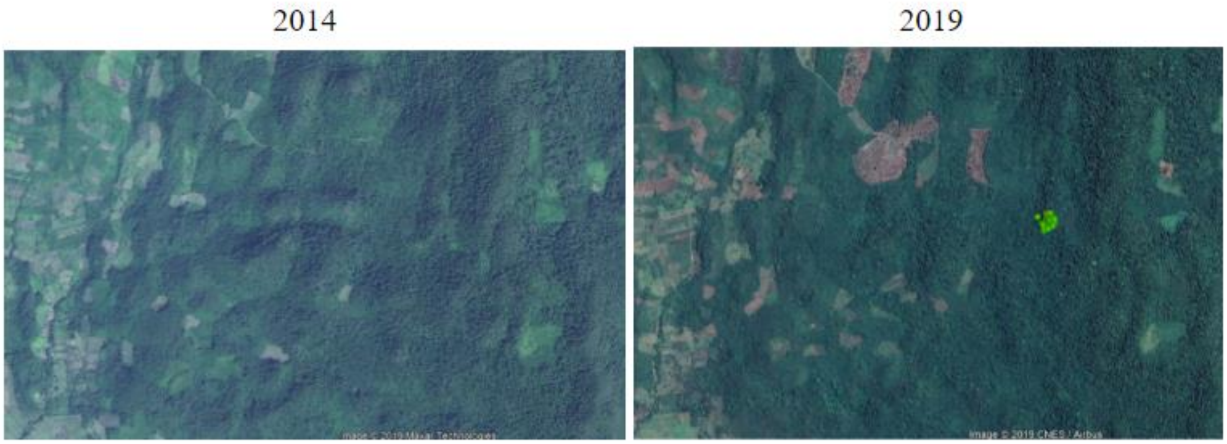

Figure 12. Comparison of the winter territory of bird 2110 in Oaxaca, Mexico from 2014 to 2019. Agricultural land in the area is expanding, encroaching on the territory from the left.

These potential landscape changes should also be considered in the context of manually digitizing and classifying land cover based on aerial imagery, which is associated with inherent uncertainty. Areas that were classified as forest may have been agroforestry (such as shade coffee plantations), and areas that were cleared for agriculture may be used for crops, plantations, or may be allowed to regenerate. The effects of these varying agricultural expansions are difficult to predict when the future land use is unknown. If shade coffee agroforestry was to move into an area, this would be less detrimental, because these plantations do still afford some canopy cover for birds wintering in the area. In contrast, the introduction of an oil palm plantation would be more damaging, as these plantations are widely accepted as a significant threat to biodiversity, and birds in particular (IUCN, 2018).

Plantations were specifically noted when classifying polygons, but may have been included in the broader forest or agriculture classifications depending on the intensity and type of plantation. Pine plantations tend to resemble actual pine forest, so it was reasonable to consider them part of the forest category, whereas oil palm plantations are much more distinct. We also classified residential areas based on density, but combined each density category as part of the broader “development” land cover type. Low-density residential development, where a few houses are spread out among an area, may have different effects on habitat selection than a town or city; future research may find it useful to keep these classifications separate to test for residential density effects. In a similar vein, we found that agriculture was positively correlated with development, but we are curious if the correlation is stronger for high-density residential areas. Re-evaluating the agriculture-development correlation at each of the three density levels may provide additional insight into areas that are most at risk for agricultural expansion based on the residential density of the surrounding land.

The results of our forest cover test between the one-territory and two-territory birds showed that all of the birds that moved had significantly less forest cover on their primary territory than those that did not. This suggests that poor habitat quality due to agricultural expansion (both prior to and during the wintering season) may be a reason for the relocation.

Three whip-poor wills from a recent study conducted by Tonra et al. (2019) also relocated during the wintering season. Multiple other studies have demonstrated that food availability is closely correlated with habitat use in other Nearctic-Neotropical migratory birds (Cooper, Sherry, & Marra, 2015; Smith, Reitsma, & Marra, 2011), which may be another related factor contributing to relocation. However, while all of the birds that relocated did so at distances >35 km, their birds relocated anywhere from 1.5 and 115 km (Tonra et al., 2019). Ng et al. (2018) also recently documented wintering ground relocation of the common nighthawk but do not comment on causation. Future research could detail how forest fragmentation impacts activity and habitat selection on the breeding grounds.

