Final Report
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Project Title: Effects of forest management on early-successional avian species in South Carolina

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Summary

Early-successional habitats are a critical habitat type for Ruffed Grouse (*Bonasa umbellus*) and Golden-winged Warblers (*Vermivora chrysoptera*). In the Southern Blue Ridge Ecoregion, early-successional habitats have declined over the last 70 years, and the extent of which Ruffed Grouse and Golden-winged Warblers occupy these habitats at the edge of their ranges is unknown. Understanding the factors that drive the presence or absence of these species in this region is critical to inform quality management of early-successional forests. Additionally, increased knowledge of these species will likely benefit other species of conservation concern that rely on early-successional forests, such as the Prairie Warbler (*Setophaga discolor*), Common Yellowthroat (*Geothlypis trichas*), Field Sparrow (*Spizella pusilla*), and Chestnut-sided Warbler (*Setophaga pensylvanica*). In this study, we examined multi-scale habitat factors to determine specific drivers of presence or absence of Ruffed Grouse, Golden-winged Warblers, and habitat indicator species. Additionally, we employed both human-observer and autonomous recording unit surveys to determine the efficacy of the two methodologies.

Our first objective was to examine the effects of landscape-scale habitat features on Ruffed Grouse occupancy. Ruffed Grouse in the Southern Blue Ridge Ecoregion seem influenced by habitats not typical of their northern range and occur more frequently in landscapes with higher mixed forest and woody wetland cover. In the absence of early-successional forests, Ruffed Grouse may be seeking habitats that act as structural mimics to early-successional forests.

Our second objective was to examine the effects of multi-scale habitat parameters on Golden-winged Warbler, Chestnut-sided Warbler, Prairie Warbler, Common Yellowthroat, and Field Sparrow. As a whole, these species seem to be influenced by landscape and composition, ground cover metrics, vegetation structure, and elevation. Chestnut-sided Warblers may act as

the most effective habitat indicator for Golden-winged Warbler habitat, as they exhibit similar preference for habitat features including elevation and vegetative visual obstruction.

Our third objective was to examine the efficacy of human-observer surveys and autonomous recording unit surveys to detect Ruffed Grouse, Golden-winged Warbler, and early-successional habitat indicator species. Autonomous recording units performed comparably to human observers and may represent an efficient tool for future monitoring protocols.

This study represents the largest known effort to inventory Ruffed Grouse and Golden- winged Warblers in the State of South Carolina. We found low Ruffed Grouse and Golden- winged Warbler occupancy rates across two seasons (spring and summer 2020 and 2021), indicating the need for both robust monitoring protocols and targeted habitat management for the benefit of these species. Our results indicate unique habitat preferences of Ruffed Grouse in the Southern Blue Ridge Ecoregion. Additionally, our results provide insight into multiple parameters that drive early-successional songbird species occupancy. This project provides information that will aid in both habitat management and conservation of high priority early- successional avian species. This project also provides context for efficient monitoring protocols.

Objective 1:
Determine distribution of Ruffed Grouse and Golden-winged Warblers in the Blue Ridge of South Carolina. We will additionally monitor and model Blue-winged Warblers, Prairie Warblers, Indigo Bunting, Field Sparrows, and Common Yellowthroat Warblers as indicators for early-successional habitat.

Accomplishments:
We conducted point count surveys on state-owned and federally managed lands. Point count survey locations were determined through ArcGIS software and stratified across varying land management practices including unmanaged lands and thinned, clear-cut, prescribed burned, and/or wildfire patches. All birds seen and heard during a survey were recorded by the observer. Additionally, survey-specific weather data was recorded for future use in detection probability models. Sites were resurveyed 1 – 3 times and repeat visits were conditional on the presence of target species. This resulted in 63 Ruffed Grouse drumming surveys between March 24 and May 1, 2020 (Fig. 1) and 86 songbird point count surveys (Fig. 2) between May 12 and July 1, 2020. Due to limited detections in 2020, we restructured the survey methodology in 2021. During the 2021 season, we surveyed for Ruffed Grouse at 664 drumming survey stations along 82 secondary and primitive roads and hiking trails. We surveyed for songbirds at 62 unique sites. Survey dates spanned the breeding season of Ruffed Grouse and Golden-winged Warbler, when they would be more likely to drum and sing, respectively. During the 2020 field season, no Ruffed Grouse or Golden-winged Warblers were detected during surveys; however, one grouse was encountered incidentally in-between surveys and there were anecdotal reports of grouse sightings by state biologists and game wardens around the area of Jocassee Gorges. During the 2021 field season, Ruffed Grouse were detected at 7 sites. Shrubland indicator species including Prairie Warbler, Field Sparrow, Indigo Bunting, and Common Yellowthroat were found across sites during both 2020 and 2021.

Key Findings and Results: Ruffed Grouse and Golden-winged Warblers both had low occupancy rates in South Carolina. Ruffed Grouse were detected at 4 sites in Georgia, 2 in North Carolina, and 1 in South Carolina, despite a substantial increase in survey effort during the 2021 season. Estimates for occupancy probability across all sites ranged from 0 to 0.6 (Fig. 3).

Prairie Warblers were the most abundant target species at study sites, detected at 76 of 111 total sites. Field Sparrows were the second most abundant and positively identified at 31 sites. Chestnut-sided Warblers and Common Yellowthroat Warblers were found at very few sites during both seasons, with Chestnut-sided Warblers detected at 9 sites and Common Yellowthroats detected at 5 sites. Chestnut-sided Warblers were found almost exclusively at high-elevation sites in Nantahala National Forest, barring one positive identification in Sumter National Forest in 2020. We detected Golden-winged Warblers at just one site in 2021, where a male and a female occupied a high-elevation Nantahala National Forest site. During both seasons, there were no detections of Blue-winged Warblers or Golden-winged Warbler/Blue-winged Warbler hybrids. Due to the sparse Golden-winged Warbler occupancy observed during both seasons, modeling attempts for this species resulted in non-convergence.

Significant Deviations: Due to the COVID-19 pandemic, funds from this State Wildlife Grant were not used to hire a field technician during the 2020 field season. We instead deferred these funds to 2021 and hired two technicians for that field season. Given the lack of detections of Ruffed Grouse and Golden-winged Warblers in South Carolina, we added additional sites near the border of South Carolina in Georgia and North Carolina and increased our survey effort in South Carolina for 2021.

Objective 2:
Conduct research to determine how management (e.g., burning frequency and intensity) of early-successional habitats influences presence/absence of Ruffed Grouse and Golden-winged Warblers on public lands (USFS and South Carolina State Parks) in the Blue Ridge of South Carolina.

Accomplishments:
Habitat surveys were conducted at all survey locations using Carolina Vegetation Survey protocol between June 1 and July 1, 2020 and 2021. With Carolina Vegetation Surveys, 10 m x 10 m quadrats were plotted randomly around point count locations within a specified buffer. Within these quadrats, we collected habitat cover including ground cover composition, stem density, and visual obstruction. Data collected from the Carolina Vegetation Surveys was at the micro-habitat scale, however we also collected habitat data at the landscape scale using ArcGIS.

Results of Occupancy Models
The top model for Ruffed Grouse suggested mixed forest and woody wetlands composition significantly influence Ruffed Grouse occupancy (Fig. 3). Above 60% mixed forest cover, increasing the composition of mixed forest by 5% concurrently increased Ruffed Grouse occupancy by an average of 2.9%. Similarly, woody wetlands composition had a small but significant effect size on Ruffed Grouse occupancy. Increasing the percentage of woody wetlands from 1% to 3% resulted in an 8% increase in occupancy estimates.

Occupancy rates for songbirds varied greatly among species despite similar influences of habitat parameters. Prairie Warblers and Field Sparrows, for example, were significantly influenced by ground cover composition at the survey site. The sole top-supported model for Prairie Warbler occupancy included effects of shrub, forb, and grass ground cover, as well as average visual obstruction, and grassland and shrub composition at the 1-km scale. Of these parameters, grass ground cover, forb ground cover, and shrubland composition significantly influenced occupancy. Similarly, only one top model existed for Field Sparrow occupancy. This included ground cover metrics (shrub, forb, and grass ground cover) as well as average visual obstruction, patch perimeter, patch perimeter-to-area ratio, and elevation. Overall occupancy estimates for Prairie Warbler and Field Sparrow were 0.87 and 0.24 respectively. Conversely to Prairie Warblers and Field Sparrows, Common Yellowthroats were influenced solely by landscape features. The top-supported model for Common Yellowthroat occupancy included additive effects of grassland and shrubland composition at the 1-km scale. Occupancy estimates were as low as 0.078 when grassland composition neared 0 yet increased to 0.99 with 14% grassland composition. This model estimates overall Common Yellowthroat occupancy at 0.22 for the 2020 and 2021 seasons. Chestnut-sided Warblers had two top-supported occupancy models. The top model indicated that years since the last burning treatment, years since the last timber thinning treatment, average visual obstruction, and elevation influenced occupancy rates. The second model indicated that shrub, grass, and forb ground cover, as well as visual obstruction and elevation influenced occupancy. Predictions indicated that occupancy for Chestnut-sided Warblers was near 0 until about 700 m in elevation. Occupancy estimates then increased dramatically, reaching a maximum estimate of 87% at 1,436 m in elevation. Over the entire study area and across both seasons, the top model estimated Chestnut-sided Warbler occupancy at 0.02.

Significant Deviations:
None.

Objective 3: Assess the use of Autonomous Recording Units (ARUs) to detect and monitor Ruffed Grouse and Golden-winged Warbler presence/absence.

Accomplishments:
We installed 6 autonomous recording units (SongMeter4, Wildlife Acoustics) at songbird point count stations in the Andrew Pickens Ranger District of Sumter National Forest in South Carolina during the 2020 season. In 2021, we deployed 14 autonomous recording units at sites with and without detections of Prairie Warblers, Common Yellowthroat, Chestnut-sided Warblers, Field Sparrow, and Golden-winged Warblers. These sites were distributed between Jocassee Gorges (3 sites), Nantahala National Forest (6 sites), and Sumter National Forest (5 sites). In that same year, we deployed autonomous recording units at six sites with a positive detection of Ruffed Grouse and six sites with no detection of Ruffed Grouse. Ruffed Grouse sites were distributed between Chattahoochee National Forest (6 sites), Sumter National Forest (3 sites), Jocassee Gorges (2 sites), and Headwaters State Forest (1 site) (Figure 2). Initial results from this analysis indicated that ARUs had similar estimates of detection probability as human observers.

We also analyzed all ARU recordings to determine if any additional Ruffed Grouse or Golden-winged Warblers were present at sites but had not been detected during manual listening of ARU recordings. We used the R package monitoR to create templates based on Ruffed Grouse drumming and two common Golden-winged Warbler songs and, according to the date of recording, analyzed recordings for drumming or singing. Our spectrogram analysis identified playback recordings conducted during point count surveys for Golden-winged Warblers, but no additional songs were detected (including at an ARU stationed at a known-presence location). When analyzing Ruffed Grouse recordings, the automated analysis returned too many false-positive detections to be useful (> 400 to 30,000, depending on template cutoff choice). The false positives were likely due to the overlap of the frequency of the drumming (< 100 Hz) and the typical frequency of background noise (< 200 Hz).

<u>Significant Deviations:</u>
None.

<u>Limitations due to COVID-19:</u>
Peak breeding season of Ruffed Grouse and Golden-winged Warbler, and thus their respective survey periods, overlapped with the onset of the COVID-19 pandemic in 2020. This provided challenges that included not hiring a technician, limited communication with land managers, and a looming threat of not being able to conduct research in the field. These external factors reduced the scope and scale of the 2020 field season.

<u>Estimated Federal Cost for 1/01/2021- 5/31/2022:</u> $85,710.79

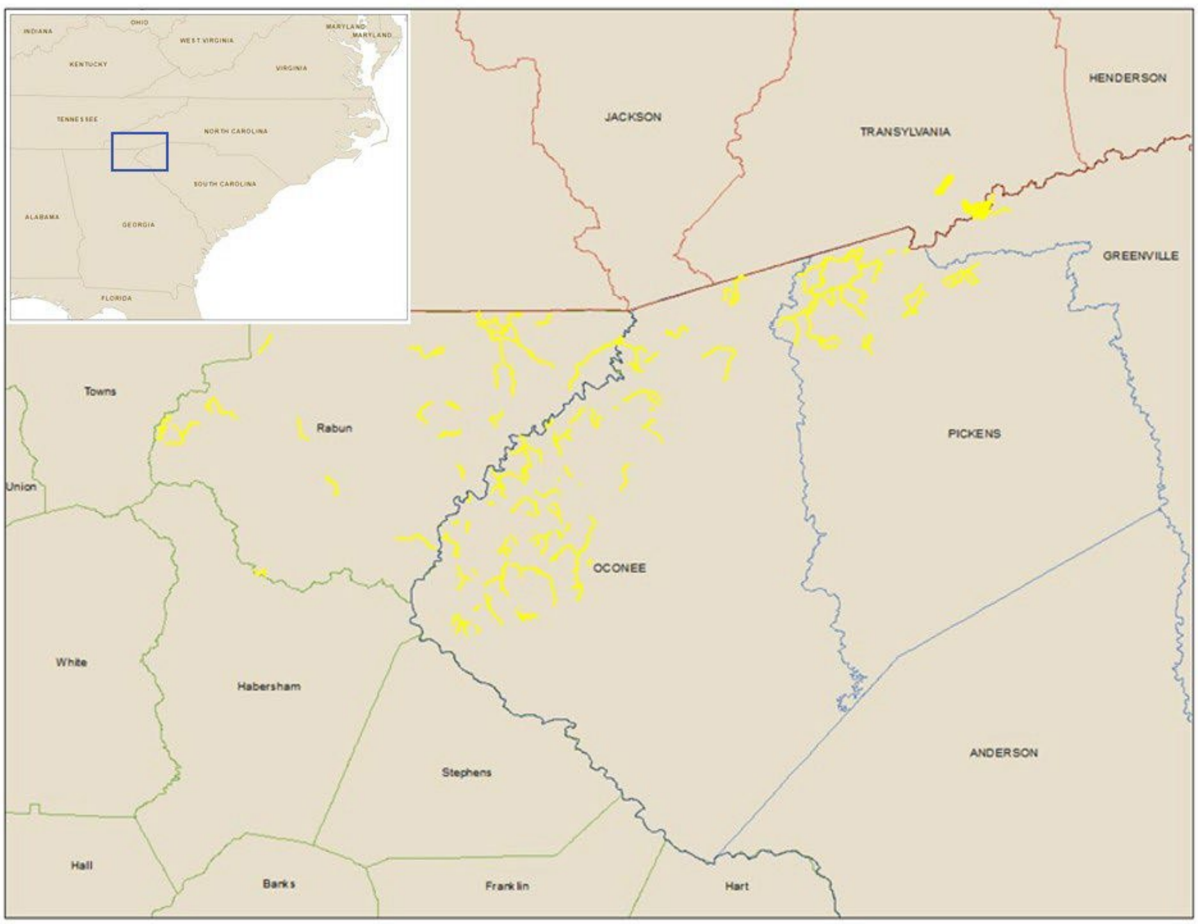

Figure 1. Distribution of 82 Ruffed Grouse drumming survey routes (yellow), comprising 664 unique survey stations, across the Southern Blue Ridge Ecoregion of South Carolina, North Carolina, and Georgia. Blue boundaries indicate South Carolina county borders. Red boundaries indicate North Carolina county borders. Green boundaries indicate Georgia county borders.

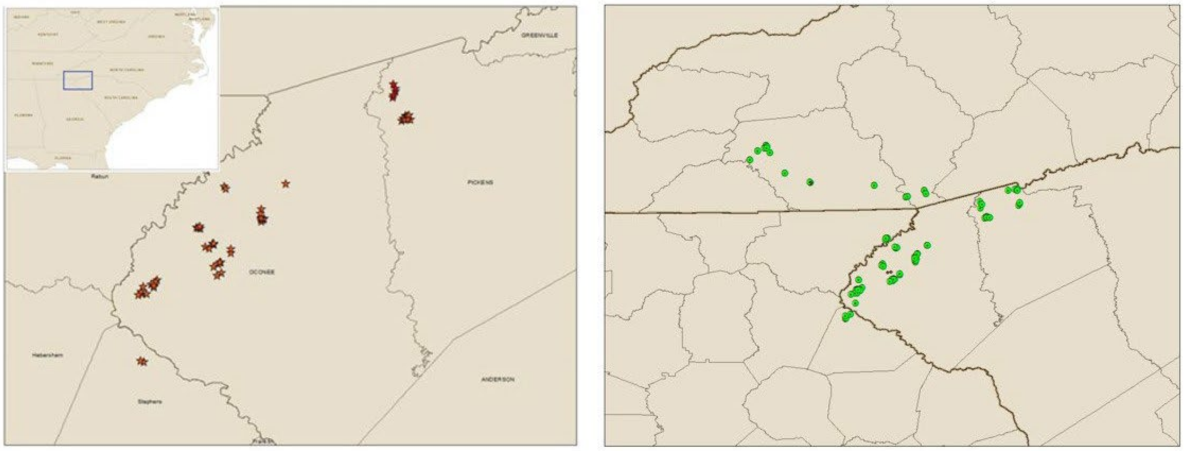

Figure 2. *Left:* Point count surveys were conducted at 49 sites during the 2020 season. 45 sites occurred in South Carolina and 4 in Georgia. Sites are indicated by red stars. *Right:* Point count surveys were conducted at 62 unique sites during the 2021 season. 44 sites occurred in South Carolina, 14 in North Carolina, and 4 in Georgia. Sites are indicated by green circles.

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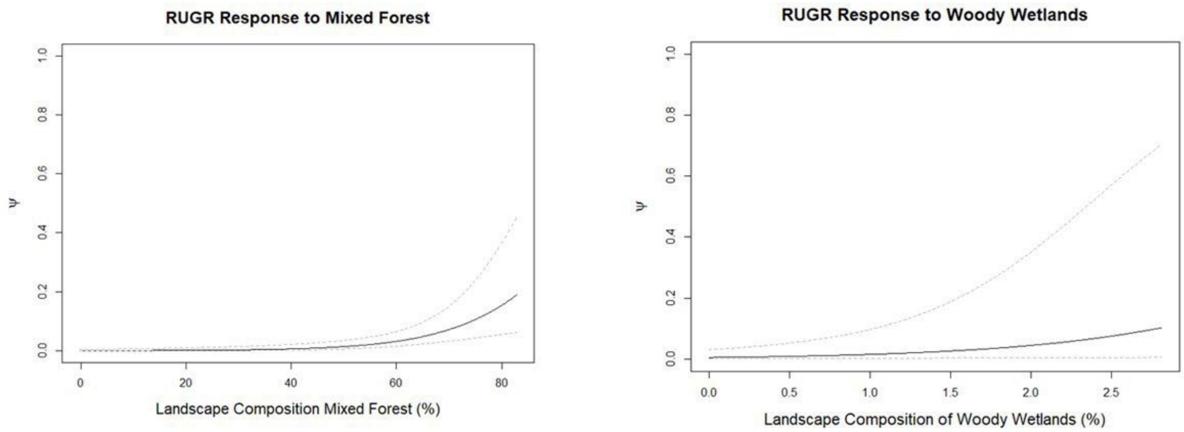

Figure 3. Influence of a) mixed forest composition and b) woody wetland composition on Ruffed Grouse occupancy in the Southern Blue Ridge Ecoregion during Spring 2020 and 2021. Dotted lines represent 85% confidence intervals.

5-2022

Effects of Forest Management on Early-Successional Avian Species in the Southern Blue Ridge Ecoregion

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EFFECTS OF FOREST MANAGEMENT ON EARLY-SUCCESSIONAL AVIAN SPECIES IN THE SOUTHERN BLUE RIDGE ECOREGION

A Thesis
Presented to
the Graduate School of
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In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Wildlife and Fisheries Biology

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by
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May 2022

Accepted by:
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ABSTRACT

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In Chapter 1, I examine the effects of landscape-scale habitat features on Ruffed grouse occupancy. Ruffed Grouse in the Southern Blue Ridge Ecoregion seem influenced by habitats not typical of their northern range, and occur more frequently in landscapes with higher mixed forest and woody wetland cover. In the absence of early-successional forests, Ruffed Grouse may be seeking habitats that act as structural mimics to early-successional forests.

In Chapter 2, I examine the effects of multi-scale habitat parameters on Golden-winged Warblers, Chestnut-sided Warblers, Prairie Warblers, Common Yellowthroat, and Field Sparrow. As a whole, these species seem to be influenced by landscape and composition, ground cover metrics, vegetation structure, and elevation. Chestnut-sided Warblers may act as the most

effective habitat indicator for Golden-winged Warbler habitat, as they exhibit similar preference for habitat features including elevation and vegetative visual obstruction.

