Using Passive Acoustic Monitoring to Estimate Bird Community Response to Land Management in Southeastern Georgia

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Abstract

Working lands, such as mine reclamation and timber production sites, may be able to provide supplementary habitat for declining disturbance-dependent birds, such as Bachman's Sparrow (*Peucaea aestivalis*) and Northern Bobwhite (*Colinus virginianus*). However, habitat use is likely contingent on specifics of land-use practices, especially those that could alter understory vegetation. My first research objective was to use autonomous recording units (ARUs) and BirdNET algorithms to compare the relative abundance of eight focal bird species across site treatments representing land management types: surface mine reclamation, timber production, young savanna, and mature savanna. All sites were established in upland pine (*Pinus* spp.) habitat throughout the southeastern Coastal Plain region of Georgia, USA from May–June 2024. I hypothesized that the mine reclamation site would support similar focal species, but in lower abundances than timber production and both savanna sites, and vegetation characteristics would also influence relative abundance along with site treatment. Model selection showed site treatment influenced relative abundance for all species and explained more variation in relative abundance than measured vegetation characteristics. The mine reclamation site had similar relative abundances for focal species when compared to the timber production site, indicating these treatments provide comparable habitat. The young savanna site exhibited the highest abundances for most species, whereas the mature savanna site had lower abundances, suggesting some focal species may prefer habitat lacking overstories. Focal species responded differently to

vegetation characteristics; for example, Common Nighthawk showed a positive response to grass cover, whereas Prairie Warbler responded negatively. My results provide strong evidence that site treatment influences the relative abundance of all focal species and highlight the need for future studies to parse out the exact mechanisms underlying these differences. Additionally, this study highlights the potential for working lands to provide habitat for disturbance-dependent birds and the effectiveness of using ARUs to assess the effects of land management on bird relative abundances.

My second research objective assessed optimal survey frequency when using Royle-Nichols (RN) models to estimate abundance or relative abundance from ARU data. Passive acoustic monitoring with ARUs can enable efficient monitoring of avian populations. RN models may be well suited for estimating abundance or relative abundance from ARU detection/non-detection data; as repeated surveys can easily be conducted with ARUs. Yet, optimal survey effort using these methods remains unexplored. Using ARU data from four site treatments in southeastern Georgia, I assessed how survey frequency and mean cumulative detection probability influenced estimates for Blue Grosbeak (*Passerina caerulea*) and Bachman's Sparrow from May–June 2024. A baseline dataset of 50 daily surveys was subsampled into reduced frequencies: 25 surveys every 2nd day, 17 every 3rd day, 13 every 4th day, 8 every 7th day, and 5 every 10th day. RN models were fitted to each subsample. Abundance estimates decreased with subsampling, showing survey frequency arbitrarily influences estimates and RN models should be viewed as relative, not absolute, abundance estimates. However, the specific order of relative abundance across site treatments remained consistent for both species during subsampling, indicating RN models can still reliably infer effects across sites. Mean cumulative detection probability decreased with subsampling yet remained >70% for both species.

Subsampling reduced precision in relative abundance estimates for both species; particularly for Bachman’s Sparrow, emphasizing species-specific sensitivity to survey effort. However, subsampling every 2nd day or every 3rd day resulted in moderate losses of precision (≤ 34%) for both species, suggesting reduced survey frequency may be a viable strategy for efficient data collection depending on species detectability and study goals. Together, these findings from my research objectives highlight the potential of working lands to support disturbance-dependent bird conservation and demonstrate how passive acoustic monitoring with ARUs can be an effective tool for the conservation and management of bird populations.

Using Passive Acoustic Monitoring to Estimate Bird Community Response to Land Management in Southeastern Georgia

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General Audience Abstract

Working lands, such as mine reclamation and timber production areas, can provide valuable habitat for bird species that require environments shaped by disturbance, such as fire or tree harvesting. However, how disturbance-dependent birds use these habitats may depend on specific land management practices, especially those that alter vegetation. In this study, I compared the abundance of eight bird species across four sites in upland pine (*Pinus* spp.) habitat across southeastern Georgia from May–June 2024. Sites represented a distinct land-use or management type: surface mine reclamation, timber production, recently harvested and replanted pine savanna, and unharvested mature savanna. I used automated recorders to monitor birds at sites and found that the mine reclamation supported many of the same bird species as the timber production site, often at similar abundance levels. The young savanna site had the highest amount of bird abundance overall, while the mature savanna site supported fewer of the birds evaluated, suggesting some species prefer open habitats lacking mature trees. Vegetation features, such as understory composition also affected bird abundances, but these effects varied between species.

I also tested how to optimize survey effort, specifically how many days of surveys are required, when using data from automated recorders to estimate bird abundance with statistical models. By focusing on two birds, Blue Grosbeak (*Passerina caerulea*) and Bachman's Sparrow (*Peucaea aestivalis*), I examined how reducing the number of survey days affected the accuracy

and precision of abundance estimates from models. Although fewer surveys reduced precision, the overall patterns in bird relative abundance across sites remained consistent. This suggests that less frequent surveys could still produce reliable results, depending on the study's goals and species detectability. Together, these findings highlight the potential of working lands to support disturbance-dependent bird conservation and demonstrate how automated recorders can be an effective tool for studying bird populations.

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Table of Contents

Abstract....................2
General Audience Abstract....................5
Acknowledgements....................7
Chapter 1: Passive Acoustic Monitoring Reveals Differences in Relative Abundance Across Land Management Types for Disturbance-dependent Birds in Southeastern Georgia....................10
  Abstract....................10
  Introduction....................11
  Methods....................16
    Study Area....................16
    Monitoring Design....................18
    Vegetation Surveys....................19
    BirdNET Processing....................19
    BirdNET Validation....................20
    Abundance Models....................22
    Detection Covariate Selection....................22
    Abundance Covariate Selection....................23
    Model Comparison and Evaluation....................23
  Results....................24
    Model Selection and Fit....................24
    Predicted Abundance in Response to Site Treatment....................25
    Effects of Vegetation Covariates....................26
  Discussion....................27
  Figures....................35
  Literature Cited....................58
Chapter 2: Influence of Autonomous Recording Unit (ARU) Survey Effort on Songbird Relative Abundance Estimates from Royle-Nichols Models....................74
  Abstract....................74
  Introduction....................75
  Methods....................79
    Study Area....................79
    Monitoring Design....................80
    BirdNET Processing and Validation....................81
    Post Hoc Subsampling....................82

Measuring Precision of Relative Abundance Estimates........83
Results........83
Model Selection........83
Model Estimates........84
Discussion........86
Figures........90
Literature Cited........100

Chapter 1: Passive Acoustic Monitoring Reveals Differences in Relative Abundance Across Land Management Types for Disturbance-dependent Birds in Southeastern Georgia