Tonra et al. (2019) had additional results that were markedly similar to ours, although their methodology differed. Instead of using territories defined by the MCP, this study utilized home range estimation to determine habitat utilized by each individual. They found that all individuals' home ranges contained >40% forest and in all cases non-forest land cover constituted <50% of the total land cover. Interestingly, all of their birds migrated to Central America and southern Mexico except one, which wintered in southern Texas. We also had one outlier (2117) that did not winter in Central America or Mexico, but rather South Carolina.

Bird 2117 was an outlier for a number of reasons. This individual's wintering territory (by MCP) was 28.9 ha while the average of all other birds was 0.88 ha (Figure 12). This drastically shifted the average territory size. In addition, this bird left the breeding grounds nine days later, arrived at the wintering territory a month earlier, and stayed on the wintering grounds at least 34 days longer than average. Unfortunately, this GPS unit ran out of battery on March 31, 2019, at which point the bird was still on its wintering territory. The fact that this bird wintered much further north (in SC) than the rest of the birds questions the possibility of a "leap frog" migration, where the northern breeding populations migrate further south than the southern breeding populations. More research would be needed to investigate the potential dynamics of such an occurrence.

Figure 13. Screenshot of aerial image of bird 2117's wintering territory in Edisto, South Carolina. Note the agricultural land use surrounding the territory.

The results of our land cover analysis tests also allowed us to both pinpoint the relevant scale for habitat selection and display which types of habitat are being selected. Given that we had the most significant differences in land covers at the 2 km scale, it seems likely that this is the most relevant scale for the bird in terms of habitat selection and therefore the most applicable for land management. Similar results were found in a study that detailed impacts of tropical forest loss and fragmentation on the occurrence of 10 bird species in eastern Guatemala (Cerezo et al., 2010). These researchers found that 8 of their 10 study species responded negatively at the 1 km level to habitat fragmentation and clearing for agriculture, which further supports the importance of local land cover in habitat selection.

In the field, we had the best capture success on clear nights with a half moon. If the moon was too bright the birds were more readily able to locate and avoid the net. If the moon was new or it was overcast, the birds were not as active. Of the tagged males in 2018, nine out of ten after-second-year birds (aged when tagged) were recaptured the next year as opposed to only three out of eleven second-year birds. We hypothesize that this might be because not all second-year birds have established a breeding territory by the end of the summer. Tonra et al. (2019) had similar recapture results, recapturing 11 of 21 birds. Given that this cryptic species lacks detailed movement information, more research is needed into how individuals interact and compete on the breeding grounds.

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Appendices

Appendix 1: Land Cover Classification Details

Land Use Type	Description
Agriculture	Cleared land; pasture, hay, crops, shade coffee; sometimes pasture/hay with a few trees
Forest	>60-70% canopy cover; could have planted bushes underneath; could include things like agroforestry
Open Water	Rivers or lakes
Plantations	Usually rows of trees; may include pine, eucalyptus, oil palm
Residential - Low	1-10 houses, may all be on one road; included in “development” category for analysis
Residential - Medium	11+ houses, some small network of roads; adjoining land use can be agriculture; included in “development” category for analysis
Residential - High	Towns and cities with clear city centers; included in “development” category for analysis
Industrial	Sand and gravel pits; included in “development” category for analysis

Appendix 2: ArcGIS notes

How to create a new shapefile

- Open ArcCatalog
- Right click on the folder name, New, Shapefile
- Name the shapefile, select the appropriate type (like point or polygon) and immediately set the projection by clicking on Edit (Geographic, World, WGS1984)

Convert a tif layer to a shapefile (used for the GLC30 layers)

- Open ArcToolbox / Conversion Tools / From Raster / Raster to Polygon
- Input raster: select the tif layer
- Output polygon features: name the new layer that will be created and place in correct folder
- Save / Okay (this can take some time to process)

How to create a new polygon from the file with all of the polygons (This was used when I exported all 12 of the winter MCPs into ArcMap as one data layer…but I really needed a data layer for each of the birds)

- Open the attribute table and select the polygon of choice (e.g., 2117) so that it is highlighted
- Right click the layer name in the Table of Contents, Data, Export Data
- Export: Selected features; Place it in the correct folder and name it, make sure to save it as a shapefile and add it to the View