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Thanks to South Carolina Department of Natural Resources for funding this project. I especially would like to thank South Carolina Department of Natural Resources biologists Michael Hook, Michael Small, and Amy Tegeler, who were fundamental in the development and progress of this project. Thanks to the staff at the Andrew Pickens Ranger District of Sumter National Forest, Nantahala District of Nantahala National Forest, and Chattooga River District of the Chattahoochee National Forest for allowing me to access and conduct research on their properties. Thank you to Chris Kelly, of North Carolina Wildlife Resources Commission, who fielded my many questions. Thank you to Brenna Byler of the South Carolina Cooperative Fish and Wildlife Research Unit for her assistance and administrative support. Thank you to all of my lab mates for their personal support and advice along the way.

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CHAPTER ONE

DISTRIBUTION OF RUFFED GROUSE IN THE SOUTHERN BLUE RIDGE ECOREGION

INTRODUCTION

The ruffed grouse (*Bonasa umbellus*) is the most widely distributed gallinaceous bird in North America, ranging from Alaska down into the Rocky Mountains of Utah, across Canada and down through the Appalachian Mountains (Johnsgard, 1973). Habitat use by ruffed grouse varies throughout the year although they are considered an early-successional habitat specialist (Thompson & Dessecker, 1997). Young forest habitats, in particular, are important to ruffed grouse throughout their range, as females use dense herbaceous stands for brood rearing and males use high-stem density habitats for concealment during drumming displays (Dobony, 2000; Hautlon, 1999; Jones, 2005a; Jones et al., 2008; Stauffer, 2011). Young forests, as the result of decreased harvest and lack of natural disturbances, have declined throughout eastern hardwood forests (Brooks 2003, Trani et al., 2001; Gobster, 2001). Now, of the 38 states where ruffed grouse are native, 18 have listed ruffed grouse as a "species of greatest conservation need" in their State Wildlife Action Plans (Rudolph, 2019).

Declining young forest habitats have led to regional ruffed grouse population declines, extirpation, and shifting habitat use patterns (Rusch et al., 2000; Dessecker et al., 2006). Ruffed grouse may use habitat types differing from young forests including mixed forests, wetlands, and stream corridors (Endrulat et al. 2005, Blomberg et al. 2009). Debate exists over whether vegetation community composition or vegetation structure exert more influence on avian abundance and site selection, however it is likely that mixed forest, wetland, and stream corridor habitats offer vegetation structure characteristics that specifically drive ruffed grouse drumming site selection (Felix-Locher & Campa III, 2010; Thompson III et al., 1987; Müller et al., 2010; Wiggers et al., 1992). Moreover, due to early-successional forest loss in the Southern Blue Ridge Ecoregion (SBRE), use of these habitats may increase (Hale et al., 1982; Schumacher et al., 2001).

The SBRE lies at the southeastern-most extent of the ruffed grouse's native range, where abrupt changes in forest succession have occurred throughout the past 200 years. Intense logging in the 19th and 20th centuries, followed by widespread farm abandonment and the loss of formerly dominant canopy species such as the American Chestnut (*Castanea dentata*) have led to dramatic changes in forest structure (Rosenberg et al., 2016; Griffith et al., 2002). Subsequent forces such as fire suppression and decreased timber harvest activity have allowed forest succession to proceed relatively unbounded for nearly 70 years, and now early-successional forest habitats may be lacking (Abella, 2002; SCDNR, 2015). The region also lacks aspen, a vital food and cover source for ruffed grouse in more northern regions (Jakubas & Gullion, 1991; Gullion, 1988). In the absence of aspen, ruffed grouse in the southern Appalachians favor oak and hickory dominated forests and often forage on acorns, herbaceous plant seeds, and the buds of birch (*Betula* spp.) and cherry (*Prunus* spp.) trees (Stafford & Dimmick, 1979). Similarly, southern Appalachian grouse forage on low-nutrient evergreen leaves and find cover under those same evergreen plants, namely mountain laurel (*Kalmia latifolia*) (Schumacher et al., 2001, Fearer & Stauffer, 2004). Ruffed grouse in this region exhibit signs of low-quality nutrition and high chick mortality, likely a reflection of low-quality habitat, which makes their populations particularly vulnerable (Haulton, 1999).

Recent evidence has characterized the SBRE as a "hotspot" for trailing edge avian populations, or populations on the receding margin of their native range (Merker & Chandler, 2020). These populations may be responding to warming climatic conditions by shifting their range northward and upslope. Climatic changes may impose changes on vegetation community structure and assemblages on an elevational gradient (Bolstad 1998; Whitaker, 1956) and this could restrict ruffed grouse habitat. If the ruffed grouse represents a trailing edge species in the SBRE, grouse may exhibit tendencies to occupy higher elevation habitats, which has been reflected by most anecdotal reports of the species in this region (Michael Hook, SCDNR, personal communication). Additionally, if ruffed grouse exist on the receding edge of their range in the SBRE, this could explain population declines in North Carolina, Georgia, and South Carolina (Tirpak, et al., 2006; Jones et al., 2005; Pardieck et al., 2020; Barnes, 2005)

Ruffed grouse monitoring in South Carolina began in 1964 with a project entitled "The Status of the Ruffed Grouse, *Bonasa umbellus monticola* (Todd), in South Carolina" (Nesbitt, 1966). Subsequent sparse, small-scale survey attempts followed through 2016 (Michael Hook, SCDNR, personal communication). These surveys demonstrated a small grouse population in Oconee, Pickens, and Greenville County in 1966. Two subsequent surveys found a small population of grouse in the same area in the 1990's. In 2018, SCDNR launched a large-scale drumming survey through the Blue Ridge Region of the state, consisting of 19 routes and a total of 542 drumming surveys. Only one grouse was heard during this survey, although state biologists and turkey hunters provided anecdotal reports in the vicinity of the transects (Michael Hook, SCDNR, personal communication).

To provide an updated index of ruffed grouse populations in the SBRE of South Carolina, I conducted remote drumming surveys in South Carolina (2020) and roadside drumming surveys in South Carolina, Georgia, and North Carolina (2021). Specifically, I collected data to determine landscape-scale predictors of occupancy and detection probability. Informed by the sparse record of grouse inhabiting South Carolina's Blue Ridge region and concerns about ruffed grouse population declines in northern Georgian and western North Carolina, I hypothesized that occupancy rates would be low. Given recent forest management on state and federally owned lands within this region, I hypothesized that ruffed grouse would occupy sites with relatively high young forest cover when available. I lastly hypothesized that ruffed grouse would occupy unmanaged sites that represent alternative habitats if young forest habitats were unavailable.

METHODS

Study Area: Region and Sites

The Blue Ridge Ecoregion spans 9.4 million acres across Virginia, Tennessee, South Carolina, Georgia, and North Carolina (Albritton, 2013) (Figure 1). The ecoregion is characterized by mixed mesophytic forests, primarily dominated by oak (*Quercus* spp.), hickory (*Carya* spp.), and pine (*Pinus* spp.). Elevations range 450 to 2037 meters (Albritton, 2013; SCDNR, 2005; The Nature Conservancy and Southern Appalachian Forest Coalition, 2000). The majority of forests in the region are privately owned, with 35% in public ownership (The Nature Conservancy and Southern Appalachian Forest Coalition, 2000).

During the 2020 season, I selected 57 drumming survey stations from within South Carolina's Blue Ridge Region. Ruffed grouse typically prefer mosaic macrohabitats composed of young forests, older growth forests, and pole-timber stands in close proximity (Gullion & Svoboda, 1972; Sharp, 1963). Drumming locations are often located in regenerating forests. Therefore, stations were selected through stratified-random sampling of both managed and unmanaged sites located on the Andrew Pickens Ranger District of Sumter National Forest, Jocasee Gorges Wildlife Management Area, and Watson-Cooper Heritage Preserve. Management practices included timber thinning, selection harvests, clear-cuts, controlled burns, wildfires, chemical treatment, and any combination of those treatments. To ensure independent detections from each survey site, drumming survey stations were selected to accommodate a 500 m buffer between sites. This distance was determined based on existing research that suggests the audible distance of a drumming male is 200-250 m (Archibald, 1974; Petraborg, 1953).

Due to limited detections in 2020 and additional personnel time, I restructured the survey methodology in 2021. During the 2021 season, I used ArcGIS 10.7.1 (Environmental Systems Research Institute, Redlands, California, USA) to plot 664 drumming survey stations along 82 secondary and primitive roads following standard roadside drumming survey methodologies (Petraborg, 1953) with additional routes along hiking trails (Figure 2). Roadside and trailside drumming surveys offered an opportunity to increase survey effort, which was deemed necessary due to few detections during the 2020 season. Routes were selected through random sampling of managed and unmanaged sites located within the Blue Ridge Ecoregion of South Carolina (Andrew Pickens Ranger District of Sumter National Forest, Jocassee Gorges Wildlife Management Area, Table Rock State Park, Ashmore Heritage Preserve, Watson-Cooper Heritage Preserve), Georgia (Chattooga River District of Chattahoochee National Forest) and North Carolina (Headwater State Forest). Drumming survey stations were separated by 500 m of road or trail length to ensure independence among sites. Many of the road and trail routes included switchbacks and sharp turns, however the likelihood of double-detections between survey sites spaced apart by 500 m of road or trail length was deemed negligible. I did not include drumming stations along primary roads, due to the likelihood of road traffic noise interfering with the ability to detect drumming ruffed grouse.

Ruffed Grouse Drumming Surveys

Standard occupancy designs involve surveying a set number of sites with a set number of repeat visits (MacKenzie et al. 2002). This survey design is well suited for more common species, however when surveying for cryptic or rare species, the standard design risks placing a large amount of survey effort into unoccupied sites (MacKenzie & Royle, 2005). Often, this will lead the surveyor to invest resources into conducting repeat visits at unoccupied sites. An alternative occupancy survey design for rare or cryptic species is the occupancy survey with conditional replicates. The conditional occupancy survey design involves surveying all sites at least once and only resurveying sites with a positive detection of the focal species. This method improves on the accuracy of detection probability and occupancy from other sampling designs and is well suited for surveying rare and cryptic species (Specht et al., 2017).

Using a conditional occupancy design, I surveyed each drumming station once. Surveys were conducted in March and April to best reflect the peak drumming period for ruffed grouse in the southern Appalachians (Jones et al., 2005). After the initial site visit, only sites with a positive identification of grouse were resurveyed. These sites were resurveyed at maximum four times. Ruffed grouse drum before sunrise, and drumming rates drop drastically by late morning (Petraborg et al., 1953). For this reason, ruffed grouse drumming surveys were conducted between 30 minutes before sunrise to 4 hours after sunrise. To reduce any potential time bias, I varied the times that each resurveyed drumming station was visited by surveying the route in the reverse direction. When possible, a different observer was assigned for each resurvey to reduce observer bias.

Surveys began with a 5-minute site cool down period to minimize the effects of observer disturbance on the survey. The cool down period was followed by a 4-minute drumming survey which included passive scanning and listening. Observers began each survey by recording the date, time, temperature, wind speed (Beaufort Scale [0 = <1mph; 1 = 1-3mph; 2 = 4-7mph; 3 = 8-12mph; 4=13+ mph), and sky code (Weather Bureau Code [0 = clear/few clouds; 1 = partly cloudy/variable; 2 = cloudy/overcast; 3 = fog; 4 = drizzle; 5 = showers). If a ruffed grouse was detected, observers recorded the number of grouse heard, whether the grouse was seen, heard, or both, the minute of detection, the distance in meters, and direction in azimuth degrees. Surveys were not conducted during periods of consistent rain or wind over 13 kmh.

Landscape Predictors of Occupancy

Early-successional forests are favored by ruffed grouse throughout their native range, but in the absence of early-successional forests, grouse may use less favorable habitats that provide adequate cover and forage (Bloomberg et al., 2009; Schumacher, 2001). Additionally, ruffed grouse prefer mosaic macrohabitats composed of varying aged stands (Gullion & Svoboda, 1972; Sharp, 1963). To identify potential predictors of ruffed grouse occupancy in the SBRE, I placed a 450 m radius buffer around each drumming survey station using ArcGIS 10.7.1 (Environmental Systems Research Institute, Redlands, Califorina, USA). This buffered distance was assumed to encompass the home range of a ruffed grouse (Thompson III & Fritzell, 1989; Schumacher, 2002). From within each buffer, I calculated the proportion of the landscape occupied by each forest patch types (mixed forest [neither deciduous nor evergreen species are greater than 75% of total tree cover], deciduous forest, evergreen forest, woody wetlands, and shrub/scrub) using National Land Cover Data (Dewitz, 2019) and FRAGSTATS (McGarigal et. al, 2012). I then calculated the Shannon Diversity Index and Shannon Evenness Index for cover types, the elevation of each drumming survey station, and the distance of each station to the nearest stream corridor.

Statistical Analysis

I used a two-stage modeling approach to examine potential predictors of ruffed grouse occupancy. First, I created 9 *a priori* models using potentially significant weather, time, and date parameters for detection probability (p). In these models, occupancy (Ψ) was assumed constant. Significant parameters from top models were included in subsequent occupancy models. If no parameters were identified as significant predictors of detection probability, detection probability was assumed constant in occupancy models.

I then developed 13 *a priori* models to estimate ruffed grouse occupancy. Models were created using landscape-scale habitat parameters collected in ArcGIS and FRAGSTATS (Table 1). I limited model degrees of freedom to 5-10% of the dataset's sample size to reduce model complexity and prevent overfitting (Fieberg & Johnson, 2015; Burnham & Anderson, 2002). I examined correlations between parameters and removed highly correlated variables ($|R| > 0.7$). All covariates were centered and scaled to 0 to normalize data.

I ran all models using the "unmarked" package (Fiske and Chandler 2011) in program R (R Core Development Team 2017). I then compared models based on their AIC values, considering models under 2ΔAIC of the top model as the top models. Significant predictors of occupancy probability were identified by evaluating the 85% confidence intervals of each parameter in the top models. Parameters with 85% confidence intervals that did not overlap 0 were considered significant. In the case that top models differed by just one parameter, that parameter was considered uninformative and inferences were made off the most parsimonious top model (Arnold, 2010).

RESULTS

I conducted 57 remote drumming surveys at 57 unique sites between March 24th to April 29th, 2020. I conducted 767 drumming surveys at 664 unique sites along 82 survey routes between March 15th to April 30th, 2021. Route lengths varied from 1 to 42 stops (mean = 9.5, SE = 7.55). Elevations varied across sites, with an average of 600.2 m (ranging 305 – 1069 m). Forest cover also varied among sites but was dominated by deciduous forests (mean = 40.4%, ranging 0 – 99.87%). Mixed forest cover (mean = 38.83%, ranging 0 – 82.8%) and evergreen forest cover (mean = 12.6%, ranging 0 – 73.44%) were the second and third most dominant forest cover classes respectively. Few sites (n=28) had woody wetland cover, and its relative composition at these sites was small (mean = 1.19%, ranging 0.13 – 2.81%). South Carolina accounted for all of the sites surveyed in 2020. In 2021, 495 sites were in South Carolina, with the remaining sites split between Georgia (150 sites) and North Carolina (19 sites). Ruffed grouse were not detected at any drumming survey station during the 2020 season. In the 2021 season, I detected grouse at 7 sites (4 in Georgia, 2 in North Carolina, and 1 in South Carolina). Six of the occupied sites were surveyed 4 times and one site was surveyed 5 times.

Detection Probability

The top-supported detection probability models under 2ΔAIC included wind speed, Julian date, temperature, sky cover, and time of day covariates (Table 2). The top model included one covariate for wind speed. This model accounted for 23% of the Akaike weight. The null model ranked second and accounted for 22% of the Akaike weight. The third ranked Julian date model accounted for 10% of the Akaike weight. Among the remaining three models, the sky cover model accounted for 9.6%, the wind speed, temperature, and sky cover models accounted for 9.1%, and the time model accounted for just 8.7% of the Akaike weight. Since the null model was among the top candidate set, I concluded that the other top-candidate models failed to explain variations in detection probability. Detection probability was estimated as $p = 0.418$ across both seasons.

Site Occupancy

Two occupancy models fell within 2ΔAIC (Table 3). These models suggested that forest stand composition influenced ruffed grouse occupancy in the SBRE. The top-ranked model included a parameter for mixed forest cover within 450 m of the survey site ($\beta = 1.67 \pm 0.64$, 85% CI [0.75, 2.6]) and a parameter for woody wetlands cover ($\beta = 0.31 \pm 0.14$, 85% CI [0.11, 0.51]) withing 450 m of the survey site. This model accounted for 47% of the Akaike weight. The second ranked model included both mixed forest ($\beta = 1.48 \pm 0.72$, 85% CI [0.45, 2.51]) and woody wetland ($\beta = 0.27 \pm 0.15$, 85% CI [0.05, 0.49]) composition with an added parameter for elevation ($\beta = 0.27 \pm 0.5$, 85% CI [-0.45, 1.0]). This model accounted for 20% of the Akaike weight, however the added parameter of elevation is likely uninformative (Arnold, 2010).

The top model suggested mixed forest and woody wetlands composition significantly influence ruffed grouse occupancy (Figure 3). Above 60% mixed forest cover, increasing the composition of mixed forest by 5% concurrently increased ruffed grouse occupancy by an average of 2.9%. Similarly, woody wetlands composition had a small but significant effect size on ruffed grouse occupancy. Increasing the percentage of woody wetlands from 1% to 3% resulted in an 8% increase in occupancy estimates. This top model estimated ruffed grouse occupancy at 0.49% between spring 2020 and 2021.

DISCUSSION

While occupancy in the Southern Blue Ridge was low during the 2020 and 2021 seasons, my study revealed a significant relationship between forest composition and ruffed grouse occupancy. In particular, the relative percentage of mixed forest and woody wetland at a study site positively correlated with ruffed grouse occupancy. Across their range, ruffed grouse prefer high stem density habitats and, most often, these habitats come in the form of early-successional habitats or young forests (Bump et al., 1947, Rusch et al., 2000). In the SBRE, early-successional and young forests habitats are generally lacking (Abella, 2002; King & Schlossberg, 2014; SCDNR, 2015; Warburton et al., 2011), and ruffed grouse may be using alternative habitats.

Mixed forests offer diverse canopy and crown composition and heterogenous light availability on the forest floor. These dynamic structures can have implications on understory vegetation, and may increase understory stem density and shrub/herbaceous cover (Clinton et al., 1994; Mestre et al., 2017; Rodríguez-Calcerrada et al., 2011). Additionally, mountain laurel (*Kalmia latifolia*) has become an increasingly dominant understory species in the Appalachian Mountain range since the 1950's (Brose, 2016). Mountain laurel, a broadleaf evergreen species, forms high-stem density thickets with a canopy around 2-3 m tall (Waterman et al., 2005). In the absence of high-quality early-successional sites, ruffed grouse may take advantage of mountain laurel thickets and heterogenous stem density and shrub/herbaceous cover provided by mixed forests (Endrulat et al. 2005, Blomberg et al. 2009). This suggestion echoes the results of Schumacher et al's (2001) research in western North Carolina, where 85% of ruffed grouse drumming logs were found in habitats dominated by a mid-story mountain laurel or flame azalea (*Rhododendron calendulaceum*).

Ruffed grouse displayed preference for woody wetland habitats, even though the availability of woody wetlands on my study sites was small (occurring at just 28 of 721 sites for an average of 1.19% forest cover). Ruffed grouse may use woody wetlands, riparian areas, and mesic-bottomland sites in the Southern Blue Ridge region because they provide dense vegetative structures similar to those preferred by ruffed grouse in early-successional forests. Habitat structure influences drumming ruffed grouse abundance and site selection throughout their native distribution, while relative vegetation composition seems to matter little (Bump et al., 1947; Lewis, 1968; Thompson III et al., 1987; Cade & Sousa, 1985). Ideal ruffed grouse habitats include high stem density stands that provide cover in close proximity to food sources. These habitats are used both for drumming and breeding (Dessecker & McAuley 2001). Forested wetland habitats provide high stem density vegetative growth and herbaceous ground cover (Brown et al, 1979; Swanson et al., 1982). Moreover, riparian areas in southern Appalachian Mountains are often dominated by thickets of rhododendron (*Rhododendron* spp.), which can grow in high stem densities (Vandermast & Van Lear, 2002). Rhododendron thickets provide dense cover for grouse and have been observed as a selected cover type in Virginia, North Carolina, and Georgia (Fearer, 1999; Hale et al, 1982; Schumacher et al, 2001). Appalachian Cooperative Grouse Research Project researchers found that in oak-hickory forests, which dominate much of Appalachian forests, grouse selected habitats in mesic bottomlands (Whitaker et al, 2006). Similarly, ruffed grouse in Maine select wetland habitats when young forest habitats were in low availability, suggesting that grouse select this habitat type because it provides structural components similar to early-successional forests (Blomberg et al, 2009). Occupancy of ruffed grouse in these areas reflects recent findings that avian species in novel habitats seem more sensitive to vegetation structure than vegetation composition (Kennedy et al., 2018). My data did not decipher between different wetland habitat types, but the results strongly indicated that ruffed grouse selected for wetland habitats even though they were in low availability, suggesting that wetlands are an important habitat type for grouse in the SBRE.