Abstract

Working lands, such as mine reclamation and timber production sites, may be able to provide supplementary habitat for declining disturbance-dependent birds, such as Bachman's Sparrow (*Peucaea aestivalis*) and Northern Bobwhite (*Colinus virginianus*). However, habitat use is likely contingent on specifics of land-use practices, especially those that could alter understory vegetation. I used autonomous recording units (ARUs) to monitor and compare the relative abundance of eight focal bird species across site treatments representing land management types: surface mine reclamation, timber production, young savanna, and mature savanna. All sites were established in upland pine (*Pinus* spp.) habitat throughout the southeastern Coastal Plain region of Georgia, USA from May–June 2024. I hypothesized that the mine reclamation site would support similar focal species, but in lower abundances than timber production and both savanna sites, and vegetation characteristics would also influence relative abundance along with site treatment. Model selection showed site treatment influenced relative abundance for all species and explained more variation in relative abundance than measured vegetation characteristics. The mine reclamation site had similar relative abundances for species when compared to the timber production site, indicating these treatments provide comparable habitat. The young savanna site exhibited the highest abundances for most species, whereas the mature savanna site had lower abundances, suggesting some focal species may prefer habitat lacking overstories. Focal species responded differently to vegetation characteristics; for example, Common Nighthawk showed a positive response to grass cover, whereas Prairie Warbler responded negatively. My results provided strong evidence that site treatment influences

the relative abundance of all focal species and highlight the need for future studies to parse out the mechanisms underlying these differences. This study highlights the potential for working lands to provide habitat for disturbance-dependent birds and the effectiveness of using ARUs to assess the effects of land management on bird relative abundances.

Introduction

Many disturbance-dependent bird populations are in decline throughout the eastern United States primarily due to loss of habitat disturbance regimes (Askins, 2001; Greene, Iglay, & Evans, 2019; King & Schlossberg, 2014; Lorimer, 2001; Rosenberg et al., 2019; Sauer et al., 2022; Thompson & DeGraaf, 2001). Species belong to the disturbance-dependent bird guild, such as Bachman's Sparrow (*Peucaea aestivalis*) and Northern Bobwhite (*Colinus virginianus*), broadly require post-disturbance habitats with an open or absent overstory, sparse midstory, and dense understory composed of a diversity of woody and herbaceous plant species. Post-disturbance habitats may be classified as early successional forest (i.e., shrubland, regenerating forest), savanna, or woodland; each type provides birds with a variety of nesting sites, foraging opportunities, and cover for predator evasion (Greene, Iglay, & Evans, 2019; Swanson et al., 2011). Pine (*Pinus* spp.) savannas were a historically abundant post-disturbance ecosystem throughout the southeastern Coastal Plain region of the United States, hereafter Southeast (Frost, 1993). Fire from indigenous practices and lightning strikes maintained a perpetual overstory composed of almost exclusively pines, sparse or absent midstories, and diverse understories which supported many regional disturbance-dependent bird populations (Hanberry & Thompson, 2019). A frequent fire-return interval (1–6 years) of low-intensity ground fires is a key component for maintaining the structural and compositional plant diversity within pine savannas (Frost, 2006; Pickens et al., 2017).

Since Euro-American settlement, the widespread loss of pine savanna ecosystems has occurred across its historic range, primarily due to extensive harvest of mature longleaf pine (*Pinus palustris*), fire suppression, and land-use change (Frost, 1993, 2006; Landers et al., 1995). Conservation efforts in the Southeast often emphasize the restoration of pine savanna through use of prescribed fire and conserving tracts of second-growth or mature longleaf pine (Lopez et al., 2009; U.S. Fish and Wildlife Service, 2003). Yet, such efforts to restore and manage pine savannas on a wide scale are often impractical due to high operational costs and competing land-use interests (Bremer & Farley, 2010; Brockerhoff et al., 2008; Lavoie et al., 2011).

A large proportion of the land that once was pine savanna in the Southeast has been converted to working lands for timber production based on loblolly pine (*Pinus taeda*), which supplies a variety of forest products (e.g., lumber, pulp, paper, fibers, and wood pellets) (Frost, 1993). Intensively managed loblolly pine stands are now widespread throughout the Southeast but can still provide benefits to disturbance-dependent bird populations given pertinent management practices. Post-disturbance habitats following clearcuts (i.e., full stand removal) and the subsequent early stages of stand reestablishment provide many of the understory vegetation characteristics (i.e., high structural and compositional diversity) needed for disturbance-dependent birds (Evans et al., 2021; Greene, Iglay, & Evans, 2019; Greene, Iglay, Evans, et al., 2019; Owens et al., 2014; Parrish et al., 2017; Thompson & DeGraaf, 2001). However, once pines are replanted, successional processes leading to canopy closure occur quickly (< 8–12 years following planting); thus, the understory vegetation characteristics that disturbance-dependent birds rely on can rapidly diminish and disappear without intermediate stand management (thinning) or short-rotation timber harvests (≤ 25 years after planting) (Evans et al., 2021; Legrand et al., 2007; Swanson et al., 2011). There are many studies investigating disturbance-dependent bird use in timber production sites (Evans et al., 2021).

Reclamation sites following heavy mineral surface mining in the Southeast have not yet been investigated in the context of disturbance-dependent bird habitat. Sand deposits containing heavy minerals are extracted through mechanical surface mining across the Southeast, where remnants of ancient shorelines contain high concentrations of titanium and zirconium (Pirkle et al., 2013; U.S. Geological Survey, 2018). This mining typically occurs within the larger landscape of timber production, as forest lands in rural areas can be leased for surface mining and then reclaimed back for timber production in a relatively short time span. Site preparation for heavy mineral surface mining and reclamation in upland areas follows a standardized process (The Chemours Company et al., 2019). The top 30 cm of the topsoil layer are temporarily stockpiled (≤ 2 years), ensuring soil layer composition is maintained. Excavation depth for materials is limited to approximately 12 m. Heavy minerals only account for ~3% of excavated material so the remainder of the mined sands are redeposited and re-contoured back to sites in accordance with the Surface Mining Control and Reclamation Act of 1977 (SMCRA 1977). Original topsoil layers are then returned to sites before site preparation for timber production begins (further details on site preparation are provided in Chapter 1 *Study Area*).

Mining and reclaiming land in incremental patches (up to approximately 4 ha) may produce a variety of post-disturbance habitats needed by disturbance-dependent birds in a shifting mosaic; however, site preparation practices, especially those that could change the composition and structure of understory habitat, may interact with these processes (Bauman et al., 2015; Brooke et al., 2016; Bruno Rocha Martins et al., 2020; Bulluck & Buehler, 2006; Dement et al., 2020; Galligan et al., 2006; Ruggles et al., 2021; Zipper et al., 2011). Previous research surrounding reclamation outcomes following heavy mineral surface mine reclamation in upland sites across the Southeast is limited. Anecdotally, the stockpiled topsoil from upland pine habitats can retain a viable seedbank and root masses that re-establish most of the native pre-mine understory once returned to sites. Yet, despite use of best practices in topsoil stockpiling, changes in vegetation regrowth may still occur due to nutrient depletion, compaction, and altered soil structure in reclaimed soils after stockpiling (Valliere et al., 2022; Young et al., 2022). Observation by natural resource managers suggests some native plant species, such as gallberry (*Ilex glabra*) and saw palmetto (*Serenoa repens*), do not return to pre-mine abundance after the stockpiled topsoil is returned at heavy mineral surface mine reclamation sites. Both of these shrubs are typically dominant in the pre-mine understory and provide necessary microhabitat for foraging, nesting, and cover for disturbance-dependent birds (Dean & Vickery, 2003; Winiarski et al., 2017). This phenomenon is just one example of potentially many unexplored effects from this mining that may influence bird response– but research is needed to provide validity and clarity to the extent of these effects.