How to make a 35km-radius clip centered on a polygon

- Open WhipHabitat (full globe aerial imagery) in ArcMap
    - If starting from scratch, go to Add Data, Add Basemap, Imagery
- Add shapefiles for desired polygon and 35km circle associated with said polygon (Add Data → Connect to Folder → Type in desired folder name → Navigate to desired shapefile)
- Right click on shapefile layer → Zoom to Layer
- Open the Editor Toolbar, select Start Editing
- Open the Create Features menu
- Select the shapefile in which you want to edit (i.e. 35km circle)
- Under Construction Tools, select Circle
    - Place the center of the circle in the center of the polygon, press R to enter a specific radius (i.e. 35000m), Enter
- Go to View → Data Frame Properties → Data Frame
    - Under Clip Options, select Clip to Shape
    - Specify Shape → Outline of Features → select appropriate feature
    - Can also edit Extent Used by Full Extent Command to be the same feature
    - Apply

- Save edits and stop editing
    - Save the file as an appropriately titled 35km clip

How to drop a random point onto the designated (e.g., 35-km) area

- Have a 35-km radius clipped area already created
- Open ArcToolbox
    - Select Data Management Tools/Sampling/Create Random Points
        - Output location should be the correct folder in the research lab
        - Name output feature class - BirdID Random (e.g., 2112 Random)
        - Constraining feature class - select the 35-km clip layer
        - Reduce the number of points to ~5 so it doesn't take as long to run
        - Hit Ok
        - It takes a while to create and then there will be a new shapefile layer
- Open the attribute table. Start editing- select the layer to edit. Delete selected points and only leave the first random point that works for this project (that can have a 5-km circle over land). Stop editing and save edits.

How to digitize land cover types

- Have a shapefile for Digitization already created
- Open the appropriate 35km clip, add the Digitization shapefile layer
- Open Editor toolbar, start editing, select Digitization shapefile in the Create Features menu
    - Under Construction Tools, select polygon
- Click to drop points around the edges of a land feature
    - Double click on the last point to complete the shape
    - To be able to see land cover in the shape, click on the box under the data layer name in the Layers menu and change fill type to Hollow (can also adjust border weight and color)
- Continue making polygons as needed
    - Can also use the freehand tool to draw along the edges of a land feature
    - Autocomplete tools are useful for connecting adjacent polygons - start dropping points on the edge of an already made polygon, drop the last point also on an already existing edge, and provided there are no other gaps, ArcMap will connect the new polygon to the existing one
- The Merge tool (both in the Editor dropdown menu and Geoprocessing tab) is useful for combining multiple polygons of the same land cover type into one
    - Select all desired polygons, select Merge, then Apply
- Be sure to save edits, stop editing, and save the file when done

How to create a buffer

- Select Geoprocessing
- Select Buffer
- Input feature: select the layer (like territory point) that you want to draw the buffer around
- Output Feature Class: name the layer appropriately and make sure it gets saved in the correct folder
- Distance – linear unit…for a 5km buffer, write 5000 m
- Hit “Okay” and it should create a new layer

How to classify land cover

- Once all polygons are digitized open the Attribute table of that layer
- Click on the top right Table Options and select Add Field
    - Name the column like ‘Landcover’
    - Type: Text
    - Length: 20 (this is how many characters it will allow)
- This will create a new column in the Attribute Table
- You will need to turn on the Editor (Start Editing) to then add information in that column
- Use GoogleEarthPro historical images to see a range of images to best classify forest, agriculture, developed, young forest, etc.

How to select digitized polygons within a buffer

- Note: the digitization layer was created larger than any of the buffer layers (2km, and 5km)
- Under the Geoprocessing tab, select Intersect
- Input Features: select the two layers that you want to combine: like ‘2114 randomization’ and ‘2114 random 2km poly’
- Output Features: name the new layer that will get created (like ‘2114 random 2km intersect’) and place in correct folder
- No need to change other pieces

How to calculate land cover area

- Once the above layer is created open the Attribute Table
- Create a new column (Table Options → Add Field)
    - Name column (like Area_ha)
    - Type: Double (this allows decimals as well)
    - Precision: 4
    - Scale: 6
    - Hit Okay
- Once the Column is created, right click on the column header
- Select Calculate Geometry (click yes at next box)
    - Property: Area

- Use coordinate system of the data frame (if everything was set up properly before you shouldn't have to change anything here)
    - Units: select Hectares [ha]
    - Hit okay
- Then go back to the Attribute Table and check to make sure that numbers are filled into the column. Also check all polygons. I sort the table by Area (by double clicking on the header of the column) to see if there are any accidental double-counted polygons. This happened a few times when a very large polygon, like forest, was 'under' small polygons of a different land use.