Although not identified as an important predictor in this study, elevation was included in my top-model candidate set and may influence ruffed grouse occupancy (Table 3). Ruffed grouse in the SBRE typically use higher elevation habitats, yet this relationship is less observed in more northern climates (Bump, 1947, Devers et al., 2007, Hein, 1970, McGowan, 1973). Preferential use of high-elevation habitats could be driven by elevational gradients in temperature and vegetative communities (Bolstad, 1998; Whittaker, 1956). Since these effects seem more pronounced in the SBRE, where grouse occur at the extent of their southeastern range, grouse in this region may represent a trailing edge population. Recent research has identified the Southern Blue Ridge as a hotspot for trailing edge avian species coping with shifting climatic conditions (Merker & Chandler, 2020). Additionally, ruffed grouse were historically encountered in lower elevation Coastal Plain regions, especially in the Northeast (Harlow, 1918), suggesting that an effect of elevation on ruffed grouse occupancy could be driven by climatic conditions. If ruffed grouse in the SBRE represent a trailing edge population, this would imply elevation is an important predictor for ruffed grouse occupancy, where high-elevation habitats may mimic conditions found in suitable northern habitats. Similarly, if climatic changes impose elevation associated changes on vegetation community or structure, ruffed grouse may respond to these changes by shifting their range both higher in elevation and northward.

While there was model selection uncertainty among the top models, there was some indication that date, time, and wind were important for detecting ruffed grouse in the SBRE.

Ruffed grouse typically exhibit a peak date for drumming detection, though this varies by latitude (Hanson et al, 2011, Mangelincx et al, 2017), which may be due to differences in photoperiod (Gullion 1966). In northern portions of the ruffed grouse's range, drumming occurs later in the year, while in southern portions drumming occurs earlier. Throughout their range, however, ruffed grouse tend to drum most often before sunrise and decrease drumming activity by mid-morning (Archibald, 1976; Hanson et al., 2011, Martin, 2021; Palmer, 1969, Petraborg et al., 1953). Studies from Maine and South Dakota also suggest that drumming detection probability decreases as wind speed increases (Hanson et al., 2011; Mangelincx et al., 2017). My study failed to demonstrate time, date, and wind as significant predictors of ruffed grouse detection and this could be due to low detections and facets of the study design. My survey interval was designed to overlap the peak period of drumming suggested in Nantahala National Forest (Jones et al, 2005), and had I surveyed earlier or later in the year, an effect for day may have been revealed. Model selection in my study did, however, include date variables among the top-supported models. While the null model was among these top-supported models, more detections or a larger sample size may have indicated effects of time and date. I limited survey durations to a 4.5-hour period starting 30 minutes before sunrise and ending 4 hours after sunrise. This design optimized detection probability, but may have revealed time as an important predictor for detection had I surveyed earlier or later in the day. These caveats, however, must be taken in the context of low overall detection, and it is likely that grouse in the SBRE exhibit a peak drumming date, decrease drumming by mid-morning, and are difficult to detect when wind speeds are high.

This study represents the largest-scale effort to index ruffed grouse populations in the state of South Carolina known to date and provides context for ruffed grouse population and distribution in the broader region. In total, I detected 1 grouse out of 553 South Carolina survey sites, reflecting the results of SCDNR's 2018 effort to survey grouse, where they detected 1 grouse out of 542 survey sites. Moreover, I detected 4 grouse in Georgia and 2 in North Carolina, indicating that grouse may be more abundant in these regions. Future monitoring for ruffed grouse in the SBRE may be most effective in habitats that might differ from northern populations, including mixed forests and forested wetlands/riparian areas. These forests seem to create the most favorable conditions for grouse in the absence of traditionally recognized high-quality young forests habitat. Given these results and other research on habitat use of ruffed grouse in the SBRE that indicate preference for early-successional habitats (Jones & Harper, 2007; Tirpak et al., 2006; Whitaker et al., 2006), management for ruffed grouse may be most effective by creating high-stem density young forest habitats in close proximity to mixed forests or forested wetlands, where source populations of ruffed grouse may already exist.

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TABLES & FIGURES

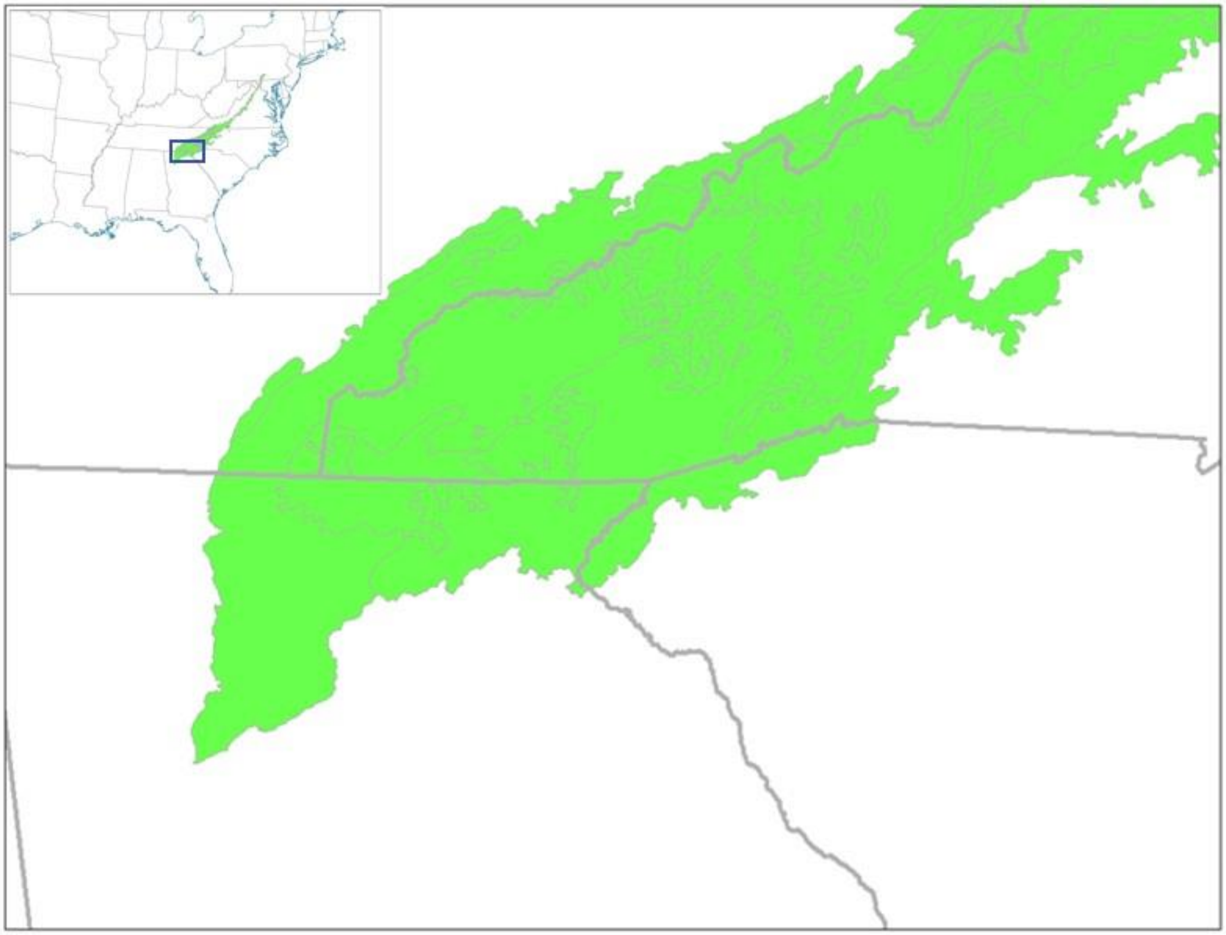

Figure 1. Map of the southern extent of the Blue Ridge Ecoregion

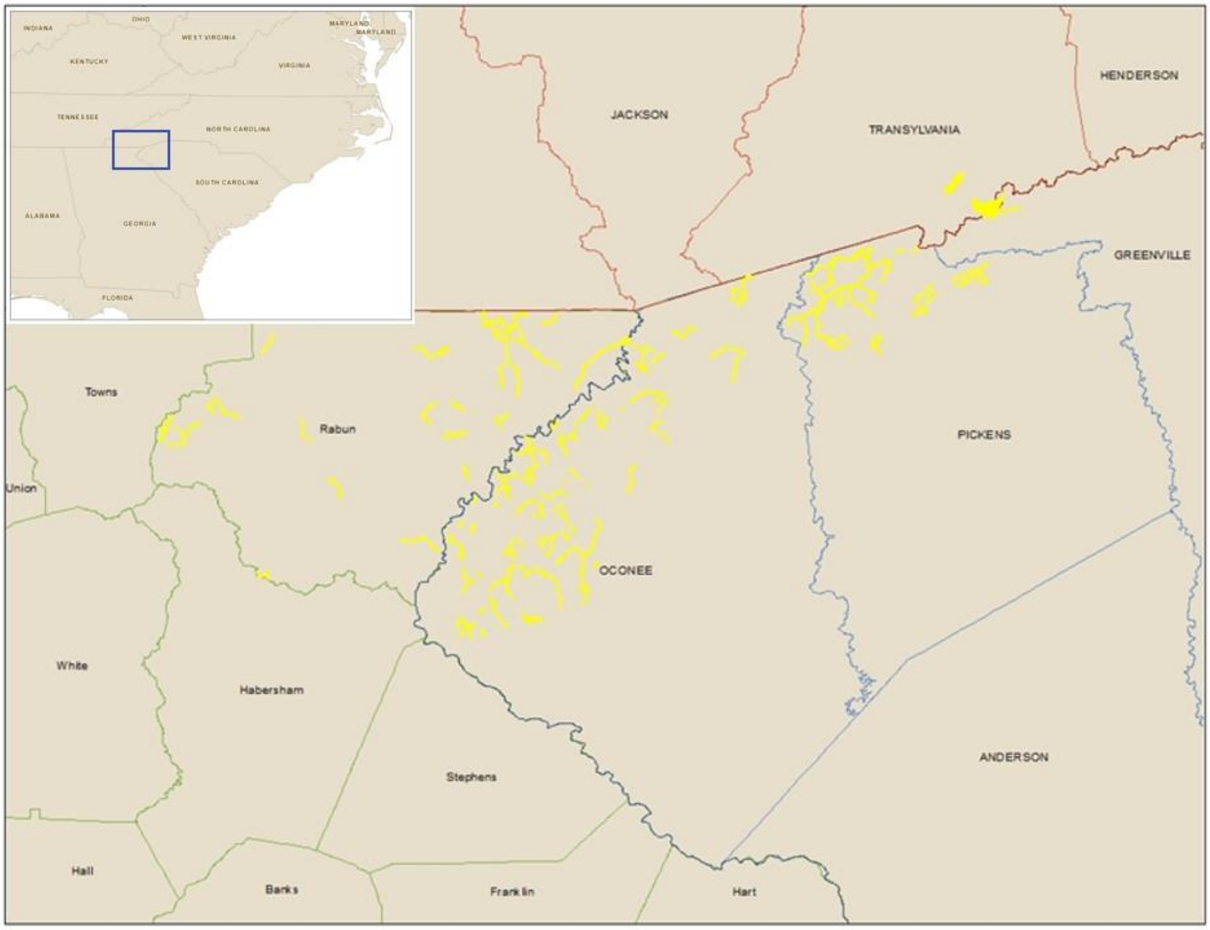

Figure 2. Distribution of 82 ruffed grouse drumming survey routes (yellow), comprising 664 unique survey stations, across the Southern Blue Ridge Ecoregion of South Carolina, North Carolina, and Georgia. Blue boundaries indicate South Carolina county borders. Red boundaries indicate North Carolina county borders. Green boundaries indicate Georgia county borders.

Table 1. List of occupancy covariates used in model selection

Covariate	Abbreviation	Description
Elevation	elev	Elevation of site in meters
Mixed Forest Composition	pland.mix	Relative percentage of mixed forest cover within a 450 m radius of survey site
Woody Wetland Composition	pland.woodywe	Relative percentage of woody wetland cover within a 450 m radius of survey site
Evergreen Composition	pland.ever	Relative percentage of evergreen cover within a 450 m radius of survey site
Stream Distance	steam_dist.m.	Distance of survey site to nearest stream in meters
Shannon Diversity Index	SHDI	Diversity index measuring the relative diversity of cover types within a 450 m radius of survey site

Table 2. Ranking of candidate models that assess the influence of temporal and weather variables on detection probability of ruffed grouse in the Southern Blue Ridge Ecoregion during spring 2021 roadside drumming surveys. K is the number of parameters including the intercept. AIC is Akaike's information criterion. ΔAIC is the difference in AIC from the top model. w_i is the Akaike weight. Null represents the null model, in which occupancy and detection are assumed constant.

Model	K	AIC	ΔAIC	w_i
wind	3	113.07	0	0.23
null	2	113.19	0.12	0.45
date	3	114.76	1.69	0.56
sky	3	114.86	1.79	0.65
wind + temp + sky	5	114.95	1.88	0.74
time	3	115.05	1.98	0.83
temp	3	115.18	2.11	0.91
date + time	4	116.61	3.54	0.95
obs	4	117.02	3.95	0.98
date + time + temp + sky + wind	7	118.35	5.28	1.00

Table 3. Ranking of candidate models that assess the influence of landscape-scale habitat metrics and forest composition on ruffed grouse occupancy in the Southern Blue Ridge Ecoregion during spring 2021 roadside drumming surveys. Detection was assumed constant in all models. K is the number of parameters including the intercept. AIC is Akaike's information criterion. ΔAIC is the difference in AIC from the top model. w_i is the Akaike weight. Null represents the null model, in which occupancy and detection are assumed constant.

Model	K	AIC	ΔAIC	w_i
pland.mix + pland.woodywe	4	98.80	0.00	0.47
pland.mix + pland.woodywe + elev	5	100.50	1.70	0.67
pland.mix + elev	4	101.52	2.72	0.79
pland.mix + pland.ever	4	102.96	4.15	0.85
pland.mix + pland.ever + elev + stream_dist.m.	6	103.30	4.50	0.90
pland.woodywe + elev + stream_dist.m.	5	104.30	5.50	0.93
pland.woodywe + elev	4	104.35	5.55	0.96
elev + stream_dist	4	104.90	6.10	0.98
elev	3	106.13	7.33	0.99
pland.woodywe	3	106.73	7.93	1.00
elev + steam_dist.m. + pland.mix + pland.ever	7	111.04	12.24	1,00
null	2	113.19	14.39	1.00
SHDI	3	115.08	16.28	1.00

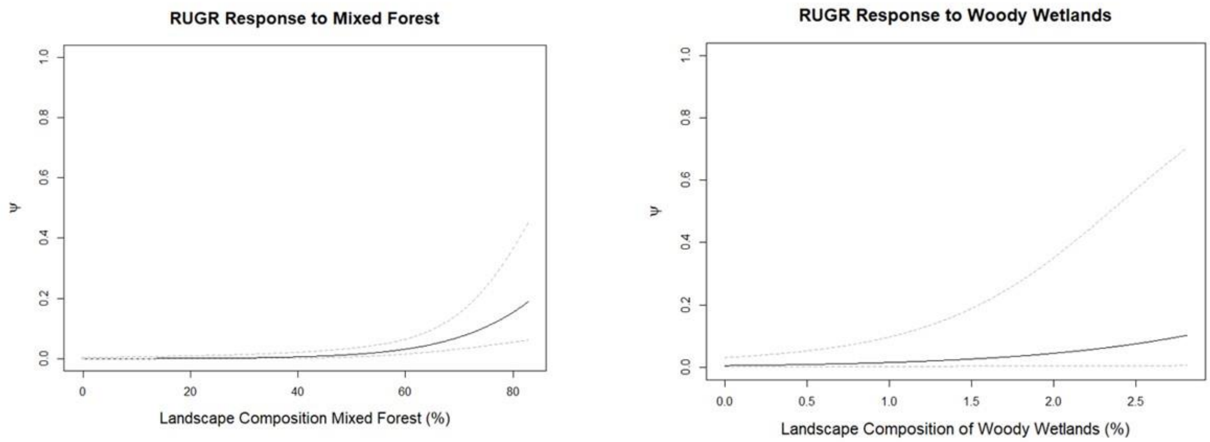

Figure 3. Influence of a) mixed forest composition and b) woody wetland composition on ruffed grouse occupancy in the Southern Blue Ridge Ecoregion during Spring 2020 and 2021. Dotted lines represent 85% confidence intervals.

CHAPTER TWO

DISTRIBUTION OF GOLDEN-WINGED WARBLERS AND EARLY-SUCCESSIONAL OBLIGATE SONGBIRDS IN THE SOUTHERN BLUE RIDGE MOUNTAINS

INTRODUCTION

The Golden-winged Warbler (*Vermivora chrysoptera*) is a neotropical migrant dependent on early-successional habitat for breeding and nesting (Confer et al., 2020). Biologists recognize two distinct Golden-winged Warbler populations, one that breeds in the Great Lakes region and one that breeds in the Appalachian Mountains (Roth et al., 2012). Golden-winged Warblers have faced precipitous declines since the mid-1900s and are at risk of extirpation across many parts of their range (Buehler et al., 2007; North American Bird Conservation Initiative, 2014; Roth et al., 2012). Annual breeding bird surveys show a net decline of Golden-winged Warblers by 2.5% every year since 1968 (North American Bird Conservation Initiative, 2014). Similarly, the breeding range of Golden-winged Warblers, especially the Appalachian population, has contracted substantially since the 1970's (Roth et al, 2012). Golden-winged Warblers have been proposed to be listed under the Endangered Species Act and are currently listed as Near Threatened by the IUCN (BirdLife International, 2020; US Fish & Wildlife Service, 2020).

Loss of early-successional habitat poses the greatest threat to Golden-winged Warbler populations (Buehler et al., 2007). Female Golden-winged Warblers use early-successional habitat for nesting (Roth et al., 2012). Nests are often found at the base of a pioneer species like goldenrod (*Solidago spp.*) or blackberry (*Rubus spp.*), and ground cover and vegetative structure often influence site selection (Klaus & Buehler, 2001; Bulluck & Buehler, 2008). Quality nesting and brood rearing habitat is also adjacent to mature forests, where Golden-winged Warblers escort their young after they have fledged (Streby et al., 2012; Frantz et al., 2016; Streby et al., 2016). Male Golden-winged Warblers establish territories and court females in early-successional habitats. Ideal habitats include the proper vegetative structure and composition for nesting and brood rearing, but males also need legacy structures like standing matures trees, dead or alive, sparsely mixed among the habitat patch (Roth et al., 2012). From these trees, male Golden-winged Warblers can perch, sing, and monitor their territory for competing males. Hard mature forest edges also provide older trees from which males can perch (Streby et al., 2012).

Scarcity of quality habitat may also exacerbate the effects of interspecies competition and hybridization between Golden-winged and Blue-winged Warblers (Conger & Knapp, 1981; Confer et al., 2003;). Since the 1970's, the breeding range of Golden-winged Warblers has severely contracted (Roth et al., 2012). In contrast, the breeding range of the Blue-winged Warbler (*Vermivora cyanoptera*) has expanded (Confer, 1992). The Golden-winged Warbler and Blue-winged Warbler, both of the genus *Vermivora*, are 99.7% genetically similar (Toews et. al, 2016) and, in areas where these two species coexist, the Blue-winged Warbler will displace the Golden-winged Warbler through competition and hybridization (Gill, 1980; Will, 1986). Hybridization of the two species results in viable offspring referred to as either Brewster's or Lawrence's warbler. The displacement of Golden-winged Warblers, and the influx of Blue-winged Warbler genetics into imperiled and isolated Golden-winged Warbler populations, create major threats to the longevity of the species, and recent evidence suggests that Blue-winged Warblers may displace Golden-winged Warblers in lower altitudes below 1000 m (Gill, 1980; Klaus & Buehler, 2001; Rosenberg et al., 2016; Rohrbaugh et al, 2016).