Mine reclamation and timber production both occur within the context of massive and practically irreversible loss of historic pine savanna. Advancing the conservation of disturbance-dependent bird species requires understanding habitat across all working lands that provide post-disturbance habitats, while also comparing them to areas undergoing explicit pine savanna restoration as reference sites. Here I address following questions: within this altered landscape, how does disturbance-dependent bird abundance differ within working lands (i.e., mine reclamation vs. timber production) and to pine savanna restoration efforts? Are disturbance-dependent bird abundance differences across these land management types due to the land-use or the vegetation composition differences (e.g., percent cover of woody shrubs vs grass)? I hypothesize that a mine reclamation site will be able to support similar disturbance-dependent bird species, but in lower abundances compared to timber production and savanna sites. Additionally, I hypothesize that abundance for most disturbance-dependent bird species will be influenced by both the site treatment (representing a land-use or management type), and the vegetation characteristics at sites. And if the vegetation characteristics are more explanatory of abundance differences than site treatment, it may suggest that the additional (and severe) land-use from heavy mineral surface mining and reclamation has negligible effects on habitat characteristics relevant to disturbance-dependent birds. To this end, I used passive acoustic monitoring with autonomous recording units (hereafter ARUs) to monitor and compare the relative abundance of focal bird species across four site treatments representing a land-use or management treatment type. I considered analyses with and without vegetation characteristics to assess the influence of each factor independently. I selected eight focal disturbance-dependent species that are locally common (yet mostly declining across their ranges), use post-disturbance upland pine habitats at least for breeding, and produce acoustic vocalizations for detection with ARUs: Bachman's Sparrow, Northern Bobwhite, Blue Grosbeak (*Passerina caerulea*), Prairie Warbler (*Setophaga discolor*), Common Yellowthroat (*Geothlypis trichas*), Indigo Bunting (*Passerina cyanea*), Common Nighthawk (*Chordeiles minor*), and Chuck-will's-widow (*Antrostomus carolinensis*). Despite all of these focal species belonging to the same disturbance-dependent guild, they also have variable life histories and nuanced habitat preferences that may produce species-specific responses to certain habitat variables.

Methods

Study Area

All sites were established in upland pine habitat across the lower Coastal Plain region of southeastern Georgia in Charlton, Folkston, and Brantley counties in 2024 (Figure 1.1). Upland pine habitat chosen for sites were characterized by relatively flat topography with acidic, poorly drained, and predominantly sandy texture soils. Though considered upland habitat, all sites contained a relatively high water table and were prone to seasonal flooding. Common understory plants across sites include saw palmetto, wiregrass (*Aristida* ssp.), bluestems (*Andropogon* ssp.), rosette grass *(Dichanthelium* ssp.), beaksedges (*Rhynchospora* ssp.), hollies (*Ilex* ssp.), brambles (*Rubus* ssp.), wax-myrtles (*Morella* ssp.), shrubby oaks (*Quercus* spp.), woody vines (*Smilax* spp., *Gelsemium* spp., *Muscadinia rotundifolia*), ericaceous shrub species (*Vaccinium* spp., *Lyonia* spp., *Gaylussacia* spp., *Kalmia* spp.), ferns (*Pteridium pseudocaudatum*, *Anchistea virginica*) and a variety of other forbs (e.g., *Rhexia* spp., *Xyris* spp.) (Weakley et al., 2024). I categorized four sites, also referred to as site treatments or treatment types, based on land-use or management practices: surface mine reclamation, timber production, young savanna, and mature savanna.

The timber production and mine reclamation site contained stands of intensively managed loblolly pine (*Pinus taeda*), typically ≤ 5 m in height. All pine stands were planted ~2–8 years ago. The mine reclamation site was previously used for timber production prior to mining and reclamation efforts were focused on restoring the mined land back for timber production. Therefore, overall site preparation and management practices of the mine reclamation site were analogous to the timber production site (i.e., only difference is mined vs. unmined).

Site preparation at both the mine reclamation and timber production site followed a common approach for short-rotation, even-aged management of pine stands in the Southeast (Schultz, 1997). After a stand is clearcut, all course woody debris was removed. Evenly spaced rows of furrowed soil beds were made to prevent inundation of pines during seasonal flooding. Hardwood and grass selective herbicides were broadcasted to control non-pine vegetation before planting pine seedlings. Pine seedlings were planted evenly along furrowed soil beds with a target of ~1,200 trees per ha, and a fertilizer application was distributed to improve stand growth. After ~15 years, pine stands are often mechanically thinned as an intermediate management practice, but typically no other active management is done until final timber harvest (~25 years after planting).

The young savanna site was established in Sansavilla Wildlife Management Area (hereafter Sansavilla WMA) managed by Georgia Department of Natural Resources. This site previously contained intensively managed loblolly pine stands for timber production, but pine savanna restoration began in 2017 with a goal to create second-growth–mature longleaf pine savanna with a stand basal area of approximately 11–16 m^2 / ha. However this site contained young stands (planted ~ 7 years ago) of longleaf pine in 2024, typically ≤ 5 m in height, and stands were managed with prescribed fire every 2–3 years to inhibit hardwood stand competition and promote desired understory characteristics (*Altamaha Corridor Management Plan*, 2021).

I established the mature savanna site at Okefenokee National Wildlife Refuge (hereafter Okefenokee NWR) managed by U.S. Fish & Wildlife Service (hereafter USFWS). Longleaf pine savanna restoration began at Okefenokee NWR in the early 1970s after widespread clearing of mature (≥ 100-years-old) longleaf pine that occurred in the early-mid 1900s and prior to the federal listing of Red-cockaded Woodpecker (*Dryobates borealis)* under the Endangered Species

Act in 1973 (U.S. Fish & Wildlife Service, 2006). The mature savanna site was selected in stands of second-growth (~50-years-old) longleaf pine savanna, but this site had many structural characteristics of a mature longleaf pine savanna. USFWS managers maintained a stand basal area of approximately 9–16 m^2 / ha and used prescribed fire every 2–3 years to maintain the structural characteristics of pine savanna habitat.

Monitoring Design

In the mine reclamation site, I established 9 monitoring points for passive acoustic monitoring, censusing all available land for this site treatment type. Thereafter, I established 9 monitoring points for the timber production site at a nearby location to the mine reclamation site, 10 monitoring points were established in the young savanna site at Sansavilla WMA, and 8 monitoring points in the second growth site at Okefenokee NWR for a balanced distribution of monitoring points across site treatment types. Every monitoring point had an ARU deployed to record acoustic data of bird vocalizations. All ARUs were placed in the center of a 225 m radius buffer from other ARUs (monitoring points) to avoid recording the same birds and minimize recordings from birds outside of the treatment area for a site. However, there were two monitoring points that overlapped and some buffer radii extended outside of site treatment areas (Figure 1.3). I deployed SongMeter Minis and SongMeter Mini 2s (Wildlife Acoustics Inc., Maynard, MA, USA) to passively record throughout the breeding season from May–June in 2024. All ARUs were secured to a t-post 1.5 m off the ground and equipped with 2 omnidirectional microphones recording in stereo at a sampling rate of 44100 Hz with 18 dB of channel gain. Every ARU was configured to record daily with same schedule (Figure 1.4). I set ARUs to record daily for 20 minutes before sunrise in addition to 3 minute intervals every hour from 1 hour before sunrise to 4 hours after sunrise; then record again for 20 minutes after sunset in addition to 3 minute intervals every hour to 3 hours after sunset. Altogether, 67 minutes of acoustic data were recorded daily at each monitoring point for 55 days.