Change symbology to reflect the landcover categories

- Right click on layer → Properties → Symbology → Categories → Unique
- From the Value Field drop down select the correct column header that represents the categories you want displayed (e.g., landcover or gridcode- for GLC)
- Add All Values (this may take a while if there are a huge number of polygons because it has to read through each one)
- Once it has them all you can go in and change the label name that is displayed and you can change the color for the polygons
- Hit Apply - you should see your map change and its labels

Appendix 3: R code for Statistical Analyses

Land Cover T-Tests

```
library(readxl)
All_birds_all_scales_landcover <- read_excel("Desktop/Bird Data/WHIPs/All birds all scales landcover.xlsx",
+     sheet = "MasterSheet", range = "A1:O73")
View(All_birds_all_scales_landcover)
AllData=setDT(All_birds_all_scales_landcover)
Territory <- AllData[Scale == "territory"]
TwoK <- AllData[Scale == "2km"]
FiveK <- AllData[Scale == "5km"]
View(Territory)
View(TwoK)
View(FiveK)
> t.test(agriculture ~ Plot, data = Territory, paired = TRUE)

Paired t-test

data:  agriculture by Plot
t = -1.1468, df = 11, p-value = 0.2758
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -50.88317  16.02201
sample estimates:
 mean of the differences
-17.43058

> t.test(agriculture ~ Plot, data = TwoK, paired = TRUE)

Paired t-test

data:  agriculture by Plot
t = -1.8106, df = 11, p-value = 0.09758
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -25.242593   2.456625
sample estimates:
 mean of the differences
-11.39298

> t.test(agriculture ~ Plot, data = FiveK, paired = TRUE)

Paired t-test
```

data: agriculture by Plot
t = -1.83, df = 11, p-value = 0.09446
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -12.712972   1.170116
sample estimates:
  mean of the differences
-5.771428

> t.test(forest ~ Plot, data = Territory, paired = TRUE)

Paired t-test

data: forest by Plot
t = 1.7409, df = 11, p-value = 0.1096
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -7.049719 60.397784
sample estimates:
  mean of the differences
26.67403

> t.test(forest ~ Plot, data = TwoK, paired = TRUE)

Paired t-test

data: forest by Plot
t = 3.0002, df = 11, p-value = 0.01208
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  4.87854 31.74910
sample estimates:
  mean of the differences
18.31382

> t.test(forest ~ Plot, data = FiveK, paired = TRUE)

Paired t-test

data: forest by Plot
t = 2.698, df = 11, p-value = 0.02073
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  2.001978 19.733298
sample estimates:

```
  mean of the differences
10.86764

> t.test(Developed ~ Plot, data = Territory, paired = TRUE)

Paired t-test

data:  Developed by Plot
t = 1, df = 11, p-value = 0.3388
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -0.1020754  0.2720614
sample estimates:
  mean of the differences
0.08499302

> t.test(Developed ~ Plot, data = TwoK, paired = TRUE)

Paired t-test

data:  Developed by Plot
t = -0.9721, df = 11, p-value = 0.3519
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -4.742238  1.836583
sample estimates:
  mean of the differences
-1.452827

> t.test(Developed ~ Plot, data = FiveK, paired = TRUE)

Paired t-test

data:  Developed by Plot
t = -1.4623, df = 11, p-value = 0.1716
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -7.511816  1.514772
sample estimates:
  mean of the differences
-2.998522

> t.test(youngforest ~ Plot, data = Territory, paired = TRUE)

Paired t-test
```

```
data:  youngforest by Plot
t = -0.18461, df = 11, p-value = 0.8569
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -14.69543  12.42105
sample estimates:
  mean of the differences
-1.13719

> t.test(youngforest ~ Plot, data = TwoK, paired = TRUE)

Paired t-test

data:  youngforest by Plot
t = -1.7481, df = 11, p-value = 0.1083
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -13.689447   1.570055
sample estimates:
  mean of the differences
-6.059696

> t.test(youngforest ~ Plot, data = FiveK, paired = TRUE)

Paired t-test

data:  youngforest by Plot
t = -1.8183, df = 11, p-value = 0.09632
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -13.626643   1.297348
sample estimates:
  mean of the differences
-6.164647
```