Today, the recognized breeding range of Golden-winged Warblers in the Appalachian region ranges from northern Georgia into New York and Vermont. South Carolina Department of Natural Resources has not officially conducted any species assessments for Golden-winged

Warblers, and their status in South Carolina remains unknown (Amy Tegeler, SCDNR, personal communication). Golden-winged Warblers were once recognized as breeding residents in the three Northwestern-most counties of South Carolina: Pickens, Greenville, and Oconee (Loomis 1890;1891, Sprunt and Chamberlain 1949). One report suggests that, by 1980, Golden-winged Warblers had disappeared from South Carolina (Rosenberg et al., 2016). However, nearby breeding populations in northern Georgia and the Nantahala National Forest of North Carolina offer the potential for the Golden-winged Warblers to expand back into South Carolina, given the existence of suitable habitat. Given the range-wide habitat loss and susceptibility of Golden-winged Warbler populations on the fringe of the core breeding range, it is important to know if and where Golden-winged Warblers occupy habitat in South Carolina (Buehler et al., 2007).

Early-successional Habitat Indicator Species

Indicator species, or those species that serve as representatives for focal species, can aid managers by providing proxies for monitoring and managing entire guilds of species (Wiens et al., 2008). Moreover, indicator species can reduce the scale, effort, time, and financial expenses invested into monitoring biological systems (Bal et al., 2018). In regards to the Golden-winged Warbler, species of the shrubland nesting songbird guild may exhibit similar habitat selection preferences at multiple scales. Foremost, the Blue-winged Warbler exhibits habitat preferences much the same as the Golden-winged Warbler (Patton et al., 2012). Blue-winged Warblers will tolerate older-aged stands than the Golden-winged Warbler and tend to occupy patches at lower elevations, but there is a distinct overlap between the two species breeding ranges (Confer & Knapp, 1981). Similarly, the Prairie Warbler (*Setophaga discolor*), Chestnut-sided Warbler (*Setophaga pensylvanica*), Common Yellowthroat (*Geothlypis trichas*), and Field Sparrow (*Spizella pusilla*) are all considered indicator species for shrubland habitats (Hunter et al., 2001;

Schlossberg & King, 2007). In this project, these species will be used to identify critical habitat components for early-successional avian species. This information can then be extrapolated to predict certain environmental variables and management practices that may positively influence Golden-winged Warbler breeding habitat. Since multi-scale factors often influence habitat selection among songbirds, including Golden-winged Warblers, evaluating parameters at the local, patch, and landscape scales will be critical to identify significant predictors of occupancy (Fiss, 2018; Kellner et al., 2016; Roberts & King, 2017).

To identify Golden-winged Warblers and shrubland species occupancy in the Southern Blue Ridge Ecoregion (SBRE) of South Carolina, I conducted point count surveys in South Carolina and Georgia in 2020, and expanded the project to include sites in North Carolina 2021. I also collected potentially significant habitat variables using a combination of ground surveys and remote sensing data to determine multi-scale predictors of occupancy. Little evidence exists of Golden-winged Warblers recently occupying habitat in South Carolina, thus I hypothesized that occupancy rates would be low. I also hypothesized that Golden-winged Warblers and shrubland indicator species would respond similarly to multi-scale habitat parameters, such as landscape composition, patch shape, and groundcover metrics.

METHODS

Study Area: Region and Sites

The Blue Ridge Ecoregion spans 9.4 million acres across Virginia, Tennessee, South Carolina, Georgia, and North Carolina (Albritton, 2013) (Figure 1). The ecoregion is characterized by mixed mesophytic forests, primarily dominated by oak (*Quercus* spp.), hickory (*Carya* spp.), and pine (*Pinus* spp.). Elevations range 450 to 2037 meters (Albritton, 2013;

SCDNR, 2005; The Nature Conservancy and Southern Appalachian Forest Coalition, 2000). The majority of forests in the region are privately owned, with 35% in public ownership (The Nature Conservancy and Southern Appalachian Forest Coalition, 2000).

Study sites were spatially constrained by public lands in the Blue Ridge Ecoregion of South Carolina (Andrew Pickens Ranger District of Sumter National Forest, Jocassee Gorges Wildlife Management Area) and Georgia (Chattooga River District of Chattahoochee National Forest) in 2020. Due to limited detections in 2020 and additional personnel time, I restructured the survey methodology in 2021 and added North Carolina (Nantahala National Forest) sites. Study site selection was further limited to managed forest stands harvested in the interval between 2005 and 2016. Regenerating stands from this age interval provide quality habitat for early-successional avian species (Conner & Dickson, 1997; DeGraaf & Yamasaki, 2003). Additionally, I included one high elevation powerline right-of-way for surveys in both the 2020 and 2021 seasons. Investigators have demonstrated the use of powerline right-of-ways (ROW) by a variety of early-successional avian species, including the Golden-winged Warbler, Chestnut-sided Warbler, and Prairie Warbler (Askins et al., 2012, DeFalco & Dey, 2003; Kubel & Yahner, 2007). Common management practices on non-ROW stands included overstory removal and two-aged harvests with subsequent management including controlled burns, chemical treatment, and additional thinnings. Using ArcGIS 10.7.1 (Environmental Systems Research Institute, Redlands, Califorina, USA), I placed a buffer distance of 200 m between sites. This distance was determined by the territory size of male Golden-winged Warblers (Patton et al., 2010) and was assumed to be an adequate distance to ensure independent detections of individuals.

Songbird Point Count Surveys

I presumed Golden-winged Warbler occupancy would be low throughout the SBRE and therefor employed an occupancy design with conditional replicates. Standard occupancy designs involve surveying a set number of sites with a set number of repeat visits (MacKenzie et al. 2002). This survey design is well suited for more common species, however when surveying for cryptic or rare species, the standard design requires a large number of visitations per site (MacKenzie & Royle, 2005). Often, this will lead the surveyor to invest resources into conducting repeat visits at unoccupied sites. The conditional occupancy survey design, however, involves surveying all sites at least once and only resurveying sites with a positive detection of the focal species. This method improves on the accuracy of detection probability and occupancy from other sampling designs and is well suited for surveying rare and cryptic species (Specht et al., 2017).

Using the conditional occupancy design, I performed unlimited-radius point count surveys at 49 unique sites during the interval of May 12th to July 1st 2020 (Figure 2). During the 2021 season, I limited the survey timeframe to the beginning of June to better reflect the Golden-winged Warbler migration and singing time period (Chris Kelly, NCWRC, 2021). Therefore, I conducted 97-point count surveys at 62 unique sites between May 3rd and June 7th 2021. South Carolina sites (Jocassee Gorges and Andrew Pickens Ranger District of Sumter National Forest) accounted a majority of the survey effort between both years (45 of 49 sites in 2020; 44 of 62 sites in 2021). Chattahoochee National Forest sites in Georgia accounted for 4 surveys in both 2020 and 2021. North Carolina (Nantahala National Forest) sites accounted for 14 sites in 2021 (Figure 2). After the initial site visit, only sites with a positive identification of Golden-winged Warbler, Blue-winged Warbler, Prairie Warbler, Field Sparrow, Common Yellowthroat, Chestnut-sided Warbler, or Golden-winged Warbler/Blue-winged Warbler hybrids were resurveyed. In total, I resurveyed 42 sites with positive identification of one or more target species. These sites were resurveyed a minimum of once and a maximum of 3 times (mean = 2.21).

Golden-winged Warblers and other songbirds sing across their territories soon after sun up. Singing wanes by late morning (Ralph et al, 1995). For this reason, I conducted surveys in the interval between 30 mins after sunrise and 4 hours after sunrise. When possible, a different observer (out of three observers) assigned for each resurvey to reduce observer bias.

Consistent with Golden-winged Warbler surveys elsewhere in its range, and to maximize detection probability, point count surveys for Golden-winged Warblers and early-successional habitat indicator species consisted of 8-minutes of passive scan and listening followed by 5-minutes of type 1 (T1) Golden-winged Warbler song playback, a 1-minute rest period, and a 1-minute period of type 2 (T2) Golden-winged Warbler song playback (Ralph et al, 1995; Kubel & Yahner, 2007; Chandler & King, 2011; McNeil et al, 2014;). Audio recordings were obtained from researchers at New Jersey Audubon (Dr. Kristin Mylecraine, personal communication) and saved to an AGPTEK U3 USB Stick Mp3 player. I played the recording by connecting the Mp3 player to a Zosam audio Bluetooth speaker. If a target species was detected, observers recorded the number of individuals, detection type (seen, heard, or both), the minute of detection, the distance in meters, and direction in azimuth degrees.

Before each survey, observers recorded the date, time, temperature, wind speed (Beaufort Scale [0 = <1mph; 1 = 1-3mph; 2 = 4-7mph; 3 = 8-12mph; 4=13+ mph), and sky code (Weather Bureau Code [0 = clear/few clouds; 1 = partly cloudy/variable; 2 = cloudy/overcast; 3 = fog; 4 =

drizzle; 5 = showers). Surveys were not conducted during periods of consistent rain or wind over 13 kmh.

Landscape Predictors of Occupancy

Landscape and patch characteristics often influence site occupancy by early-successional avian species (Barkermans et al, 2015; Roberts & King, 2017, Shake et al, 2012). To assess potentially significant predictors of early-successional avian species occupancy, I analyzed data on patch shape and area, within-patch ground cover and visual obstruction, and landscape forest composition (Table 1).

Evidence suggests that the amount of shrub/scrub forest surrounding an early-successional patch may influence occupancy by Golden-winged Warblers (Bakermans et al, 2015). Therefore, I placed a 1 km buffer around each point-count location using ArcGIS 10.7.1 (Environmental Systems Research Institute, Redlands, Califorina, USA). I calculated the proportion of the landscape occupied by each forest patch types (grassland/herbaceous [areas dominated by grassland or herbaceous vegetation, generally greater than 80% of total vegetation], shrub/scrub [areas dominated by shrubs less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation], and cumulative deciduous, evergreen, and mixed forest cover) in each buffer using National Land Cover Data (Dewitz, 2019) and FRAGSTATS (McGarigal et. al, 2012). Between cover classes of the same type, I calculated the Euclidean nearest distance and proximity index (the spatial context of each patch in relation to neighbors of the same class). Additionally, I used ArcGIS 10.7.1 to calculate metrics including elevation, patch area, patch perimeter, and perimeter-to-area ratio.

Local Predictors of Occupancy

Due to the unique structure and composition of vegetative communities in early-successional habitats, I hypothesized that early-successional obligate songbirds may display differences in preferential habitat with regards to ground cover composition, stem densities, visual obstruction metrics (Table 1). Differences in within-stand composition could be associated with management regimes (DeGraaf & Yamasaki, 2003), so I first collected management histories for each site (timber harvests, controlled burns, and chemical treatments).

I characterized vegetative composition and structure of each patch using a modified Level 3 Carolina Vegetation Survey (CVS), which is typically used to capture cover classes and woody stem densities (Peet et al. 1988). I randomly plotted eight CVS survey within a 100 m buffer around each survey point. This distance was used as an approximate territory size of male Golden-winged Warblers (Patton et al., 2010). I conducted surveys at the first six locations in sequential order, and only surveyed sites 7 and 8 if points 1-6 could not be accessed or if a survey location fell outside the early-successional patch, dictated by the edge where older-growth forest meets the managed patch. I determined that six replicates would be an appropriate trade-off between surveyor time cost and data obtained, although a lesser number (4-5) may be sufficient in homogeneous landscapes. Using the 10 m x 10 m plot method of CVS protocol, I visually measured ground cover composition by differing classes (shrub, grass, forb, fern, litter, bare ground, and rock) and seedling (10-137 cm in height), saplings (>137cm in height and less than 2.5 cm diameter at breast height), and tree (<2.5 cm diameter base height) stem densities. Often, cover classes within a survey plot overlap. Therefore, cover class collections may total over 100%. Ground cover metrics were recorded on the Daubenmire scale (Daubenmire, 1959). Similarly, I used a Robel pole to capture vertical complexity of the understory and midstory

(Robel et al. 1970). To perform Robel measurements, I divided each 10 x 10 m quadrat into four smaller quadrats (5 m x 5m) and measured visual obstruction at the center of each of these new quadrats. I averaged these four readings to obtain one visual obstruction value for each plot. I conducted vegetation surveys once per site per season. I assumed temporal variations in patch vegetative cover to be minimal during the survey period (June – July).

Statistical Analysis

I used a two-stage modeling approach to examine potential predictors of early-successional songbird occupancy. First, I created 9 *a priori* models using potentially significant weather, time, date, and observer parameters for detection probability (p; Table 2). In these models, occupancy (ψ) was assumed constant. Significant parameters from top models were included in subsequent occupancy models. If no parameters were identified as significant predictors of detection probability, detection probability was assumed constant in occupancy models.

I then developed 14 *a priori* models for each species to estimate occupancy (Table 3). Models were created using landscape-scale and patch-scale habitat parameters collected from CVS surveys, ArcGIS, and FRAGSTATS. I limited model degrees of freedom to 5-10% of the dataset's sample size to reduce model complexity and prevent overfitting (Fieberg & Johnson, 2015; Burnham & Anderson, 2002). I examined correlations between parameters and removed highly correlated variables ($|R| > 0.7$). All covariates were centered and scaled to 0 to normalize data.

I ran all models using the "unmarked" package (Fiske and Chandler 2011) in program R (R Core Development Team 2017). I then compared models based on their AIC values, considering models under 2 ΔAIC of the top model as the top models. Significant predictors of occupancy probability were identified by evaluating the 85% confidence intervals of each parameter in the top models. Parameters with 85% confidence intervals that did not overlap 0 were considered significant. In the case that top models differed by just one parameter, that parameter was considered uninformative and inferences were made off the most parsimonious top model (Arnold, 2010).

RESULTS

Habitats varied by shape, management history, vegetative composition, and elevation (Table 4). At the landscape scale, patches were found in a mosaic of mature forest cover (evergreen, deciduous, and mixed forests) as well as shrubland and grassland. Grassland was more prevalent on the landscape than shrubland, accounting for an average of 2.43% of the total landscape at a 1-km radius scale. Shrubland accounted for an average of 2.22% of the total landscape at a 1-km radius scale. Patch perimeter-to-area ratios for each site ranged from 0.007 m/m^2 to 0.058 m/m^2 ($\bar{x} = 0.026$), reflecting a wide scope of habitat sizes and configurations.

Overall Species Detections

Prairie Warblers were the most abundant target species at study sites, detected at 76 of 111 total sites. Field Sparrows were the second most abundant and positively identified at 31 sites. Chestnut-sided Warblers and common yellow-throat warblers were found at very few sites during both seasons, with Chestnut-sided Warblers detected at 9 sites and Common Yellowthroats detected at 5 sites. Chestnut-sided Warblers were found almost exclusively at high-elevation sites in Nantahala National Forest, barring one positive identification in Sumter National Forest in 2020. I detected Golden-winged Warblers at just one site in 2021, where a male and a female occupied a high-elevation Nantahala National Forest site. During both seasons, there were no detections of Blue-winged Warblers or Golden-winged Warbler/Blue-winged Warbler hybrids. Due to the sparse Golden-winged Warbler occupancy observed during both seasons, modeling attempts for this species resulted in non-convergence.

Individual Species Detection Probabilities

Few covariates significantly affected species detection probabilities, and top candidate models varied greatly among species. Top models indicated that combinations of date, time, and temperature influenced an observer's ability to detect Prairie Warbler. The top model for detection probability included date and time, however the only significant predictor of Prairie Warbler detection was temperature (β= -0.128 ± 0.077, 85% CI [-0.24, -0.018]). This model revealed that Prairie Warbler detection probabilities decrease as temperature rises. More particularly, Prairie Warbler detection probabilities drop drastically from 23.88° to 37.8° C, decreasing from 0.85 to 0.2 (Figure 3).

Similarly, Common Yellowthroat detection probability was significantly influenced by temperature (β= 0.28 ± 0.096, 85% CI [0.14, 0.42]) and the model including temperature as the sole covariate was the only model under 2 ΔAIC (w = 0.7). Unlike Prairie Warblers, temperature had a positive effect on Common Yellowthroat detection probability. According to predictions from this top model, Common Yellowthroat detection probabilities are likely near 0 at 10° C. As temperature increases from 10° to 24° C, detection probability increases dramatically to 0.91 (Figure 4).

Model section indicated 5 top-supported models for Chestnut-sided Warbler detection probability. The top model included additive effects of wind, temperature, and sky (w_i = 0.272). The second-ranked model included a sole covariate for wind (w_i = 0.29). A date model (w_i = 0.13) and null model (w_i = 0.11) comprised remaining two models under 2ΔAIC. Since the null model was among the top candidate set, I concluded that the other top-candidate models failed to explain sufficient variation in detection probability. Chestnut-sided Warbler detection probability was estimated at 0.86 for both the 2020 and 2021 seasons.

The sole top model under 2ΔAIC for Field Sparrow detection indicated an influence of observer on detection probability. The effect of observer on detection probability, however, was not significant. Field Sparrow detection probability was estimated at 0.71 for both the 2020 and 2021 seasons.

Individual Species Occupancy Probabilities

Occupancy rates varied greatly among species despite similar influences of habitat parameters. Prairie Warblers and Field Sparrows, for example, were significantly influenced by ground cover composition at the survey site. The sole top-supported model for Prairie Warbler occupancy included effects of shrub, forb, and grass ground cover, as well as average visual obstruction, and grassland and shrub composition at the 1-km scale (Table 5). Of these parameters, grass ground cover, forb ground cover, and shrubland composition significantly influenced occupancy. Prairie Warblers occupied stands with greater grass ground cover (β= 1.41 ± 0.59, 85% CI [0.56, 2.26]) and less forb ground cover (β= -0.64 ± 0.34, 85% CI [-1.14, -0.15]). Patches surrounded by more shrubland patches were more likely to be occupied than those with less (β = 0.56 ± 0.37, 85% CI [0.03, 1.09]) (Figure 5). Similarly, only one top model existed for Field Sparrow occupancy (w_i = 0.99; Table 6). This included ground cover metrics (shrub, forb, and grass ground cover) as well as average visual obstruction, patch perimeter, patch perimeter-to-area ratio, and elevation. Shrub cover (β = 0.93 ± 0.6, 85% CI [0.07, 1.8]) and grass cover ((β = 1.24 ± 0.62, 85% CI [0.35, 2.13]) positively influenced Field Sparrow occupancy. Yet, Field Sparrows displayed preference for open patches with greater interior area compared to edge habitat (β = -1.92± 0.8, 85% CI [-3.06, -0.79]). Field Sparrows also responded negatively to increasing elevation (β = -1.62± 0.9, 85% CI [-2.91, -0.32]). At 240 m above sea level, Field Sparrow occupancy was estimated at 0.74. Moving up to 1000 m, however, decreased occupancy estimates to just 0.018 (Figure 6). Overall occupancy estimates for Prairie Warbler and Field Sparrow were 0.87 and 0.24 respectively.

Conversely to Prairie Warblers and Field Sparrows, Common Yellowthroats were influenced solely by landscape features. The top-supported model for Common Yellowthroat occupancy included additive effects of grassland and shrubland composition at the 1 km scale. This model was the sole top-supported model (w_i = 0.93; Table 7) and demonstrated a simultaneous increase in Common Yellowthroat occupancy as grassland composition increased (β = 2.4± 1.32, 85% CI [0.5, 4.31]). Occupancy estimates were as low as 0.078 when grassland composition neared 0, yet increased to 0.99 with 14% grassland composition (Figure 7). This model estimates overall Common Yellowthroat occupancy at 0.22 for the 2020 and 2021 seasons.

Chestnut-sided Warblers had two top-supported occupancy models. The top model indicated that years since the last burning treatment, years since the last timber thinning treatment, average visual obstruction, and elevation influenced occupancy rates. The second model indicated that shrub, grass, and forb ground cover, as well as visual obstruction and elevation influenced occupancy. Together, these two models carried 94% of the Akaike weight (Table 8). Average visual obstruction was the sole significant predictor from the first model. This parameter had a negative relationship with Chestnut-sided Warbler occupancy (β = -1.26± 0.71, 85% CI [-2.28, -0.24]). Elevation, however, had a strong positive influence on occupancy (β = 2.52± 0.88, 85% CI [1.25, 3.79]). Predictions indicated that occupancy for Chestnut-sided

Warblers was near 0 until about 700 m in elevation. Occupancy estimates then increased dramatically, reaching a maximum estimate of 87% at 1436 m in elevation (Figure 8). Over the entire study area and across both seasons, the top model estimated Chestnut-sided Warbler occupancy at 0.02.