Vegetation Surveys

To estimate ground cover composition and understory vegetation classes (shrubs [broadleaf and saw palmetto], grasses, forbs, conifers), I used line-intercept vegetation sampling (Canfield, 1941) at each monitoring point. Focal disturbance-dependent species largely rely on understory vegetation for nesting, cover, and forage. Thus, I surveyed understory vegetation and did not measure tree canopy height or cover estimates (though this is likely an important variable too). I included small trees as an understory vegetation class (in either conifers or shrubs) if it had live foliage ≤ 1 m from the ground (i.e., only seedlings, saplings, or shrubby trees). Two line-intercepts were established in the center of each monitoring point, intersecting where the ARU was deployed. The first 40 m line-intercept was established from a randomly generated azimuth (0–360°) and the other with the perpendicular azimuth (Allred et al., 2025). Every cover class that covered at least 20 cm of continuous length of the line was recorded along with values for length (cm) and maximum height (dm). The measurements from both 40 m line-intercepts were combined for final calculations. Mean height was obtained by averaging height values (dm) across all segments recorded along both lines. Percent cover was calculated by summing the lengths (cm) of each vegetation class, then dividing by the total combined length of 80 m to yield a final percent cover (0–100%) for each understory vegetation class at each monitoring point.

BirdNET Processing

I processed acoustic data with BirdNET (v1.2.0, Kahl et al., 2021), an application that provides deep neural network machine-learning algorithms to annotate recordings of bird vocalizations. BirdNET scripts were activated in a Python environment on a high-performance computing console (*Advanced Research Computing at Virginia Tech*, 2024; *Python Language Reference, v3.12.4*, 2024). BirdNET processed acoustic data in .wav files as input with base settings. Geographic coordinates were specified in BirdNET for species list filtering through eBird databases (Sullivan et al., 2009). BirdNET produced output for each audio file with a series of species predictions for all potential species identified along with a BirdNET confidence score, which is a unitless numeric value ranging from 0.1–1 of how "confident" BirdNET was for a given prediction (Kahl et al., 2021; Wood & Kahl, 2024).

BirdNET Validation

Comparing BirdNET output with manual validation (i.e., human listens and annotates a subset of recordings) is an important step in evaluating performance of BirdNET predictions to avoid including false positives in models (Cole et al., 2022; Pérez-Granados, 2023b; Ware et al., 2023; Wood & Kahl, 2024). I followed the guidelines in Wood & Kahl, 2024 for generating species-specific BirdNET score thresholds through manual validation with BirdNET prediction segments and their associated confidence scores. I randomly selected BirdNET prediction segments (3-second segments of annotated recording, *n* =12) for each of the following bins of BirdNET confidence scores [(0.10, 0.20), (0.21, 0.30), (0.31, 0.40), (0.41, 0.50), (0.51, 0.60), (0.61, 0.70), (0.71, 0.80), (0.81, 0.90), (0.91, 0.99)] for each species (maximum of 108 BirdNET prediction segments per species). This allowed me to evaluate the predictions across an even distribution of BirdNET confidence scores. Because many species were likely to require high confidence score thresholds, I also randomly selected another 100 BirdNET prediction segments for the confidence score range of 0.95–1.0 (removing any duplicated segments).

Maximum number of segments was limited for some species by availability of BirdNET predictions with certain BirdNET confidence score values in my dataset for the 'segements.py' script to draw from during random selections (See Table 1.1 for total number of segments examined by species). All selected segments were listened to and also evaluated visually with spectrograms using audio editing software (v3.6.1, *Audacity*, 2024). I denoted BirdNET prediction segments with a binary outcome (correct [1] or incorrect [0]). I selected this sample size of BirdNET prediction segments (165–208 per species) before proceeding with analysis, as this sample size balanced evaluating variation in BirdNET predictive performance sufficiently for my dataset and was efficient for the manual validation process (~2–3 hours of listening per species). However, I repeated the manual validation process twice (416 segments) for Bachman's Sparrow due to high uncertainty in BirdNET predictions (Table 1.1).

Lastly, I used program R (R Core Team, 2024) to model relationships between BirdNET confidence scores and prediction outcomes for each focal species. I first transformed the 0-1 bound BirdNET confidence scores to their original logit scale [-4– 7], henceforth referred to as "BirdNET logit score", as the higher scores tend to be compressed on the 0.1–1 scale which makes finding the appropriate confidence threshold challenging on that scale for species with greater uncertainty. I then fitted three logistic regression models with prediction outcome as the response variable: a null model, a model relating BirdNET confidence score to prediction outcome, and a model relating BirdNET logit score to prediction outcome. I evaluated models with Akaike's Information Criterion (AIC) (Burnham & Anderson, 2002) and selected the BirdNET score type from the best model (i.e., model with lowest AIC score). I then solved the logistic regression model for a desired score threshold (either in confidence score [0.1–1] or logit score [-4–7] scale) corresponding to a 99% probability of a true positive BirdNET prediction for each species (Table 1.1; Figure 1.7). Thresholds for Bachman's Sparrow were the exception, which could only have its logistic regression model solved for a score threshold corresponding to a 95% probability of true positive detection. I did not measure true-positive rates (i.e., recall, sensitivity) in my data from validated BirdNET predictions as my goal was to create detection/non-detection data for each species. BirdNET data filtered with a score threshold needed to contain at least one prediction of the focal species in the 67 minutes of recordings stratified across a day to be counted as a detection for that species, site, and survey. Therefore, it was unlikely for BirdNET to miss all true positive predictions for a given species, monitoring point and survey, even for species that had BirdNET data filtered with a high score threshold (e.g., Bachman's Sparrow).

Abundance Models

I estimated relative abundance by fitting single-season, single-species Royle-Nichols models (hereafter RN models) for all eight disturbance-dependent focal species using the R package '*unmarked*' (v1.4.3, Fiske & Chandler, 2011) (Table 1.2). RN models are an adaptation of the classic occupancy model (MacKenzie et al., 2002) that allow for estimation of relative abundance through heterogeneity in detection probability across monitoring points derived from repeated surveys/visits (Royle & Nichols, 2003). Passive acoustic monitoring data are well suited for RN models, as numerous repeated surveys are easily conducted via deployed ARUs and allow for robust estimates of detection probabilities (Fiss et al., 2024). After validation for a 99% (95% for Bachman's Sparrow) probability of true positive BirdNET predictions, I filtered BirdNET predictions by date and monitoring point from May to June 2024, which created a detection/non-detection matrix with 55 daily surveys for each species across the breeding season.

Detection Covariate Selection

I selected Julian day, average daily wind speed (kph), average daily temperature (°F), and average daily precipitation (in) as potential detection covariates for use in RN models.