CorrelationTests

```
> library(readxl)
> All_birds_all_scales_landcover <- read_excel("Desktop/Bird Data/WHIPs/All birds all scales landcover.xlsx",
+     sheet = "MasterSheet", range = "A1:O73")
> View(All_birds_all_scales_landcover)
> AllData=(All_birds_all_scales_landcover)
> AllData=setDT(All_birds_all_scales_landcover)
```

```
>
> Territory <- AllData[Scale == "territory"]
> TwoK <- AllData[Scale == "2km"]
> FiveK <- AllData[Scale == "5km"]
>
> setDF(AllData)
> setDF(Territory)
> setDF(TwoK)
> setDF(FiveK)

> Territory <- select(Territory, agriculture, forest, YoungForest, Developed)
> View(Territory)
> library("FSA", lib.loc="/Library/Frameworks/R.framework/Versions/3.5/Resources/library")
## FSA v0.8.22. See citation('FSA') if used in publication.
## Run fishR() for related website and fishR('IFAR') for related book.
> library(FSA)
> headtail(Territory)
   agriculture     forest YoungForest Developed
1      0.00000 100.000000     0.00000         0
2     93.26425   6.735751     0.00000         0
3      0.00000 100.000000     0.00000         0
22     0.00000 100.000000     0.00000         0
23     0.00000  57.167576    42.83242         0
24    93.39564   6.604362     0.00000         0
> install.packages("psych")
> library("psych", lib.loc="/Library/Frameworks/R.framework/Versions/3.5/Resources/library")
> library("mnormt", lib.loc="/Library/Frameworks/R.framework/Versions/3.5/Resources/library")
> corr.test(Territory,
+           use = "pairwise",
+           method="pearson",
+           adjust="none",
+           alpha=.05)
Call:corr.test(x = Territory, use = "pairwise", method = "pearson",
    adjust = "none", alpha = 0.05)
Correlation matrix
            agriculture forest YoungForest Developed
agriculture        1.00  -0.78       -0.20     -0.06
forest            -0.78   1.00       -0.16      0.09
YoungForest       -0.20  -0.16        1.00     -0.06
Developed         -0.06   0.09       -0.06      1.00
Sample Size
[1] 24
Probability values (Entries above the diagonal are adjusted for multiple tests.)
            agriculture forest YoungForest Developed
agriculture        0.00   0.00        0.35      0.77
```

```
forest          0.00   0.00        0.46      0.67
YoungForest       0.35   0.46        0.00      0.77
Developed         0.77   0.67        0.77      0.00

 To see confidence intervals of the correlations, print with the short=FALSE option
> AllDataCorr <- select(AllData, agriculture, forest, YoungForest, Developed)
> TwoKCorr <- select(TwoK, agriculture, forest, YoungForest, Developed)
> FiveKCorr <- select(FiveK, agriculture, forest, YoungForest, Developed)
> corr.test(AllDataCorr,
+           use = "pairwise",
+           method="pearson",
+           adjust="none",
+           alpha=.05)
Call:corr.test(x = AllDataCorr, use = "pairwise", method = "pearson",
    adjust = "none", alpha = 0.05)
Correlation matrix
            agriculture forest YoungForest Developed
agriculture        1.00  -0.77       -0.14      0.18
forest            -0.77   1.00       -0.28     -0.25
YoungForest       -0.14  -0.28        1.00      0.11
Developed          0.18  -0.25        0.11      1.00
Sample Size
[1] 72
Probability values (Entries above the diagonal are adjusted for multiple tests.)
            agriculture forest YoungForest Developed
agriculture        0.00   0.00        0.23      0.13
forest             0.00   0.00        0.02      0.04
YoungForest        0.23   0.02        0.00      0.36
Developed          0.13   0.04        0.36      0.00

 To see confidence intervals of the correlations, print with the short=FALSE option
> corr.test(TwoKCorr,
+           use = "pairwise",
+           method="pearson",
+           adjust="none",
+           alpha=.05)
Call:corr.test(x = TwoKCorr, use = "pairwise", method = "pearson",
    adjust = "none", alpha = 0.05)
Correlation matrix
            agriculture forest YoungForest Developed
agriculture        1.00  -0.78       -0.21      0.18
forest            -0.78   1.00       -0.36     -0.24
YoungForest       -0.21  -0.36        1.00     -0.09
Developed          0.18  -0.24       -0.09      1.00
Sample Size
```

```
[1] 24
Probability values (Entries above the diagonal are adjusted for multiple tests.)
            agriculture forest YoungForest Developed
agriculture        0.00   0.00        0.34      0.39
forest             0.00   0.00        0.09      0.25
YoungForest        0.34   0.09        0.00      0.69
Developed          0.39   0.25        0.69      0.00

 To see confidence intervals of the correlations, print with the short=FALSE option
> corr.test(FiveKCorr,
+           use = "pairwise",
+           method="pearson",
+           adjust="none",
+           alpha=.05)
Call:corr.test(x = FiveKCorr, use = "pairwise", method = "pearson",
    adjust = "none", alpha = 0.05)
Correlation matrix
            agriculture forest YoungForest Developed
agriculture        1.00  -0.71        0.03      0.30
forest            -0.71   1.00       -0.38     -0.36
YoungForest        0.03  -0.38        1.00      0.30
Developed          0.30  -0.36        0.30      1.00
Sample Size
[1] 24
Probability values (Entries above the diagonal are adjusted for multiple tests.)
            agriculture forest YoungForest Developed
agriculture        0.00   0.00        0.88      0.15
forest             0.00   0.00        0.07      0.09
YoungForest        0.88   0.07        0.00      0.16
Developed          0.15   0.09        0.16      0.00

 To see confidence intervals of the correlations, print with the short=FALSE option
```