DISCUSSION

My study provided the first known comprehensive effort to index Golden-winged Warbler populations in South Carolina, and the results suggest that breeding populations of Golden-winged Warblers are either absent from the state or at very low occurrence. My study identified just one site with a positive identification of Golden-winged Warbler, at a high-elevation managed patch in Nantahala National Forest, North Carolina. Historically, Golden-winged Warblers occupied sites and had successful breeding seasons in South Carolina's Blue Ridge region. These sites, however, were confined to high-elevation mountains like Caesars Head (Loomis, 1891).

While there was model selection uncertainty, my study supports the notion that Golden-winged Warblers are affiliated with high-elevation habitats since the only positive detection of a Golden-winged Warbler occurred at 1231 m. The only habitat indicator species detected at the same site as Golden-winged Warblers was the Chestnut-sided Warbler. The Golden-winged Warbler Status Review and Conservation Plan lists Chestnut-sided Warblers as an indicator species with "medium to high" association with Golden-winged Warblers in the Appalachian region (Roth et al., 2012). Furthermore, historic accounts of Golden-winged Warblers in South Carolina also include Chestnut-sided Warblers (Loomis, 1891).

My study revealed significant effects of elevation on Chestnut-sided Warbler occupancy, and similar responses to elevation may indicate shared habitat preferences between Golden-winged Warblers and Chestnut-sided Warblers in the Southern Blue Ridge. In contrast, Prairie Warblers, Common Yellowthroats, and Field Sparrows were absent from sites above 900 m, indicating that these species may not act as indicators for quality Golden-winged Warbler habitat. In portions of their range, Golden-winged Warblers likely occupy high-elevation habitats as a response to Blue-winged Warblers occupying lower elevations (Gill, 1980). Particularly, high-elevation habitats provide refuge where Golden-winged Warblers can escape hybridization and competition (Gill, 1980; Klaus & Buehler, 2001; Rosenberg et al., 2016). It is important to note, however, that I did not encounter Blue-winged Warblers or golden-winged x Blue-winged Warbler hybrids at any of my study sites. Additionally, Chestnut-sided Warblers commonly occupied lower elevation sites in South Carolina in the past (Loomis, 1891), yet 8 out of 9 observations of Chestnut-sided Warblers in my study occurred at or above 950 m. This result reflects findings that Chestnut-sided Warblers occupy isolated habitats above 1000 m in the Southern Appalachians (Buehler et al., 2005). In northern tiers of their range, however, Chestnut-sided Warblers occur at lower elevations (Roberts & King, 2017; King & Byers, 2002), and that same trend is observed in Golden-winged Warblers (Roth, 2012). This may suggest disparate habitat preferences of both species in the SBRE when compared to the rest of their native range. Additionally, these observations indicate paralleling trends of Chestnut-sided and Golden-winged Warblers to occupy higher-elevation habitats at the southern edge of their range, and the lack of Blue-winged Warblers at my study sites suggests that interspecies competition may not be driving this effect.

One potential driver of species' range shifts could be the effects of climate change, and that Golden-winged Warblers and Chestnut-sided Warblers in the SBRE may be at the receding edge of their population range. These species may prefer vegetation communities or structures that were commonly found in lower elevations in the past, but may be occurring at increasingly higher elevation gradients as our climate warms (Bolstad, 1998; Whittaker, 1956). Additionally, if these species are at the receding edge of their range in response to climate change, it is likely that their ranges have been and will continue to shift upslope and northward. The Southern Blue Ridge has recently been identified as a hotspot for trailing edge avian species coping with shifting climatic conditions (Merker & Chandler, 2020), and future research may consider examining the effects of warming climates in this region on Chestnut-sided Warblers and Golden-winged Warblers specifically.

Golden-winged and Chestnut-sided Warblers may also avoid lower elevation habitats in the Southern Blue Ridge due to nuances of habitat preferences exhibited by both species. Average visual obstruction inversely correlated with Chestnut-sided Warbler occupancy, and if Chestnut-sided Warblers indicate Golden-winged Warbler habitat, then one might expect similar relationships between vegetation density and Golden-winged Warblers. The tendency of Chestnut-sided Warblers to occupy sites with significantly lower visual obstruction indicate preference for sites with reduced midstory vegetation. In southern New England, abundance of early-successional avian species is greater at sites with lower vegetation, and Chestnut-sided Warbler abundance is driven by low vegetation height and low tree density (Peterson, 2015). In New York, Golden-winged Warblers establish territories on sites with large openings, particularly in mowed and bare ground habitats with low visual obstruction (Frech & Confer, 1987). Reduction of midstory vegetation also correlates positively with grass and herbaceous groundcover productivity (Singleton et al., 2013), which has been associated with Golden-winged Warbler occupancy (Klaus & Buehler, 2001). Similarly, habitat management recommendations for Golden-winged Warbler include providing habitats with no more than 10 years of forest succession, which would limit vegetation height (Roth et al., 2012). The bulk of my study sites represented relatively old (average age of succession = 7.26 years) and relatively dense (average visual obstruction = 115 cm) patches, which may explain the pervasive absence of both species.

While the other shrubland obligate species used in my study seem to be poor indicators of Golden-winged Warbler habitat, they do demonstrate overall trends of shrubland obligate birds to select habitat at multiple biotic and abiotic scales, and it is likely that Golden-winged Warblers and Chestnut-sided Warblers select habitat based on parameters at multiple scales as well (Lehnen & Rodewald, 2009; Schlossberg & King, 2008; Shoe, 2018). For example, Prairie Warbler and Field Sparrow occupancy were influenced by within-patch, patch-scale, and landscape-scale characteristics. In addition, Common Yellowthroat occupancy was be predicted by landscape composition. Golden-winged Warblers prefer landscapes with high herbaceous cover (Klaus & Buehler, 2001), and may increase in abundance as the proportion of young forest cover within 1 km of the patch also increases (Bakermans, et al., 2015). Considered as a whole, local and landscape habitat parameters can influence nest survival and community assemblages, which may drive selection of these sites (Thompson III & Capen, 1988; Hughes et al., 2000; Schlossberg et al., 2010). It remains unclear how multi-scale habitat parameters influence Golden-winged Warblers in the SBRE, but it is probable that occupancy of the species would be influenced by local and landscape-scale factors.

Detection Probabilities

Detection probabilities varied among target species, ranging from moderately-cryptic (p = 0.42 for Common Yellowthroat) to conspicuous (p = 0.86 for Chestnut-sided Warbler). Despite interspecies variation, there was a strong temperature regulating effect on Prairie

Warbler and Common Yellowthroat detection probability. Temperature had an opposite effect on both species, increasing detection probability for Common Yellowthroats and decreasing detection probability for Prairie Warblers. However, temperature maximized detection probability within the same general range, near 21° C. Temperature could be correlated with date and time of day, and it is likely that date and time influence detection rates as a function of both migration interval and higher relative frequency of singing activity in the morning (Ralph et al., 1995; Huff, 2000). My point-count-survey protocol strategically overlapped both the migratory period and peak singing activity time period to maximize detection probability. Similarly, point counts were not conducted in periods of heavy rain or wind, which may explain why these effects did not influence detection in my study. Detection rates for Chestnut-sided Warblers and Field Sparrows were particularly high and not significantly influenced by any covariates. Limiting point count surveys to strategic time and date intervals, as well as optimal weather conditions, likely maximizes detection probability for these species.

Conclusion

My results support the notion that early-successional obligate species should not be considered a guild with uniform habitat preferences, and that considering both the structure and composition of regenerating patches at multiple scales is important when managing for specific species. My research also suggests that Golden-winged Warblers and Chestnut-sided Warblers represent a sub-group of the early-successional guild that display explicit preferences for high-elevation habitats. Moreover, the Chestnut-sided Warbler seems to be an efficient indicator for Golden-winged Warbler habitat in the Southern Blue Ridge. Since Chestnut-sided Warblers are more prevalent than Golden-winged Warblers in this region, they may be more affordable to monitor and manage. Additionally, monitoring and managing for Chestnut-sided Warblers may save managers time and effort while still benefiting a host of early-successional species that occupy high-elevation habitats, such as the Golden-winged Warbler (Bal et al., 2018; Wiens et al., 2008). Monitoring efforts for Chestnut-sided and Golden-winged Warblers in the SBR may be most efficient if directed at sites at or above 1000 m in elevation with relatively low vegetation height-density.

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TABLES & FIGURES

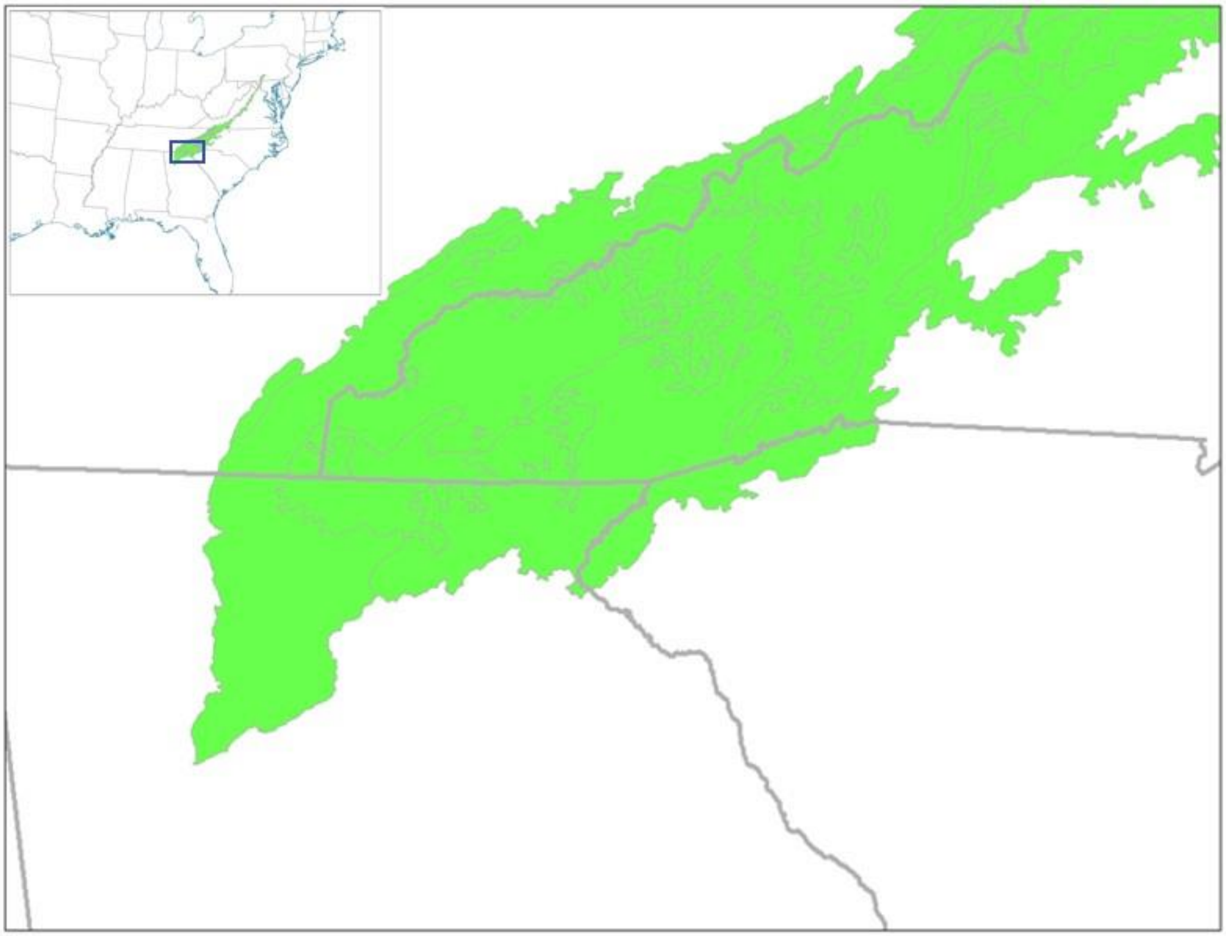

Figure 1. Map of the southern extent of the Blue Ridge Ecoregion.

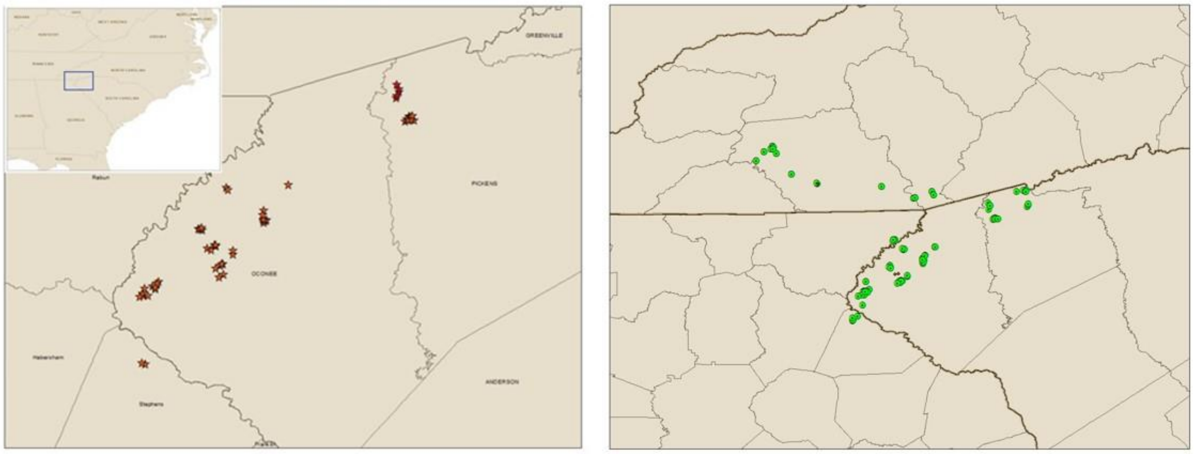

Figure 2. *Left:* Point count surveys were conducted at 49 sites during the 2020 season. 45 sites occurred in South Carolina and 4 in Georgia. Sites are indicated by red stars. *Right:* Point count surveys were conducted at 62 unique sites during the 2021 season. 44 sites occurred in South Carolina, 14 in North Carolina, and 4 in Georgia. Sites are indicated by green circles.

Table 1. List of occupancy covariates used in model selection.

MANAGEMENT	LOCAL	PATCH	LANDSCAPE
Years Since Partial or Complete Overstory Removal	Shrub Groundcover (%)	Perimeter-to-area ratio (m/m^2)	Shrubland composition (%)
Years Since Last Burn	Grass Groundcover (%)	Perimeter (m)	Grassland composition (%)
	Forb Groundcover (%)	Elevation (m)	Euclidean nearest neighbor grassland
	Average Visual Obstruction (cm)		Euclidean nearest neighbor shrubland
	Mature Tree Density (per $10m^2$)		
	Sapling Density (per $10m^2$)		
	Seedling Density (per $10m^2$)		

Table 2. Candidate models for detection probability model selection.

Model	Components
Global	Date + Time + Temp + Wind + Sky
Timing	Date + Time
Weather	Wind + Temp + Sky
Time	Time
Date	Date
Wind	Wind
Temp	Temp
Sky	Sky
Observer	Observer

Table 3. Candidate models for species occupancy model selection. Models marked with asterisk (*) indicates models that were used exclusively in Chestnut-sided Warbler model selection.

Model	Components
Ground Cover (Quadratic)	(Shrub Groundcover^2) + (Grass Groundcover^2) + (Forb Groundcover^2) + Visual Obstruction
Ground Cover	Shrub Groundcover + Grass Groundcover + Forb Groundcover + Visual Obstruction
Management History	Years Since Last Thin + Years Since Last Burn
Stem Density	Trees + Saplings + Seedlings
Timber Management	Years Since Last Thin
Burn Management	Years Since Last Burn
Ground Cover and Stem Density	Shrub Groundcover + Grass Groundcover + Forb Groundcover + Visual Obstruction + Trees + Saplings + Seedlings
Patch Configuration, Ground Cover, and Elevation	Shrub Groundcover + Grass Groundcover + Forb Groundcover + Visual Obstruction + Perimiter-to-Area Ratio + Perimeter + Elevation
Landscape Composition	Shrubland Composition + Grassland Composition
Patch Euclidean Nearest Neighbor (ENN)	ENN Shrubland + ENN Grassland
Landscape Composition and Groundcover	Shrub Groundcover + Grass Groundcover + Forb Groundcover + Visual Obstruction + Shrubland Composition + Grassland Composition
Groundcover and Management History	Shrub Groundcover + Grass Groundcover + Forb Groundcover + Visual Obstruction + Years Since Last Thin + Years Since Last Burn
Shrubs and Visual Obstruction	Shrub Groundcover + Visual Obstruction
Forbs and Visual Obstruction	Forb Groundcover + Visual Obstruction
***Groundcover and Elevation**	Shrub Groundcover + Grass Groundcover + Forb Groundcover + Visual Obstruction + Elevation
***Management History and Elevation**	Years Since Last Thin + Years Since Last Burn + Elevation

Table 4. Summary statistics for patch and landscape-scale habitat parameters collected at study sites. Ground cover metrics were measured in the Daubenmire Scale [(0) = 0% ; (1) = 1 - 5% ; (2) = 5 - 25% ; (3) = 25 - 50% ; (4) 50 - 75% ; (5) 75 - 95% ; (6) 95 - 100%].

Parameter	Abbreviation	Mean	SE	Range
Shrub Groundcover	gc.shrubs	3.34	1.08	0.17 – 5.17
Forb Groundcover	gc.forbs	2.16	1.29	0 – 5.17
Grass Groundcover	gc.grass	2.19	1.03	0.17 – 5
Average Visual Obstruction (dm)	avg.vo	11.5	3.71	2.71 – 19.79
Tree Density per 10m^2	trees	7.28	8.8	0 – 31.83
Sapling Density per 10m^2	saplings	29.41	22.81	0.14 – 118.33
Seedling Density per 10m^2	seedlings	34.14	19.66	0 – 100.5
Perimeter-to-area Ratio (m/m^2)	para	0.026	0.013	0.008 – 0.06
Perimeter (m)	perim.m.	2762.29	2140.4	428 – 11483
Elevation (m)	elev	578.26	248.8	241 – 1432
Shrubland Composition (%)	pland.shrub	2.22	2.64	0 – 11.15
Grassland Composition (%)	pland.grass	2.43	4.8	0 – 31.57
ENN Grassland (m)	enn__mn_grass	185.96	217.0	0 – 1408.7
ENN Shrubland (m)	enn_mn_shrub	226.25	284.22	0 – 1380
Years Since Last Thin (years)	years.lastthin	7.26	4.32	0 – 15
Years Since Last Burn (years)	years.lastburn	1.21	1.81	0 – 9

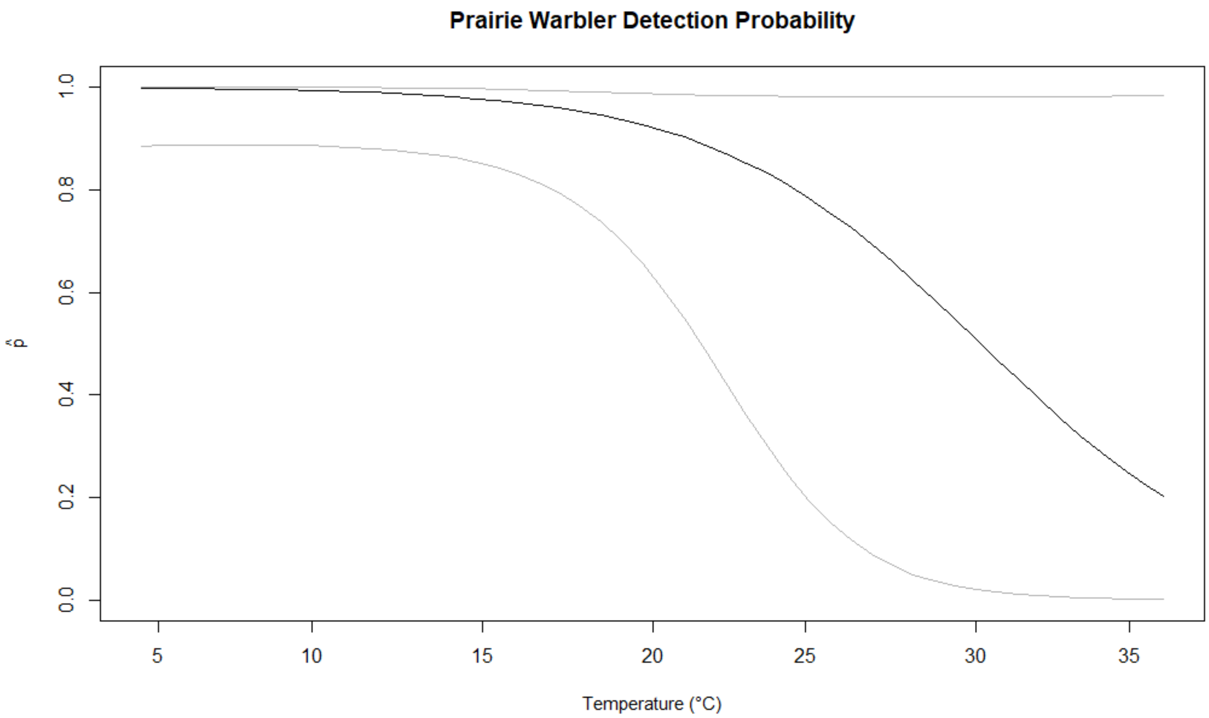

Figure 3. Influence of temperature on Prairie Warbler detection probability during the 2020 and 2021 field seasons. Gray lines indicate 85% confidence intervals.