Values for average daily precipitation, average daily temperature, and wind speed were derived from local Automated Surface Observing System weather stations (KJES, AYS) with the '*riem*' R package (v0.3.2, Salmon, 2024). I assessed detection covariates for multicollinearity using the '*corrplot*' R package (Figure 1.6) (v0.9.5, Wei et al., 2024). I eliminated average daily temperature as a covariate, as it was correlated (|r| ≥ 0.60) with Julian day. All detection covariates were standardized using the 'scale' function to improve model performance and Julian day was included as a linear and quadratic effect in RN models (Table 1.2).

Abundance Covariate Selection

I assessed vegetation variables (shrub cover, grass cover, forb cover, conifer cover, shrub height, grass height, and conifer height) with boxplots grouped by site treatment type to look for potential confounding effects with site treatment (Figure 1.5). The planting process of pine trees at mine reclamation and timber site treatments resulted in conifer cover and conifer height being highly confounded with site treatment and were excluded from further analysis (Figure 1.5). I then evaluated potential multicollinearity between remaining vegetation variables using '*corrplot*' and only uncorrelated (|r| ≤ 0.60) variables were tested together in models (Figure 1.6) (Wei et al., 2024).

Model Comparison and Evaluation

After abundance and detection submodel formulas were determined, I fit four RN models with different abundance submodels for each species (site treatment + vegetation [global model], site treatment only, vegetation only, null [only detection covariates]) (Table 1.2). I treated site treatment as a factor in abundance submodels for which it was included as a covariate (Table 1.2). I standardized all continuous variables used in abundance submodels (i.e., vegetation variables) and detection submodels with the 'scale' function to improve model performance, and Julian day was included as a linear and quadratic effect in detection submodels (Table 1.2).

For the site treatment + vegetation model (global model), I used the 'vif' function to calculate Variance Inflation Factor (VIF) values between covariates in both submodels as a final check for multicollinearity (see Table 1.5). I then compared Akaike Information Criterion Corrected for a Small Sample Size (AICc) scores from the '*AICcmodavg*' R package (v2.3.3, Marc J. Mazerolle, 2023) from candidate RN models and selected the top model (see Table 1.3). I tested top models using Mackenzie and Bailey's Goodness-of-Fit tests with the '*AICcmodavg*' R package to evaluate model fit to the observed data (MacKenzie & Bailey, 2004; v2.3.3, Marc J. Mazerolle, 2023). I assessed each top model using a Chi-square (χ^2) test, with corresponding *p*-values, *c*-hat, and number of bootstrap simulations (Table 1.4). Each species model ran for 1,000 bootstrap simulations to stabilize Chi-square estimates, ensuring robust goodness-of-fit evaluation across all tested models.

Results

Model Selection and Fit

The site treatment model + vegetation model was the top model (ΔAICc ≥ 2 over the next best model) for Bachman's Sparrow, Common Nighthawk, Prairie Warbler, and Common Yellowthroat (Table 1.3). The site treatment + vegetation model was also designated as the top model for Blue Grosbeak, although there was some uncertainty in model selection (ΔAICc = 1.37), most model weight was given to the site treatment and vegetation model ($W_i = 0.66$). The treatment only model was the top model (ΔAICc ≥ 2) for Chuck-will's-widow and Northern Bobwhite. And the treatment only model was also designated as the top model for Indigo Bunting as it had most of the model weight ($W_i = 0.70$) with only slight model uncertainty

(ΔAICc = 1.71). The vegetation only and null models were not ranked as top models for any focal species. Evaluation of VIF from the global models (i.e., site treatment + vegetation models) produced values ranging from 1.1–1.28 for detection submodels, and 1.08–5.28 for abundance submodels, indicating no major issues with multicollinearity between covariates (Table 1.5). Model evaluation for top models with Mackenzie and Bailey's Goodness-of-Fit tests produced good results for model fit and dispersion for Common Nighthawk (*p*-value = 0.505, *c*-hat = 0.87), Prairie Warbler (*p*-value = 0.05, *c*-hat = 0.87), Common Yellowthroat (*p*-value = 0.109, *c*-hat = 1.52), Indigo Bunting (*p*-value = 0.214, *c*-hat = 1.49), and Chuck-will's-widow (*p*-value = 0.084, *c*-hat = 2.95). There were marginal results for Bachman's Sparrow (*p*-value = 1, *c*-hat = 0.1) and poor results for Northern Bobwhite (*p*-value = 0, *c*-hat = 15.46) and Blue Grosbeak (*p*-value = 0.008, *c*-hat = 4.15).

Predicted Abundance in Response to Site Treatment

Predicted relative abundances for Bachman's Sparrow were similar between mine reclamation and timber production sites (Figure 1.8). Moreover, predicted relative abundance estimates for Northern Bobwhite and Common Nighthawk were highest at the mine reclamation site when compared to all other treatments. Estimates for Prairie Warbler, Common Yellowthroat, and Chuck-will's-widow were lower in the mine reclamation site when compared to the timber production site. However, there was considerable overlap in 95% confidence intervals (CIs) for relative abundance estimates between these two site treatment types for Indigo Bunting and Chuck-will's-widow. The young savanna site exhibited the highest relative abundances for many focal species, such as Prairie Warbler, Common Yellowthroat, and Indigo Bunting. Whereas the mature savanna site often had lower relative abundances for many focal species when compared to other treatments, such as Prairie Warbler, Blue Grosbeak, Indigo

Bunting, and Chuck-will's-widow. Bachman's Sparrow was the only species to have its highest predicted relative abundance in the mature savanna site (Figure 1.8).

Effects of Vegetation Covariates

The directionality and significance ($p \leq 0.05$) of parameter estimates varied across species in response to vegetation covariates for species where the site treatment + vegetation model was the top model (Bachman's Sparrow, Prairie Warbler, Common Nighthawk, Common Yellowthroat, Blue Grosbeak) (Figure 1.9). Shrub cover had a significantly positive effect on relative abundance for Common Nighthawk and Common Yellowthroat (Figure 1.9). There was also a positive effect of shrub cover for Prairie Warbler and Blue Grosbeak; however, these effects failed to meet statistical significance as 95% CIs for parameter estimates extended below 0. In contrast to other species, increased shrub cover had a strong negative effect on Bachman's Sparrow relative abundance. The effects of forb cover were largely non-significant; however, Common Nighthawk showed a significant positive response to forb cover and Bachman's Sparrow had a marginally significant negative response in relative abundance. Response to grass cover was mostly positive across species, apart from Bachman's Sparrow and Prairie Warbler. This negative effect for Prairie Warbler was only marginally significant as 95% CIs for parameter estimates extended above 0. Most responses to shrub height were nonsignificant, aside from Bachman's Sparrow, which showed negative responses in abundance to shrub height (Figure 1.9). Blue Grosbeak and Common Yellowthroat showed a significant positive response in relative abundance to grass height in models. Though Bachman's Sparrow also showed a positive response to grass height, this effect was nonsignificant with 95% CIs for parameter estimates somewhat extending below 0. Lastly, Prairie Warbler and Common Nighthawk had significant negative responses in relative abundance to increased grass height.

Discussion

The mine reclamation site I surveyed supported many of the same focal species found in other sites treatment types (Figure 1.8). Though there were many differences in relative abundance across sites, the hypothesized trend of lower abundances in the mine reclamation site largely was not observed for most focal species. This provided partial support for my hypothesis that the mine reclamation site will be able to support similar disturbance-dependent bird species, but in lower abundances compared to timber production and both savanna sites. However, other trends in relative abundance for focal species were observed across site treatment types.