Forest Cover T-Tests

```
> library(readxl)
> TerrForCov <- read_excel("Desktop/Bird Data/WHIPs/All birds all scales landcover.xlsx",
+     sheet = "MasterSheet", range = "L76:M88")
> View(TerrForCov)
> library(readxl)
> TwoKForCov <- read_excel("Desktop/Bird Data/WHIPs/All birds all scales landcover.xlsx",
+     sheet = "MasterSheet", range = "L90:M102")
> View(TwoKForCov)
> library(readxl)
> FiveKForCov <- read_excel("Desktop/Bird Data/WHIPs/All birds all scales landcover.xlsx",
```

```
+    sheet = "MasterSheet", range = "L104:M116")
> View(FiveKForCov)
> bartlett.test(Value ~ Group, data=TerrForCov)

	Bartlett test of homogeneity of variances

data:  Value by Group
Bartlett's K-squared = 2.3034, df = 1, p-value = 0.1291

> bartlett.test(Value ~ Group, data=TwoKForCov)

	Bartlett test of homogeneity of variances

data:  Value by Group
Bartlett's K-squared = 0.090822, df = 1, p-value = 0.7631

> bartlett.test(Value ~ Group, data=FiveKForCov)

	Bartlett test of homogeneity of variances

data:  Value by Group
Bartlett's K-squared = 0.053504, df = 1, p-value = 0.8171

> t.test(Value ~ Group, data=TerrForCov,
+        var.equal=TRUE,
+        conf.level=0.95)

	Two Sample t-test

data:  Value by Group
t = 5.296, df = 10, p-value = 0.0003495
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 27.42439 67.26001
sample estimates:
mean in group OneTerr mean in group TwoTerr
	93.94344		46.60124

> t.test(Value ~ Group, data=TwoKForCov,
+        var.equal=TRUE,
+        conf.level=0.95)

	Two Sample t-test

data:  Value by Group
```

```
t = 0.48444, df = 10, p-value = 0.6385
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -29.08411  45.24475
sample estimates:
mean in group OneTerr mean in group TwoTerr
             70.39576              62.31544

> t.test(Value ~ Group, data=FiveKForCov,
+        var.equal=TRUE,
+        conf.level=0.95)

	Two Sample t-test

data:  Value by Group
t = 0.031253, df = 10, p-value = 0.9757
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -37.24653  38.30627
sample estimates:
mean in group OneTerr mean in group TwoTerr
             62.20768              61.67781
```