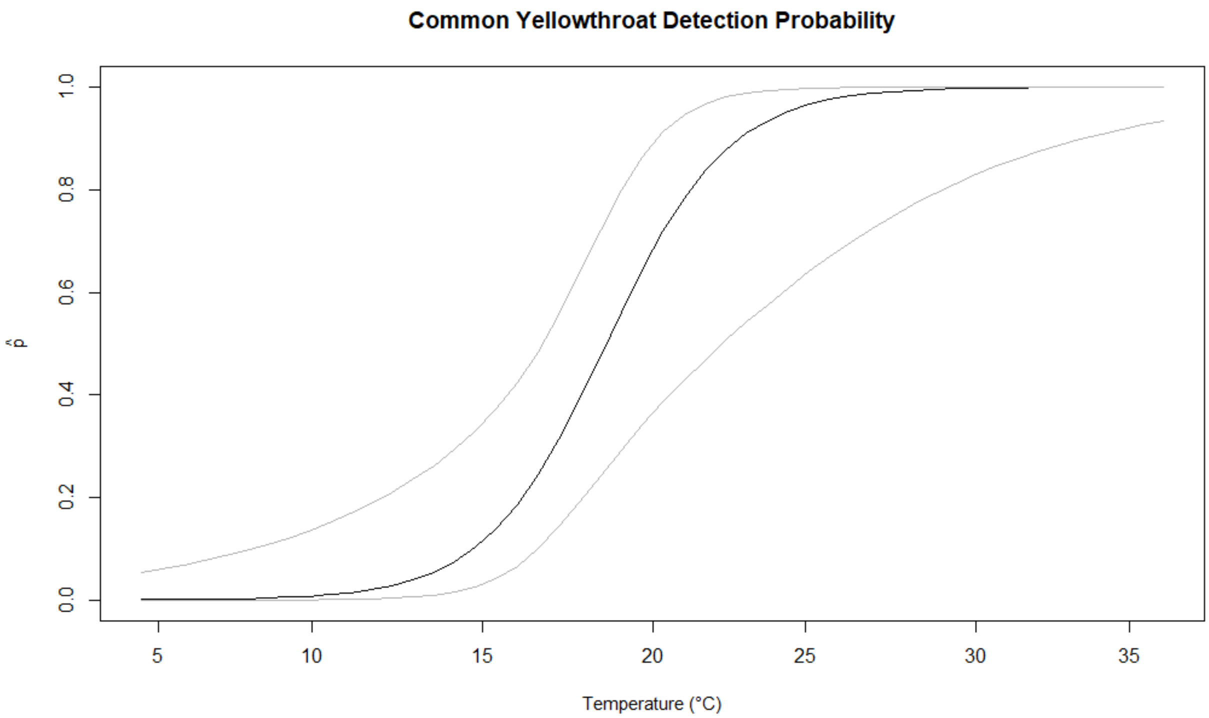

Figure 4. Influence of temperature on Common Yellowthroat detection probability during the 2020 and 2021 field seasons. Gray lines indicate 85% confidence intervals.

Table 5. Ranking of candidate models that assess the influence of landscape-scale habitat metrics and forest composition on Prairie Warbler occupancy in the Southern Blue Ridge Ecoregion during spring 2021 roadside drumming surveys. ^{q} represents the quadratic structural form of a covariate. K is the number of parameters including intercept. AIC is Akaike's information criterion. ΔAIC is the difference in AIC from the top model. w_i is the Akaike weight. Null represents the null model where occupancy and detection probabilities were held constant. All models were run with TEMP as a detection covariate.

Model	K	AIC	ΔAIC	w_i
gc.shrubs + gc.grass + gc.forbs + avg.vo + pland_shrub + pland_grass	9	187.34	0.00	0.69
gc.shrubs + gc.grass + gc.forbs + avg.vo + years.lastthin + years.lastburn	9	190.37	3.03	0.84
gc.grass +gc.shrubs + gc.forbs +avg.vo	7	191.71	4.36	0.92
gc.shrubs + gc.grass + gc.forbs + avg.vo + trees + saplings + seedling	10	192.07	4.73	0.98
gc.shrubs^q+ gc.shrubs + gc.grass^q + gc.grass + gc.forbs^q + gc.forbs + avg.vo	10	196.21	8.86	0.99
pland_shrub + pland_grass	5	196.62	9.27	1.00
years.lastthin + years.lastburn	5	199.77	12.42	1.00
gc.forbs + avg.vo	5	200.51	13.16	1.00
trees + saplings + seedlings	56	203.98	16.63	1.00
gc.shrubs + avg.vo	5	206.57	19.23	1.00
null	2	207.53	20.18	1.00

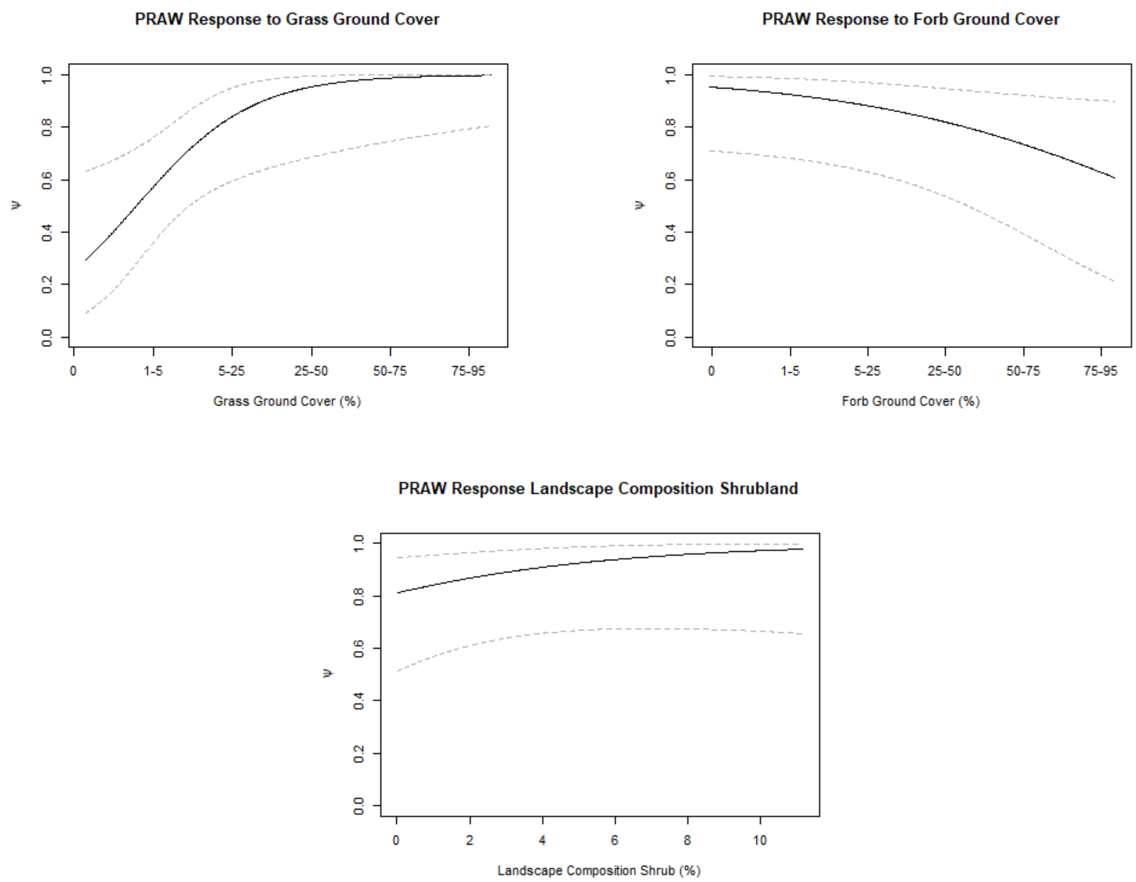

Figure 5. Influence of forb cover, grass cover, and shrubland composition on Prairie Warbler occupancy probability during the 2020 and 2021 field seasons. Dashed lines indicate 85% confidence intervals.

Table 6. Ranking of candidate models that assess the influence of landscape-scale habitat metrics and forest composition on Field Sparrow occupancy in the Southern Blue Ridge Ecoregion during spring 2021 roadside drumming surveys. ^{q} represents the quadratic structural form of a covariate. K is the number of parameters including intercept. AIC is Akaike's information criterion. ΔAIC is the difference in AIC from the top model. w_i is the Akaike weight. Null represents the null model where occupancy and detection probabilities were held constant.

Model	**K**	**AIC**	**ΔAIC**	w_i
gc.shrubs + gc.grass + gc.forbs + avg.vo + para + perim + elev	9	161.53	0.00	0.99
gc.shrubs + gc.grass + gc.forbs + avg.vo + pland_shrub + pland_grass	8	172.30	10.77	1.00
gc.shrubs + gc.grass + gc.forbs + avg.vo + years.lastthin + years.lastburn	8	173.55	12.02	1.00
pland_shrub + pland_grass	4	176.56	15.03	1.00
gc.grass +gc.shrubs + gc.forbs +avg.vo	6	180.36	18.83	1.00
gc.shrubs^q + gc.shrubs + gc.grass^q + gc.grass + gc.forbs^q + gc.forbs + avg.vo	9	180.91	19.38	1.00
years.lastthin + years.lastburn	4	181.78	20.25	1.00
years.lastthin	3	182.66	21.13	1.00
gc.shrubs + gc.grass + gc.forbs + avg.vo + trees + saplings + seedlings	9	183.58	22.05	1.00
enn_mn_shrub + enn_mn_grass	4	184.06	22.53	1.00
gc.shrubs + avg.vo	4	185.83	24.30	1.00
null	2	189.40	27.97	1.00
gc.forbs + avg.vo	4	189.86	28.33	1.00
trees + saplings + seedlings	5	190.62	29.09	1.00
years.lastburn	3	191.24	29.71	1.00

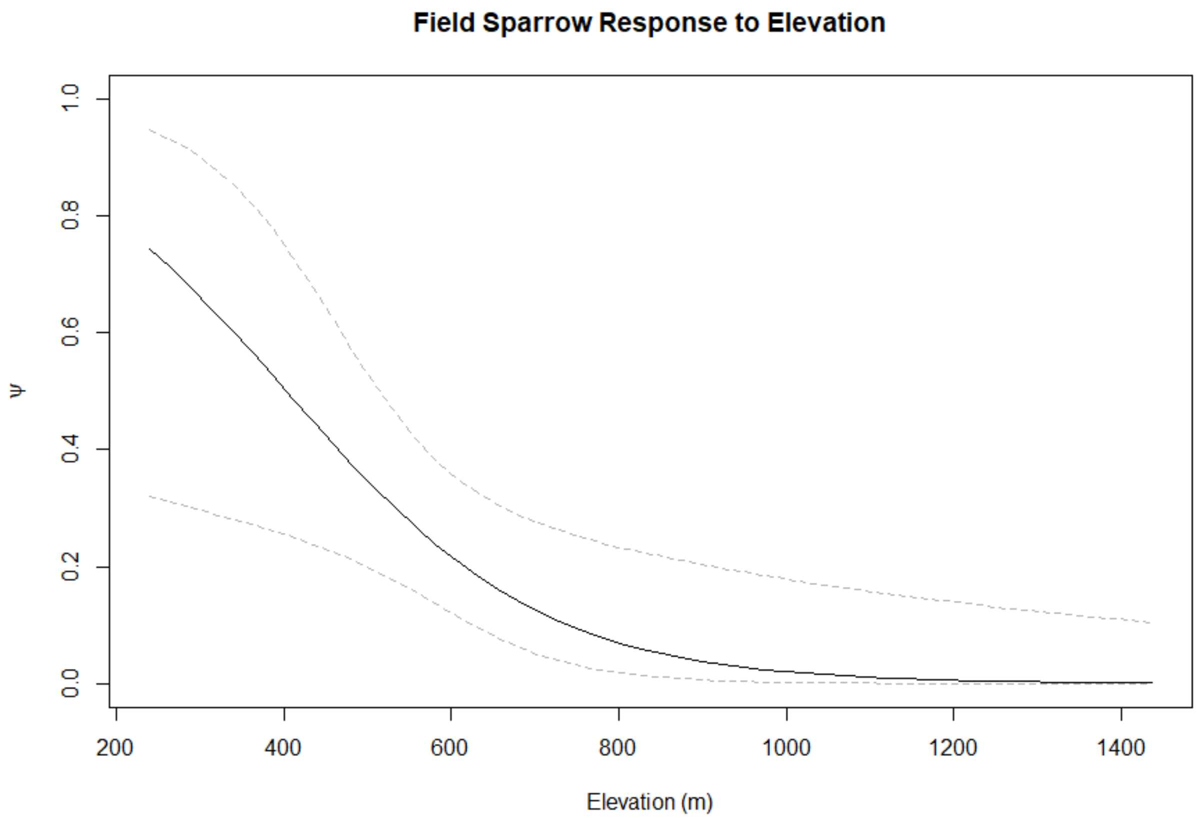

Figure 6. Influence of elevation on Field Sparrow occupancy probability during the 2020 and 2021 field seasons. Dashed lines indicate 85% confidence intervals.

Table 7. Ranking of candidate models that assess the influence of landscape-scale habitat metrics and forest composition on Common Yellowthroat occupancy in the Southern Blue Ridge Ecoregion during spring 2021 roadside drumming surveys. ^{q} represents the quadratic structural form of a covariate. K is the number of parameters including intercept. AIC is Akaike's information criterion. ΔAIC is the difference in AIC from the top model. w_i is the Akaike weight. Null represents the null model where occupancy and detection probabilities were held constant. All models were run with TEMP as a detection covariate.

Model	**K**	**AIC**	**ΔAIC**	$\boldsymbol{w_i}$
pland_shrub + pland_grass	5	76.07	0.00	0.93
gc.shrubs + gc.grass + gc.forbs + avg.vo + pland_shrub + pland_grass	9	82.73	6.66	0.97
years.lastthin	4	84.68	8.61	0.98
enn_mn_shrub + enn_mn_grass	5	85.76	9.69	0.99
years.lastthin + years.lastburn	5	86/04	9.97	0.99
years.lastburn	4	87.66	11.59	1.00
gc.forbs + avg.vo	5	88.57	12.50	1.00
trees + saplings + seedlings	6	89.81	13.74	1.00
gc.shrubs + avg.vo	5	89.89	13.82	1.00
gc.shrubs + gc.grass + gc.forbs + avg.vo + years.lastthin + years.lastburn	9	91/13	15.06	1.00
gc.grass +gc.shrubs + gc.forbs +avg.vo	7	91.32	15.25	1.00
gc.shrubs^{q} + gc.shrubs + gc.grass^{q} + gc.grass + gc.forbs^{q} + gc.forbs + avg.vo	10	91.37	15.30	1.00
null	2	100.78	24.71	1.00

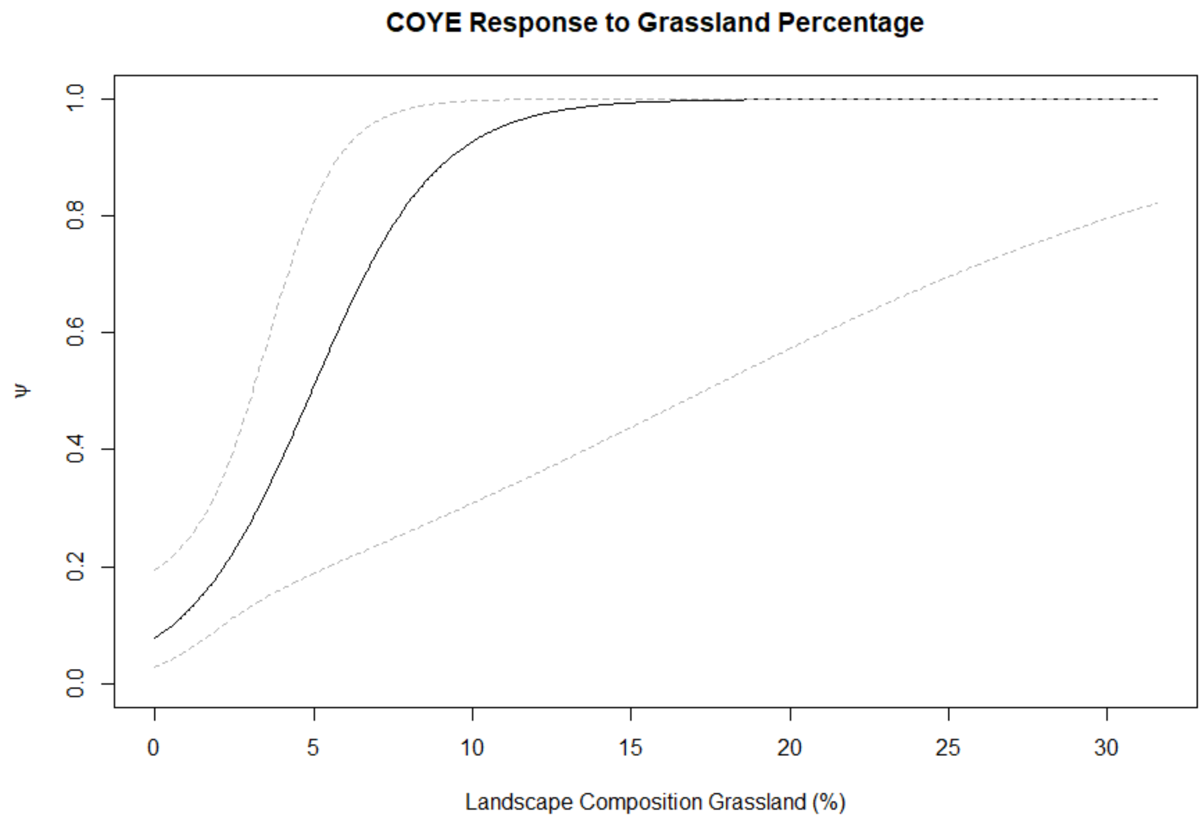

Figure 7. Influence of grassland composition within 1 km of the patch on Common Yellowthroat occupancy probability during the 2020 and 2021 field seasons. Dashed lines indicate 85% confidence intervals.

Table 8. Ranking of candidate models that assess the influence of landscape-scale habitat metrics and forest composition on Chestnut-sided Warbler occupancy in the Southern Blue Ridge Ecoregion during spring 2021 roadside drumming surveys. ^{q} represents the quadratic structural form of a covariate. K is the number of parameters including the intercept. AIC is Akaike's information criterion. ΔAIC is the difference in AIC from the top model. w_i is the Akaike weight. Null represents the null model where occupancy and detection probabilities were held constant.