The mine reclamation and timber production site had similar predicted relative abundances for many focal species and predicted relative abundance for Northern Bobwhite and Common Nighthawk were actually highest overall at the mine reclamation site (Figure 1.8). This could be explained by both species having a positive response in relative abundance with increased grass cover (although the site treatment + vegetation model was not the top model for Northern Bobwhite) and grass cover was often highest at monitoring points within the mine reclamation site (Figure 1.5). Native warm-season, perennial grasses, such as *Andropogon* ssp. and *Dichanthelium* ssp., a favored habitat component for Northern Bobwhite in the Southeast (Brooke et al., 2016), were common at the mine reclamation site as well. Common Nighthawk may be responding to potential aerial foraging opportunities provided by the open airspace and flying insects at the grassy monitoring points at the mine reclamation site (Brigham et al., 2020). This suggests the process of mine reclamation following heavy mineral surface mining may provide habitat characteristics (e.g., increased grass cover) advantageous to some disturbance-dependent birds. The trade-off could be the increased grass cover results in decreased shrub cover preferred by other focal disturbance-dependent species, such as Prairie Warbler, which had low relative abundance at the mine reclamation site (Figure 1.8). Though my study is one of the first to evaluate avian response to heavy mineral surface mine reclamation in the Southeast, my results align with previous research that found differences in bird abundances between a coal surface mine reclamation site and other early successional habitats in eastern deciduous forests (Bulluck & Buehler, 2006).

The overall predicted relative abundance was highest for species such as Prairie Warbler, Common Yellowthroat, Blue Grosbeak, and Indigo Bunting in the young savanna site (Figure 1.8). This pattern may be initially attributed to the high shrub cover at the young savanna site, as many of these species rely on habitat with abundant shrub cover for nesting, foraging, and cover (Guzy & Ritchison, 2020; Lowther & Ingold, 2020; Nolan Jr., 1978; Nolan Jr et al., 2020; Payne, 2020). Many of my models for these species also showed a positive response in relative abundance with increased shrub cover– further supporting this line of thinking (Figure 1.9). However, this was contradicted by the overall lowest predicted relative abundance for these species being at the mature savanna site which had the overall highest shrub cover (Figure 1.5). Moreover, this was unexpected as the mature savanna site treatment type at the Okefenokee NWR had an understory that has been managed with frequent prescribed fire (every 2–3 years) for many decades, along with a well-established longleaf pine overstory. This is often a target state for longleaf pine savanna restoration and management in the Southeast (Greene, Iglay, & Evans, 2019).

An explanation for this apparent lower abundance could be that my focal disturbance-dependent species may favor areas that entirely lack overstories or prefer overstories with highly reduced stand density, perhaps due to lack of perches for predators or some other structural habitat preference (King & Schlossberg, 2014; Roberts & King, 2017, 2020; Shake et al., 2012).

The persistent overstory present at the mature savanna site may simply be at too high of a stand density for some focal species. Patches of early successional (i.e., regenerating) forest habitat following stand-clearing disturbances were historically less common prior to Euro-American settlement in the Southeast (Hanberry & Thompson, 2019), though they were occasionally created from powerful storms blowing down whole tree stands across the landscape (Lorimer, 2001). Nevertheless, some area-sensitive, disturbance-dependent bird species, such as Prairie Warbler, Blue Grosbeak, and Indigo Bunting, seem to highly prefer large regenerating stands that lack overstory trees as habitat. Stand removal through clearcutting for timber production or mine reclamation has the potential to provide these habitat conditions, given the disturbance occurs in a sufficiently large spatial extent (> 1 ha; Roberts & King, 2017) and understory growth is not inhibited.

Furthermore, the overall highest predicted relative abundance for most focal species at the young savanna site could stem from the benefits of having both forms of disturbances. The young savanna site treatment type at Sansavilla WMA had a recent stand-removal disturbance from clearcuts conducted prior to planting longleaf pine and frequent prescribed fire maintaining abundant shrub cover. In contrast, Bachman's Sparrow was the only species to have highest predicted relative abundance in the mature savanna site treatment found at the Okefenokee NWR, suggesting it is more closely associated with mature pine savanna habitats than my other focal species (Dunning et al., 2020; Dunning & Watts, 1990). This study was limited by not measuring canopy height and stand density– these could be important variables that should be explored in future research.

Another consideration across all site treatments is how species diversity (i.e., species richness and evenness) may influence abundances of individual bird species. It is important to emphasize greater abundances for a certain number of species does not necessarily correlate to higher bird diversity in a site treatment type, especially if species richness is low (Shannon & Weaver, 1949; Van Dyke, 2008). Previous research within the upland habitats of Okefenokee NWR reported high diversity and low dominance (Shannon diversity index = 3.3, evenness index = 0.9) across censused bird communities (Meyers & Odum, 1991). Developing robust measures of diversity across all site treatment types was beyond the scope of this study. Yet based on limited observation, the overstory at the mature savanna site treatment at Okefenokee NWR also provided habitat for cavity nesting species, including Brown-headed Nuthatch (*Sitta pusilla*), Great Crested Flycatcher (*Myiarchus crinitus*), Eastern Bluebird (*Sialia sialis*), Red-headed Woodpecker (*Melanerpes erythrocephalu*) and Northern Flicker (*Colaptes auratus*), that were absent or less abundant at other site treatments. It is possible the high bird diversity at Okefenokee NWR and potentially increased competition for resources between these sympatric species resulted in my observed measures of lower relative abundances for many focal species here (Cotgreave & Harvey, 1994). Evaluating bird diversity and community dynamics across site treatments will be an important next step for future research.

Another potential bias in my findings could have arisen from the possibility of erroneous abundance estimates, particularly if BirdNET had extreme difficulty detecting focal species calls in recordings with loud, simultaneously calling non-focal species (e.g., particularly with Red-headed Woodpecker and Great Crested Flycatcher vocalizations at Okefenokee NWR in the mature savanna site treatment) or other background noise. The influence of many simultaneously calling species (and any other background noise) on BirdNET performance is an area of active research and a worthy consideration when evaluating models built with data processed from BirdNET (Pérez-Granados, 2023b, 2023a). However, I believe it was unlikely to have caused error in estimating abundance with RN models, as BirdNET only needed to detect the focal species once in the 67 minutes of recordings stratified across a day to be counted as a detection for that monitoring point and survey. Furthermore, occasional noisy soundscapes in recordings (i.e., low signal-to-noise) were common across all site treatment recordings, reducing any potential effects of background noise.

Another limitation of my study was the non-random sampling used and small sample size for site treatment and monitoring points in each site treatment. I exhausted as many monitoring points as possible in the mine reclamation site that were available to me (*n* = 9) and then sought to balance this number of monitoring points across all other site treatments. This lack of random sampling means that inferences about bird abundance differences from this study cannot be confidently extrapolated to additional mine reclamation, timber production, or pine savanna sites. Moreover, the spacing of our monitoring points were also constrained by the limited availability of site treatment areas. My minimum buffer radius of 225 m for each monitoring point was likely sufficient to still ensure monitoring point independence for my focal territory songbird species, Chuck-will's-widow, and Northern Bobwhite. But independence for Common Nighthawk may need to be re-evaluated. Dynamic territory sizes (~10–30 ha) and the possibility of occasional aerial foraging outside of territories for this species may have rendered my minimum buffer radius of 225 m insufficient for monitoring point independence (i.e., a single individual could have been detected across multiple monitoring points) (Kéry & Royle, 2016b; R. M. Brigham et al., 2020).

I found mixed support for my hypothesis that abundance for most disturbance-dependent bird species was influenced by both site treatment and vegetation characteristics. This hypothesis was supported for species such as Bachman's Sparrow, Prairie Warbler, Common Nighthawk, Common Yellowthroat, and Blue Grosbeak as the site treatment + vegetation models were top models for these species (Table 1.3). Lack of support came from site treatment only models being top models for Northern Bobwhite, Indigo Bunting, and Chuck-will's-widow. This may provide evidence that vegetation characteristics are not necessarily more explanatory of relative abundance differences than the land-use or management types represented by site treatment. However, the lack of explanatory power from added vegetation covariates during model selection in accounting for changes of relative abundance for many focal species may also stem from the omission of potentially key vegetation covariates (e.g., stand height or density) or the inclusion of less relevant vegetation covariates (Kéry & Kellner, 2024a). My study was limited by only measuring percent cover and height for functional vegetation groups (e.g., shrubs, grasses, forbs). Moreover, low model ranking for vegetation-only models during AICc model selection, even ranked lower than some null models, warrants evaluating other vegetation or habitat covariates. Further research could benefit from examining variables such as cover type heterogeneity at both micro- and macro-habitat scales, edge density, patch size, and the proximity to the nearest suitable habitat for each species.

Top model evaluation with Mackenzie and Bailey's Goodness-of-Fit Tests provided promising results for most focal species, such as Bachman's Sparrow, Common Nighthawk, Prairie Warbler, Common Yellowthroat, and Indigo Bunting; with a relatively low Chi-square value paired with a high *p*-value (≥ 0.05), indicating that the observed relative abundance patterns align well with those predicted by the model (Table 1.4). Conversely, relatively high Chi-square values, low p-values (≤ 0.05), and high *c*-hat values (≥ 4) suggested a lack of model fit, as seen for species such as Northern Bobwhite and Blue Grosbeak. A relatively low *c*-hat value (0.1) for Bachman's Sparrow may also suggest an issue with under-dispersion, potentially indicating that relevant covariates were also missing from the model, leading to inflated standard errors (SEs) for parameter estimates and possibly masking true effects. Unfortunately, approaches to account for under-dispersion in these models are underdeveloped (Cooch & White, 2013; Kéry & Royle, 2016a; MacKenzie & Bailey, 2004b). A final consideration is the potential influence of zero-inflated data, which can result from long (55 visits) detection/non-detection matrices provided by acoustic monitoring data (Kéry & Kellner, 2024b). RN models fitted in the unmarked package can only adopt a Poisson distribution for its abundance submodel, but adapting to an alternative distribution (e.g., zero-inflated Poisson, negative binomial) potentially would provide a better fit for fitting zero-inflated or over-dispersed data, though this may be challenging in practice (Dorazio, 2007; Fiske & Chandler, 2011; Kéry & Royle, 2016a; Richards, 2008).

Whereas lack of model fit for some species may suggest there are more environmental variables to explore, existing models still provide strong evidence for the effect of site treatment type on relative abundance for all the focal disturbance-dependent bird species, along with evidence for the effects of the measured vegetation characteristics for those species which the site treatment + vegetation model was the top model. I observed reduced shrub cover at some of the monitoring points at the mine reclamation site, that perhaps benefited some focal species, such as Northern Bobwhite, while negatively effecting others, such as Prairie Warbler– yet based on my models, this unlikely fully explains the observed differences in relative abundances across site treatment types for each species. Future research will be required to parse out the exact mechanisms that underlies the observed differences in relative abundances across site treatment, and perhaps more importantly, to understand if and how long differences between site treatments persists over time, particularly at the mine reclamation site. If inhibited shrub regrowth is persistent at the reclamation site following topsoil stockpiling, it may suggest there is a loss of natural recovery potential following the heavy mineral surface mining process– particularly for slow-growing and long-lived species, such as saw palmetto, that may take decades or centuries to return to pre-mine abundance at sites (Takahashi et al., 2011; Young et al., 2022).

The effects to soil and vegetation regrowth following heavy mineral surface mining are not only important considerations for disturbance-dependent birds, but future studies are warranted to evaluate impacts on the wider ecological community at the mine reclamation site, particularly for macroinvertebrates. Reduction of macroinvertebrate density has the potential to ripple up through trophic levels, ultimately influencing the bird community through loss of food-availability. Nevertheless, working lands can provide supplementary habitat for birds, either inadvertently (e.g., shorebird use of commercial salt ponds) or through careful management for desired conditions (e.g., conservation agriculture programs supporting grassland bird communities) (Jackson et al., 2020; Pavlacky Jr. et al., 2021). Efficient monitoring will be needed to continually evaluate habitat use in these working lands compared to ‘natural’ areas, identify potential threats, and determine if passive or active management is appropriate to maximize the ecological potential of working lands. This study provides not only an initial step in understanding the effects and potential value of heavy mineral surface mine reclamation sites on disturbance-dependent birds but also provides a framework for using passive acoustic monitoring to simultaneously monitor bird communities in working lands (or ecological restoration sites) and compare them with their respective reference sites. Mine reclamation sites following heavy mineral surface mining in the Southeast may present a unique opportunity to support disturbance-dependent birds, especially in the absence of ‘natural’ areas, and other growing anthropogenic threats.