Model	K	AIC	ΔAIC	w_i
years.lastthin + years.lastburn + elev	5	58.17	0.00	0.52
gc.shrubs + gc.grass + gc.forbs + avg.vo + elev.m.	7	58.65	0.48	0.94
gc.shrubs + gc.shrubs^{q} + gc.grass + gc.grass^{q} + gc.forbs + avg.vo + para + perim.m	8	63.72	5.54	0.97
gc.shrubs + gc.grass + gc.forbs + avg.vo + pland_shrub + pland_grass	8	65.55	7.37	0.98
gc.shrubs + gc.grass + gc.forbs + avg.vo + trees + saplings + seedlings	9	66.90	8.73	0.99
gc.shrubs + gc.grass + gc.forbs + avg.vo	6	66.97	8.79	0.99
gc.shrubs + gc.grass + gc.forbs + avg.vo + years.lastthin + years.lastburn	8	67.74	9.56	1.00
gc.shrubs + gc.shrubs^{q} + gc.grass + gc.grass^{q} + gc.forbs + gc.forbs^{q} + avg.vo	9	71.24	13.07	1.00
trees + saplings + seedlings	5	74.33	16.16	1.00
enn_mn_shrub + enn_mn_grass	4	74.95	16.77	1.00
pland_shrub + pland_grass	4	78.88	20.71	1.00
years.lastburn	3	82.84	24.66	1.00
null	2	83.94	25.77	1.00
years.lastthin	3	85.55	27.38	1.00

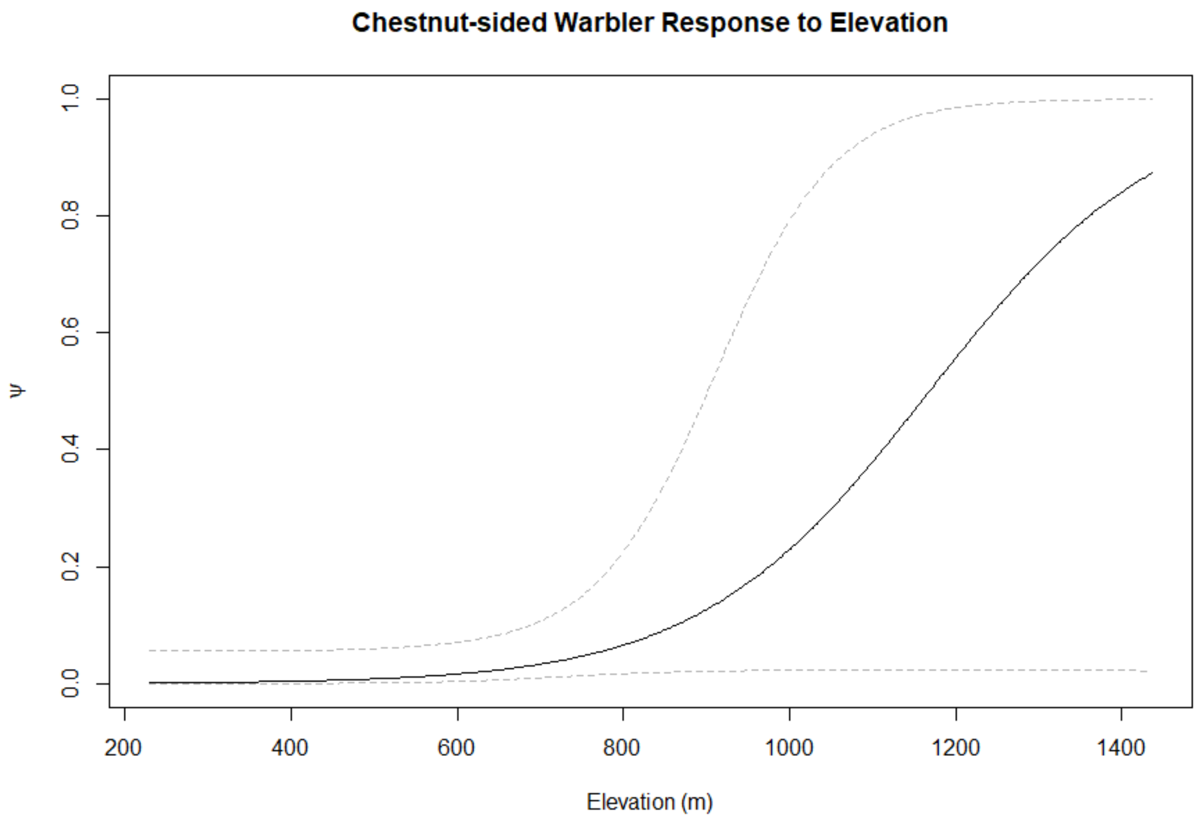

Figure 8. Influence elevation on Chestnut-sided Warbler occupancy probability during the 2020 and 2021 field seasons. Dashed lines indicate 85% confidence intervals.

CHAPTER THREE

EVALUATING THE EFFICACY OF AUTONOMOUS RECORDING UNITS TO DETECT AND MONITOR EARLY-SUCCESSIONAL AVIAN SPECIES

INTRODUCTION

Robust monitoring protocols are critical to species conservation efforts, especially for those deemed rare, cryptic, or of greatest conservation need (Yoccoz, 2001). Species monitoring can aid in determining species distribution, occupancy, abundance, and site use, which can have large implications on conservation and management decisions (Pellet & Schmidt, 2005; Noon et al., 2002). Specifically, designing quality monitoring programs involves examining multiple methodologies and accounting for differences in detection probabilities which may induce survey bias (Williams et al., 2002). Autonomous recording units are a new and emerging technology that, in recent years, have been increasingly used in amphibian, bat, and bird surveys (Lee et al., 2021; Beason et al., 2019; Shonfield & Bayne, 2017). Autonomous recording units are deployed at survey sites, where they passively record audio files. Researchers can pre-program recording times to reflect preferred survey windows, and files can be extracted and analyzed by researchers either manually or by aid of recognition software (Pérez-Granados et al., 2018; Shonfield & Bayne, 2017).

Recent research that has aimed to compare the efficacy of autonomous recording units and human-observer surveys provides conflicting results (Pankratz et al., 2017; Turgeon et al., 2017; Kułaga & Budka, 2019; Jorge et al., 2018). Autonomous recording units can be useful for monitoring rare and cryptic species (Duchhac et al., 2002; Leach et al., 2016), but detection probabilities may be influenced or degraded by vocal complexity (Bobay et al., 2018). Similarly, issues may arise with low-frequency sounds, such as resultant false negatives and false positives when using soundwave analyzing programs (Shonfield & Bayne, 2017; Zwart et al., 2014). This creates monitoring problems for species with vocalizations that fall within the frequency range of background noises, such as wild turkey (Colbert et al., 2015). Ruffed Grouse, similarly, have a drumming frequency below 100hz (Garcia et al., 2012), and little research has examined the efficacy of autonomous recording units to detect drumming (Van Wilgenburg, 2017). Additionally, autonomous recording unit surveys can increase temporal and spatial coverage, but may miss individuals at long distances (Sidie-Slettedahl et al., 2015; Hutto, & Stutzman 2009). This provides specific challenges for using autonomous recording units as a substitute for point count surveys and can be exacerbated by other recording unit variables such as internal noise (Hutto & Stutzman, 2009; Bobay et al., 2018. Rempel et al., 2013).

The South Carolina Department of Natural Resources (SCDNR) State Wildlife Action Plan includes monitoring as a top priority for species on the state's Priority Species List, which includes Ruffed Grouse and Golden-winged Warblers (highest priority), as well as Prairie Warblers and Field Sparrow (high priority), and Chestnut-sided Warbler (moderate priority). Assessing the use of autonomous recording units to detect these species will be critical to inform future monitoring protocols. Moreover, it is important to determine the efficacy of autonomous recording units by comparing relative detection probabilities with human-observer surveys. To compare the two methodologies, I evaluated site occupancy by conducting drumming surveys and point count surveys in the spring and early summer of 2020 and 2021. I recorded detection/non-detection data for Ruffed Grouse, Golden-winged Warbler, Prairie Warbler, Common Yellowthroat warbler, Chestnut-sided Warbler, and Field Sparrow. I subsequently placed autonomous recording units at sites with and without detections and resurveyed sites at least once with a subsequent autonomous recording unit recording. I hypothesized that human-observer surveys and autonomous recording unit surveys would result in similar detection probabilities. I also hypothesized that manually analyzing recording data with the aid of a visual spectrogram would provide an efficient means to identify species detections.

METHODS

Study Area: Region and Sites

The Blue Ridge Ecoregions spans 9.4 million acres across Virginia, Tennessee, South Carolina, Georgia, and North Carolina (Albritton, 2013). The ecoregion is characterized by mixed mesophytic forests, primarily dominated by oak (*Quercus* spp.), hickory (*Carya* spp.), and pine (*Pinus* spp.). Elevations range 450 to 2037 meters (Albritton, 2013; SCDNR, 2005; The Nature Conservancy and Southern Appalachian Forest Coalition, 2000). The majority of forests in the region are privately owned, with 35% in public ownership (The Nature Conservancy and Southern Appalachian Forest Coalition, 2000).

Ruffed Grouse Drumming Surveys

During the 2021 season, I used ArcGIS 10.7.1 (Environmental Systems Research Institute, Redlands, Califorina, USA) to plot 664 drumming survey stations along 82 secondary and primitive roads following standard roadside drumming survey methodologies (Petraborg, 1953) with additional routes along hiking trails (Figure 1). Roadside and trailside drumming surveys offered an opportunity to increase survey effort, which was deemed necessary due to few detections during the 2020 season. Routes were selected through stratified random sampling of managed and unmanaged sites located within the Blue Ridge Ecoregion of South Carolina (Andrew Pickens Ranger District of Sumter National Forest, Jocassee Gorges Wildlife Management Area, Table Rock State Park, Ashmore Heritage Preserve, Watson-Cooper Heritage Preserve), Georgia (Chattooga River District of Chattahoochee National Forest) and North

Carolina (Headwater State Forest). Drumming survey stations were separated by 500 m of road or trail length to ensure independence among sites. Many of the road and trail routes included switchbacks and sharp turns, however the likelihood of double-detections between survey sites spaced apart by 500 m of road or trail length was deemed negligible. I did not include drumming stations along primary roads, due to the likelihood of road traffic noise interfering with the ability to detect drumming Ruffed Grouse.

Standard occupancy designs involve surveying a set number of sites with a set number of repeat visits (MacKenzie et al. 2002). This survey design is well suited for more common species, however when surveying for cryptic or rare species, the standard design requires a large number of visitations per site (MacKenzie & Royle, 2005). Often, this will lead the surveyor to invest resources into conducting repeat visits at unoccupied sites. An alternative occupancy survey design for rare or cryptic species is an occupancy survey with conditional replicates. The conditional occupancy survey design involves surveying all sites at least once and only resurveying sites with a positive detection of the focal species. This method improves on the accuracy of detection probability and occupancy from other sampling designs and is well suited for surveying rare and cryptic species (Specht et al., 2017).

Using a conditional occupancy design, I surveyed each drumming station once. Surveys were conducted in March and April to best reflect the peak drumming period for Ruffed Grouse in the southern Appalachians (Jones et al., 2005). After the initial site visit, only sites with a positive identification of grouse were resurveyed. These sites were resurveyed at maximum four times. Ruffed Grouse drum before sunrise, and drumming rates drop drastically by late morning (Petraborg et al., 1953). For this reason, Ruffed Grouse drumming surveys were conducted between 30 minutes before sunrise to 4 hours after sunrise. To reduce any potential time bias, I varied the times that each resurveyed drumming station was visited by surveying the route in the reverse direction. When possible, a different observer was assigned for each resurvey to reduce observer bias. Surveys began with a 5-minute site cool down period, which was employed to minimize the disturbance of observers arriving to a site. The cool down period was followed by a 4-minute drumming survey which included passive scanning and listening.

Songbird Point Count Surveys

Study sites were spatially constrained by public lands in the Blue Ridge Ecoregion of South Carolina (Andrew Pickens Ranger District of Sumter National Forest, Jocassee Gorges Wildlife Management Area) and Georgia (Chattooga River District of Chattahoochee National Forest) in 2020. Due to limited detections in 2020 and additional personnel time, I restructured the survey methodology in 2021 and added North Carolina (Nantahala National Forest) sites. Study site selection was further limited to managed forest stands harvested in the interval between 2005 and 2016. Regenerating stands from this age interval provide quality habitat for early-successional avian species (Conner & Dickson, 1997; DeGraaf & Yamasaki, 2003). Additionally, I included one high elevation powerline right-of-way for surveys in both the 2020 and 2021 seasons. Investigators have demonstrated the use of powerline right-of-ways (ROW) by a variety of early-successional avian species, including the Golden-winged Warbler, Chestnut-sided Warbler, and Prairie Warbler (Askins et al., 2012, DeFalco & Dey, 2003; Kubel & Yahner, 2007). Common management practices on non-ROW stands included overstory removal and two-aged harvests with subsequent management including controlled burns, chemical treatment, and additional thinnings. Using ArcGIS 10.7.1 (Environmental Systems Research Institute, Redlands, Califorina, USA), I placed a buffer distance of 200 m between sites. This distance was determined by the territory size of male Golden-winged Warblers (Patton et al., 2010) and was assumed to be an adequate distance to ensure independent detections of individuals.

Using the conditional occupancy design, I performed unlimited-radius point count surveys at 49 unique sites during the interval of May 12th to July 1st 2020. During the 2021 season, we limited the survey timeframe to the beginning of June to better reflect the Golden-winged Warbler migration and singing time period (Personal communication, Chris Kelly, NCWRC, 2021). Therefore, I conducted 97-point count surveys at 62 unique sites between May 3rd and June 7th 2021. South Carolina sites (Jocassee Gorges and Andrew Pickens Ranger District of Sumter National Forest) accounted for a majority of the survey effort between both years (45 of 49 sites in 2020; 44 of 62 sites in 2021). Chattahoochee National Forest sites in Georgia accounted for 4 surveys in both 2020 and 2021. North Carolina (Nantahala National Forest) sites accounted for 14 sites in 2021 (Figure 3). After the initial site visit, only sites with a positive identification of Golden-winged Warbler, blue-winged warbler, Prairie Warbler, Field Sparrow, Common Yellowthroat warbler, Chestnut-sided Warbler, or Golden-winged Warbler/blue-winged warbler hybrids were resurveyed. In total, I resurveyed 42 sites with positive identification of one or more target species. These sites were resurveyed a minimum of once and a maximum of 3 times (mean = 2.21).

Golden-winged Warblers and other songbirds sing across their territories soon after sunrise. Singing wanes by late morning (Ralph et al, 1995). For this reason, I conducted surveys in the interval between 30 mins after sunrise and 4 hours after sunrise. When possible, a different observer was assigned for each resurvey to reduce observer bias.

Consistent with Golden-winged Warbler surveys elsewhere in its range, and to maximize detection probability, point count surveys for Golden-winged Warblers and early-successional habitat indicator species consisted of 8-minutes of passive scan and listening followed by 5-minutes of type 1 (T1) Golden-winged Warbler song playback, a 1-minute rest period, and a 1-minute period of type 2 (T2) Golden-winged Warbler song playback (Chandler & King, 2011; Kubel & Yahner, 2007, McNeil et al, 2014; Ralph et al, 1995). Audio recordings were obtained from researchers at New Jersey Audubon (Dr. Kristin Mylecraine, personal communication) and saved to an AGPTEK U3 USB Stick Mp3 player. I played the recording by connecting the Mp3 player to a Zosam audio Bluetooth speaker. If a target species was detected, observers recorded the number of individuals, detection type (seen, heard, or both), the minute of detection, the distance in meters, and direction in azimuth degrees.

Autonomous Recording Units

I installed autonomous recording units (SongMeter4, Wildlife Acoustics) at songbird point count stations and drumming survey stations with and without positive detection of focal species in 2020 and 2021. For songbird locations without detections of target species, I deployed autonomous recording units in managed areas dominated by regenerating vegetative growth. Since Ruffed Grouse occupancy was extremely low during the 2021 season, I visually evaluated non-detection sites for vegetation structure characteristics preferred by grouse, such as high-stem density stands. I only placed autonomous recording units at non-detection sites with favorable grouse habitat.

I fastened recorders to trees using weather and theft proof cables. I selected trees to minimize sound disturbance and effects of obstructive vegetation, which can impact the ARU's ability to record (Tegeler et al., 2012). Units were programmed to reflect the respective drumming survey and point count survey time intervals for target species, and therefor units placed at songbird stations recorded from 30 minutes after sunrise to 4 hours after sunrise, while

Ruffed Grouse units recorded from 30 minutes before sunrise to 4 hours after sunrise. Similarly, I only deployed recorders during the date intervals for drumming surveys (March – May) and point count surveys (May – June). Recorders were deployed for a minimum of four consecutive mornings and overlapped at least one simultaneous point count or drumming survey to reduce bias.

Since low frequency sounds, such as Ruffed Grouse drumming, often lead to "false positive" or "false negative" detections in autonomous recording unit analyses (Shonfield & Bayne, 2017; Zwart et al., 2014), I chose to manually analyze recording files with Raven Pro software (Bioacoustics Research Program 2014), which provided visual aid in the form of a spectrogram. I performed three audio-visual surveys while listening to recording files and recorded species detection or non-detection. I used a random number generator to select the beginning minute of each survey, and did not conduct surveys during the same time intervals as in-person surveys. Survey time durations reflected those of in-person surveys, with 8-minutes surveys for songbird files and 4-minute surveys for Ruffed Grouse files. I did not survey time intervals with periods of excessive rain, wind, or other ambient noises that interfered with detection.

Statistical Analysis

I combined autonomous recording unit and human survey data into a joint occupancy modeling framework and compared two competing occupancy models for each species. The first model included a binary observer covariate (human or autonomous recording unit) for detection probability (p) while holding occupancy (ψ) constant. The second model held both p and ψ constant. This model represented the null model, which assumed no difference in detection probability between humans and observers.

I then compared models based on their AIC values. To identify potential effects, I evaluated the 85% confidence intervals of the observer parameter if it was included in the top model. If the 85% confidence intervals overlapped 0, observer effects were considered non-significant. I ran models using the "unmarked" package (Fiske and Chandler 2011) in program R (R Core Development Team 2017).

RESULTS

I installed 6 autonomous recording units (SongMeter4, Wildlife Acoustics) at songbird point count stations in the Andrew Pickens Ranger District of Sumter National Forest in South Carolina during the 2020 season. In 2021, I deployed 14 autonomous recording units at sites with and without detections of Prairie Warblers, Common Yellowthroat, Chestnut-sided Warblers, Field Sparrow, and Golden-winged Warblers. These sites were distributed between Jocassee Gorges (3 sites), Nantahala National Forest (6 sites), and Sumter National Forest (5 sites) (Figure 4). In that same year, I deployed autonomous recording units at six sites with a positive detection of Ruffed Grouse and six sites with no detection of Ruffed Grouse. Ruffed Grouse sites were distributed between Chattahoochee National Forest (6 sites), Sumter National Forest (3 sites), Jocassee Gorges (2 sites), and Headwaters State Forest (1 site) (Figure 2).

Although individual species detection probabilities varied greatly, I failed to reject the null hypothesis and found no significant differences between human and autonomous recording unit detection probabilities. Model selection indicated the null model as the top supported model for all target species (Table 1). Although differences were not significant, predicted detection probabilities for human observers were slightly greater than autonomous recording units for Common Yellowthroat, Field Sparrows, Chestnut-sided Warblers, Golden-winged Warblers, and Ruffed Grouse. Prairie Warbler detection probabilities were greater with autonomous recording units than human observers (Figure 5). Autonomous recording units did not yield novel detections of target species except in the case of Prairie Warblers and Common Yellowthroats. Recording data revealed one site occupied by both species that had been previously recorded as non-detected by human surveys.

DISCUSSION

Autonomous recording units performed comparably to human-observer surveys and likely represent a cost-efficient means to monitor and detect early-successional avian species. The results of my study indicate that recording units effectively detect conspicuous species such as Prairie Warblers, Common Yellowthroat, Field Sparrows, and Chestnut-sided Warblers. Moreover, it seems these technologies hold promise for detecting rare and cryptic species during long-term monitoring programs. The South Carolina Department of Natural Resources State Wildlife Action Plan lists species monitoring as a top priority, and two species of highest conservation priority are the Ruffed Grouse and Golden-winged Warbler (SCDNR, 2016). Both species present logistical challenges in both detection and monitoring. These species exist at low occupancy rates in the Blue Ridge region of the state, and likely occupy high-elevation habitats characterized by thick vegetation. These sites are often found along secondary or tertiary roads (Hein, 1970; Jones, 2005; Klaus & Buehler, 2001; Rosenberg et al., 2016). The lack of apparent differences between autonomous recording units and human-observer detection probability for these species indicates that recording units could be an effective tool for future monitoring programs. Autonomous recording units reduce detection error rates and increase sampling windows (Bobay et al., 2018). This is especially pertinent in the case of Golden-winged Warblers and Ruffed Grouse, since accessing suitable habitat for these species often takes time and effort, much of which is spent navigating through difficult terrain. For example, I found that surveying Ruffed Grouse in remote habitats limited my total survey scope in the 2020 season, and although switching to road and trailside surveys increased survey effort in 2021, accessing points along gated roads and hiking trails consumed survey time. Additionally, complications with low-frequency sound detection are common in autonomous recording unit surveys (Shonfield & Bayne, 2017; Zwart et al., 2014), however I did not find issues in manually detecting Ruffed Grouse drumming on audio files, and the sounds produced were often conspicuous on the Raven Pro spectrogram. Autonomous recording units provide an efficient means to passively survey grouse and Golden-winged Warbler habitat in difficult to access areas.

While increased temporal effort in remote locations may benefit monitoring programs, playback recordings dramatically increase the detection probability for species such as the Golden-winged Warbler, and passive recordings risk decreasing Golden-winged Warbler detection probabilities (Aldinger, 2010; Kubel & Yahner, 2007). Therefore it, it seems likely that human-observer detection probabilities would be greater than passive autonomous recording unit for Golden-winged Warblers if the survey includes a playback component. Yet, Golden-winged Warbler occupancy in the Southern Blue Ridge is extremely low, and monitoring programs may benefit from autonomous recording units by increasing their survey scope. Sampling designs for rare or cryptic species emphasize placing survey effort at many locations rather than replicated surveys at relatively fewer locations. This sampling design has demonstrated more precise predictions of occupancy (Specht, et al., 2017). Consequently, in the case of species like Golden-winged Warblers, monitoring efforts may benefit from a combined human-observer and autonomous recording unit methodology.

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TABLES & FIGURES

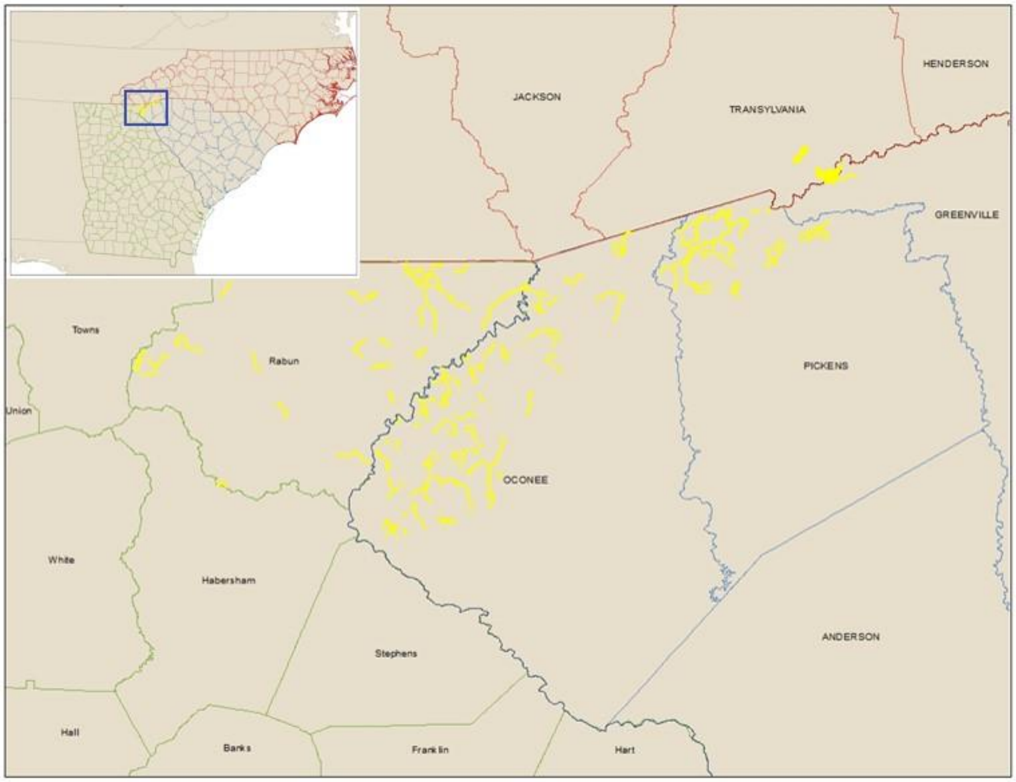

Figure 1. Distribution of 82 Ruffed Grouse drumming survey routes (yellow) across the Southern Blue Ridge Ecoregion of South Carolina, North Carolina, and Georgia. Blue boundaries indicate South Carolina county borders. Red boundaries indicate North Carolina county borders. Green boundaries indicate Georgia county borders.

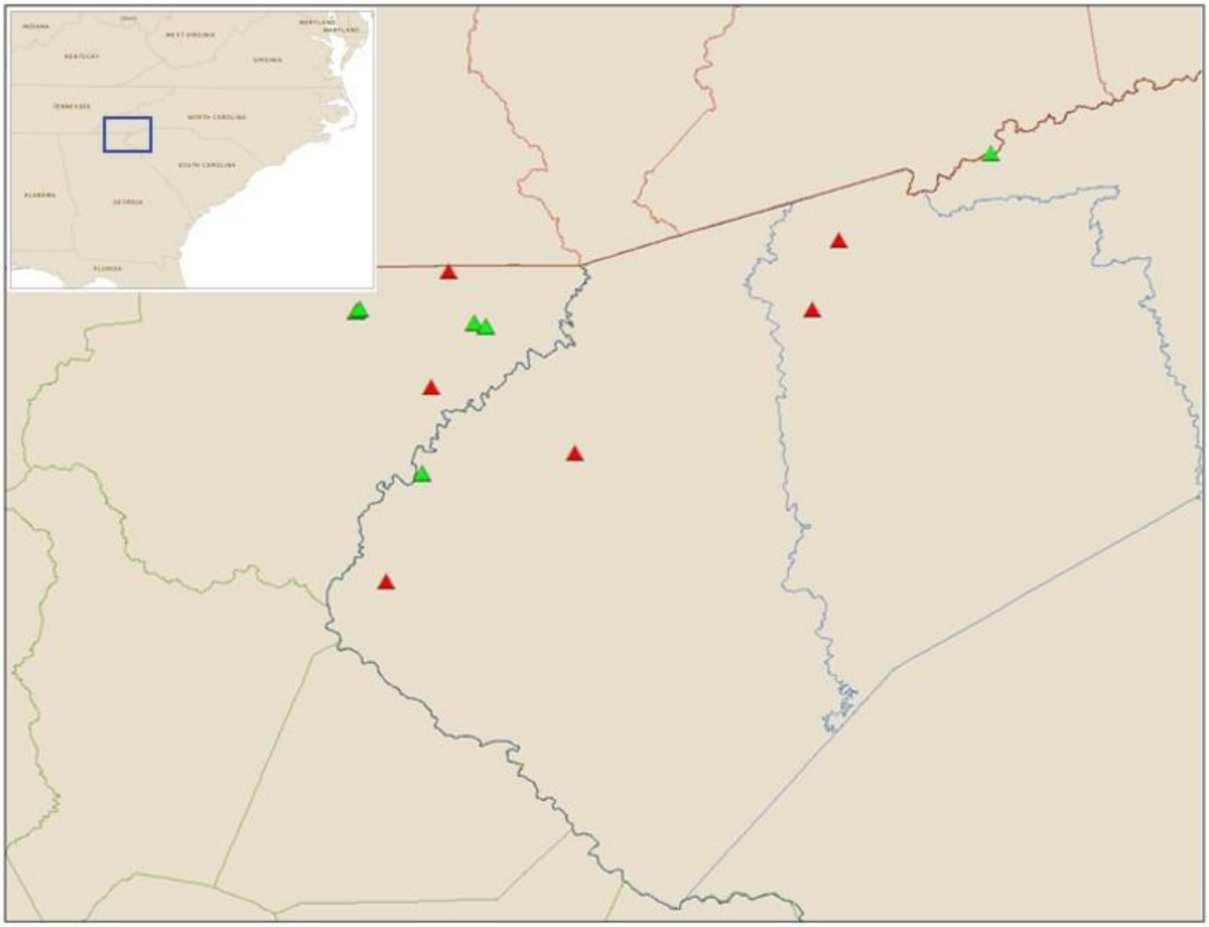

Figure 2. Distribution of 12 autonomous recording units at Ruffed Grouse drumming survey sites across North Carolina, South Carolina, and Georgia. Blue boundaries indicate South Carolina county borders. Red boundaries indicate North Carolina county borders. Green boundaries indicate Georgia county borders. Green triangles indicate autonomous recording units deployed at sites with a positive detection of grouse. Red triangles indicate autonomous recording units deployed at sites with no detection of grouse.

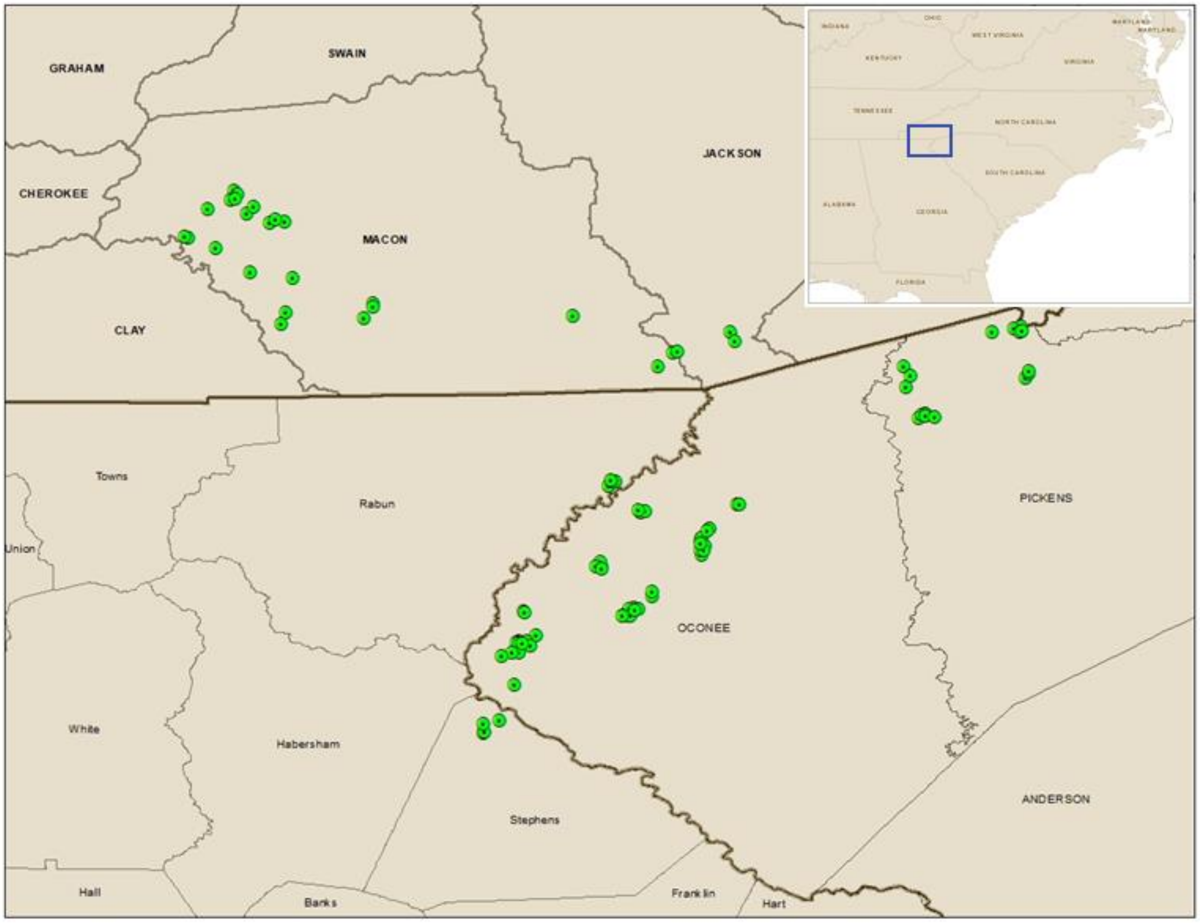

Figure 3. Point count surveys for songbirds were conducted at 62 unique sites during the 2021 season. Sites are indicated by green circles.

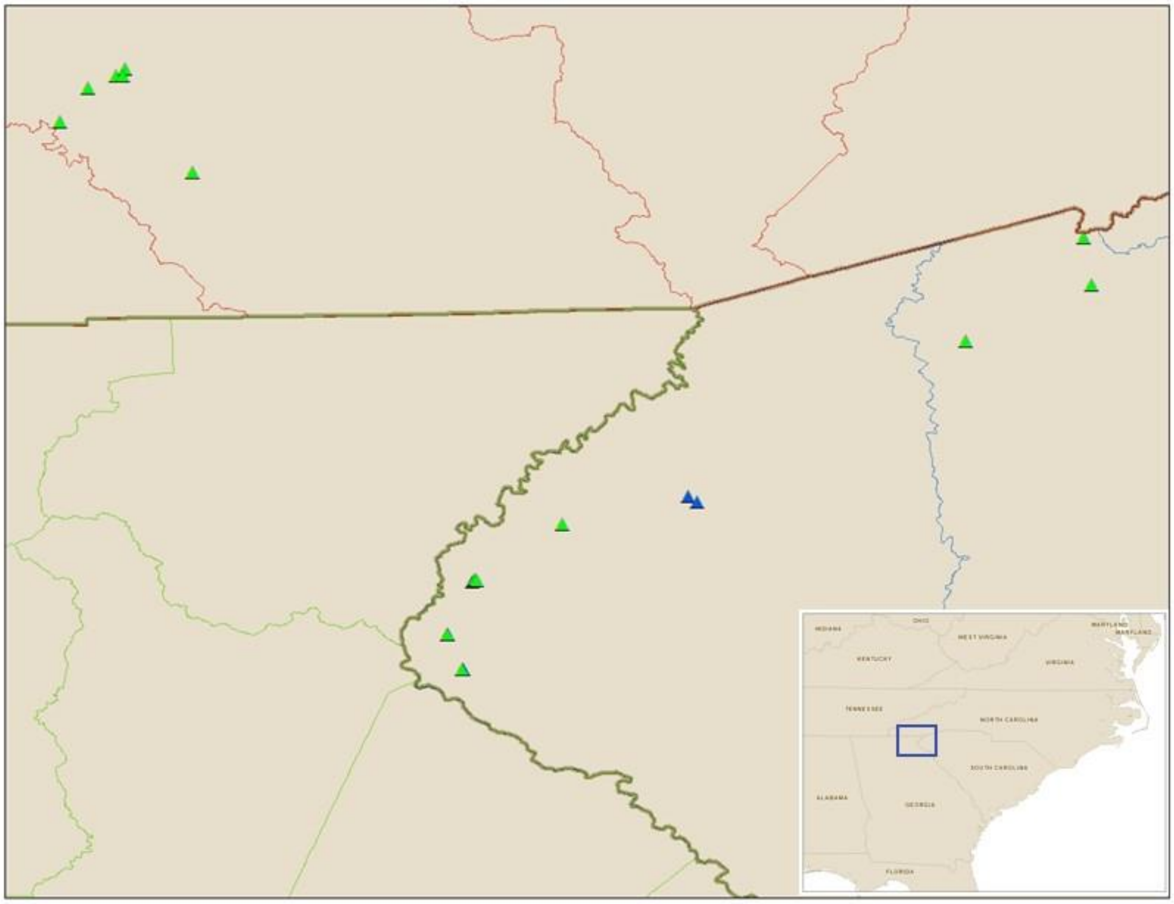

Figure 4. Distribution of 20 autonomous recording units at songbird point count survey sites across North Carolina and Georgia during spring of 2020 and 2021. Blue boundaries indicate South Carolina county borders. Red boundaries indicate North Carolina county borders. Green boundaries indicate Georgia county borders. Blue triangles indicate autonomous recording units deployed in 2020. Green triangles indicate autonomous recording units deployed in 2021.

Table 1. Ranking of candidate models that assess the influence of observer effect on (a) Ruffed Grouse, (b) Golden-winged Warbler, (c) Prairie Warbler, (d) Common Yellowthroat, (e) Field Sparrow, and (f) Chestnut-sided Warbler detection probability in the Southern Blue Ridge Ecoregion. Occupancy was assumed constant in all models. K is the number of parameters including intercept. AIC is Akaike's information criterion. ΔAIC is the difference in AIC from the top model. w_i is the cumulative Akaike weight. Null represents the null model, in which occupancy and detection are assumed constant between ARU and human-observer surveys. Obs represents a model with an observer effect for detection probability.

a)

Ruffed Grouse Model	K	AIC	ΔAIC	w_i
null	2	72.29	0.00	0.68
obs	3	80.79	1.50	0.32

b)

Golden-winged Warbler Model	K	AIC	ΔAIC	w_i
null	2	19.15	0.00	0.73
obs	3	21.15	2.00	1.00

c)

Prairie Warbler Model	K	AIC	ΔAIC	w_i
null	2	98.43	0.00	0.70
obs	3	100.17	1.74	1.00

d)

Common Yellowthroat Model	K	AIC	ΔAIC	w_i
null	2	40.78	0.00	0.72
obs	3	42.65	1.87	1.00

e)

Field Sparrow Model	K	AIC	ΔAIC	w_i
null	2	81.41	0.00	0.57
obs	3	81.99	0.57	1.00

f)

Chestnut-sided Warbler Model	K	AIC	ΔAIC	w_i
null	2	53.05	0.00	0.59
obs	3	53.75	0.71	1.00

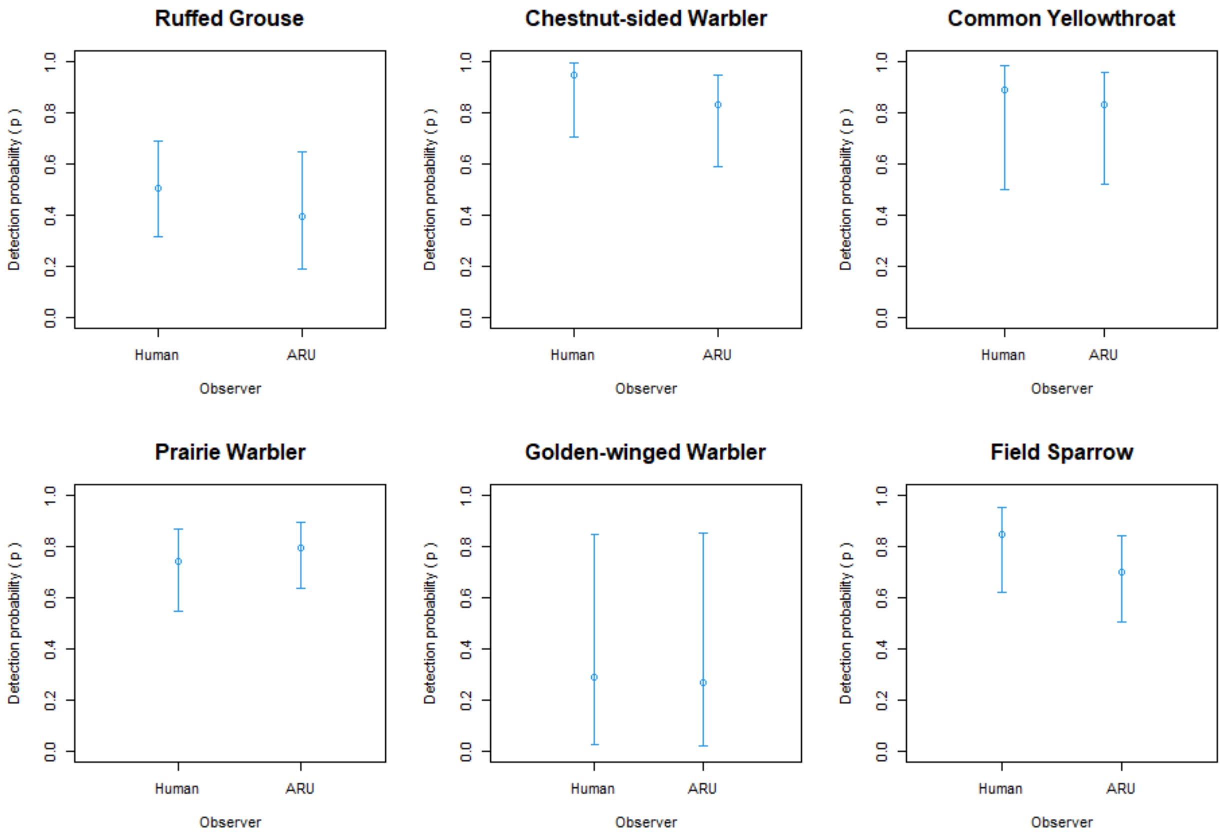

Figure 5. Detection probabilities for target species by human and autonomous recording unit surveys. Whiskers indicate 85% confidence intervals.