Figures

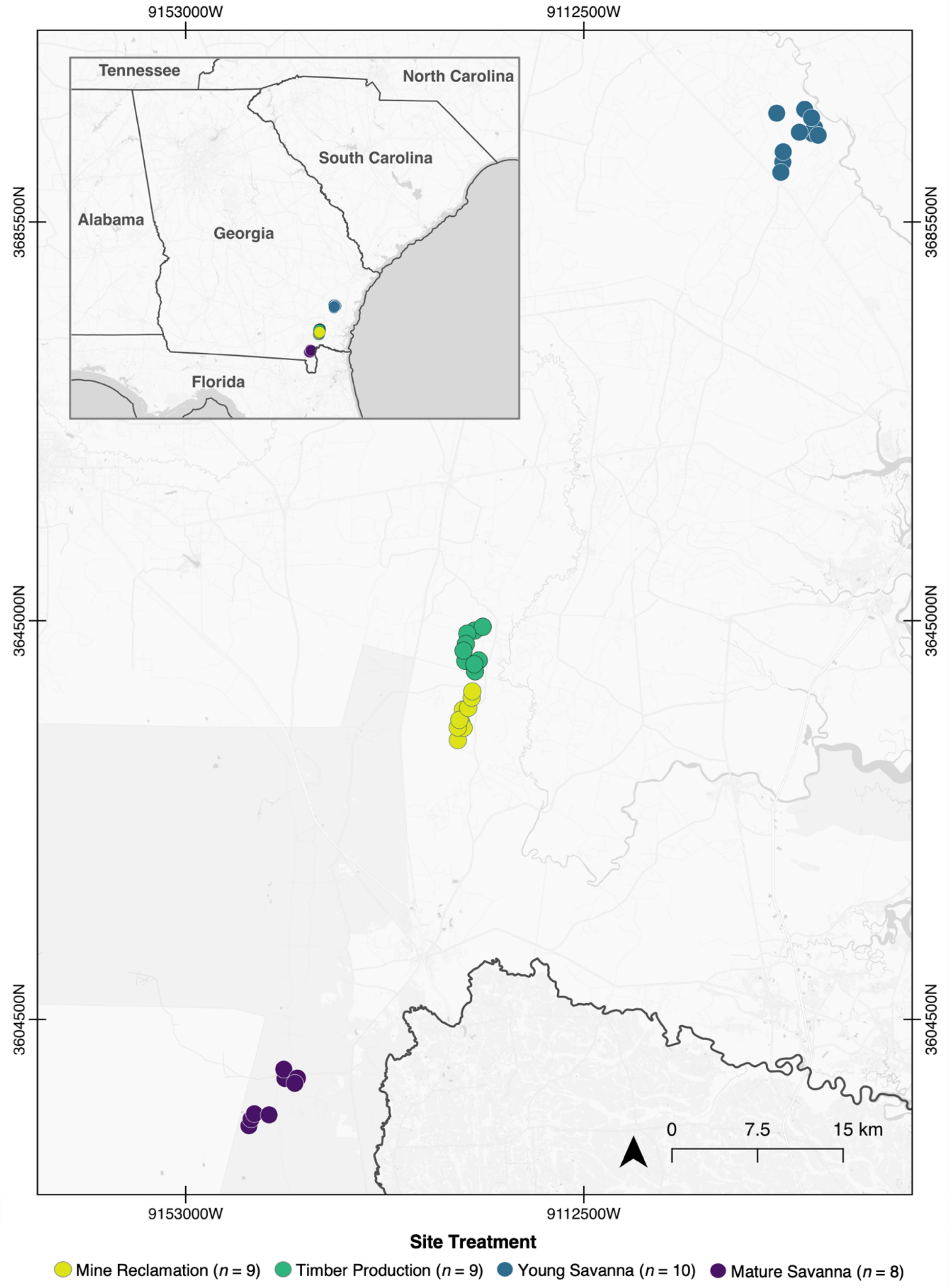

9153000W
9112500W
3685500N
3645000N
3604500N
Tennessee
North Carolina
South Carolina
Alabama
Georgia
Florida
0
7.5
15 km
Site Treatment
Mine Reclamation (n = 9)
Timber Production (n = 9)
Young Savanna (n = 10)
Mature Savanna (n = 8)

Figure 1.1: Map of monitoring points established in 2024 for passive acoustic monitoring with autonomous recording units (ARUs) across four site treatment types (mine reclamation, timber production, young savanna, mature savanna; see Figure 1.2) in the Coastal Plain region of southeastern Georgia (GA), USA, spanning Charlton, Folkston, and Brantley counties. Map points enlarged for visibility. Mine reclamation monitoring points (*n* = 9) established for passive acoustic monitoring censused all available land for this site treatment type. Thereafter, 9 timber production monitoring points were established at a nearby location to the mine reclamation site, 10 monitoring points were established in the young savanna site, and 8 monitoring points were established in the mature savanna site for a roughly even distribution of monitoring points across site treatment type.

A) Mine Reclamation **B) Timber Production**

C) Young Savanna **D) Mature Savanna**

Figure 1.2: Site treatment types established across the Coastal Plain region of southeastern Georgia in 2024. The A) Mine Reclamation and B) Timber Production site had stands of loblolly pine with similar timber management practices (i.e., only difference is mined vs. un-mined). The C) young savanna sites and D) mature savanna site contained stands of longleaf pine and receive low intensity prescribed burns every 2–3 years. The C) young savanna site had been managed like this for 10 years, while the D) mature savanna site had been managed like this for 50 years.


9125214.4W
9123876.2W
3637239.0N
3635900.8N
3634562.6N
3633224.4N
0
250
500 m

Figure 1.3: Example of monitoring points used for passive acoustic monitoring at the mine reclamation site treatment in Charlton County, Georgia from May–June 2024. Before autonomous recording units (ARU) were deployed at a monitoring point (blue point), a 225 meter buffer radius (transparent blue circle) was established to ensure monitoring point independence and association with site treatment area. Only two buffer radii for monitoring points overlapped and monitoring points were situated to minimize potential for recording birds in non-treatment areas along the edges of buffer radii. This process was repeated across monitoring point establishment in all site treatment types (mine reclamation, timber production, young savanna, mature savanna; see Figure 1.2).

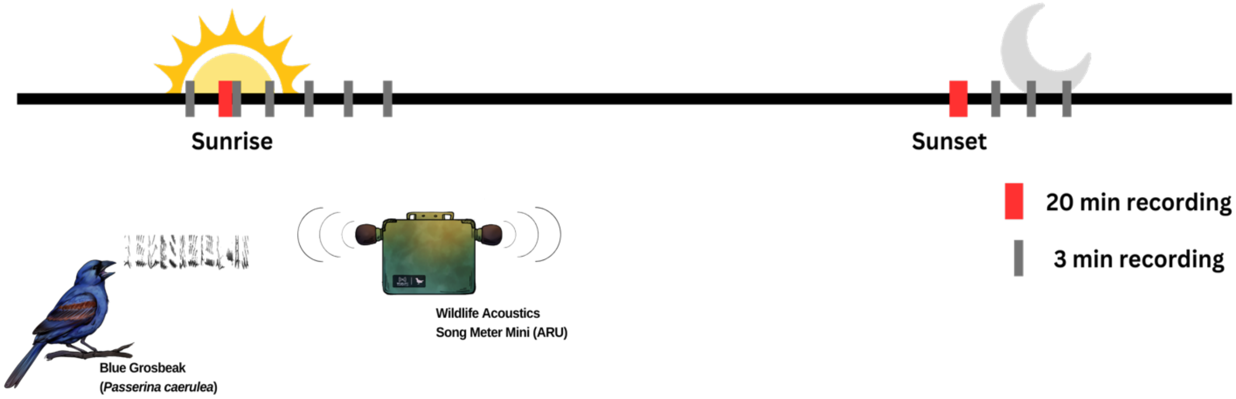


Figure 1.4: Passive acoustic monitoring daily schedule for autonomous recording units (ARUs) deployed at monitoring points across site treatments from May–June 2024 in southeastern Georgia. SongMeter Minis or SongMeter Mini 2s produced by Wildlife Acoustics Inc. (Maynard, MA, USA) were secured to a t-post 1.5 m off the ground and equipped with 2 omnidirectional microphones recording in stereo at a sampling rate of 44100 Hz with 18 dB of channel gain. Every ARU was configured to record daily with same schedule. ARUs recorded daily, for 20 minutes before sunrise in addition to 3 minute intervals every hour from 1 hour before sunrise until 4 hours after sunrise; and then record again for 20 minutes after sunset in addition to 3 minute intervals every hour until 3 hours after sunset. Altogether, 67 minutes of acoustic data were recorded daily at each monitoring point for 55 days.

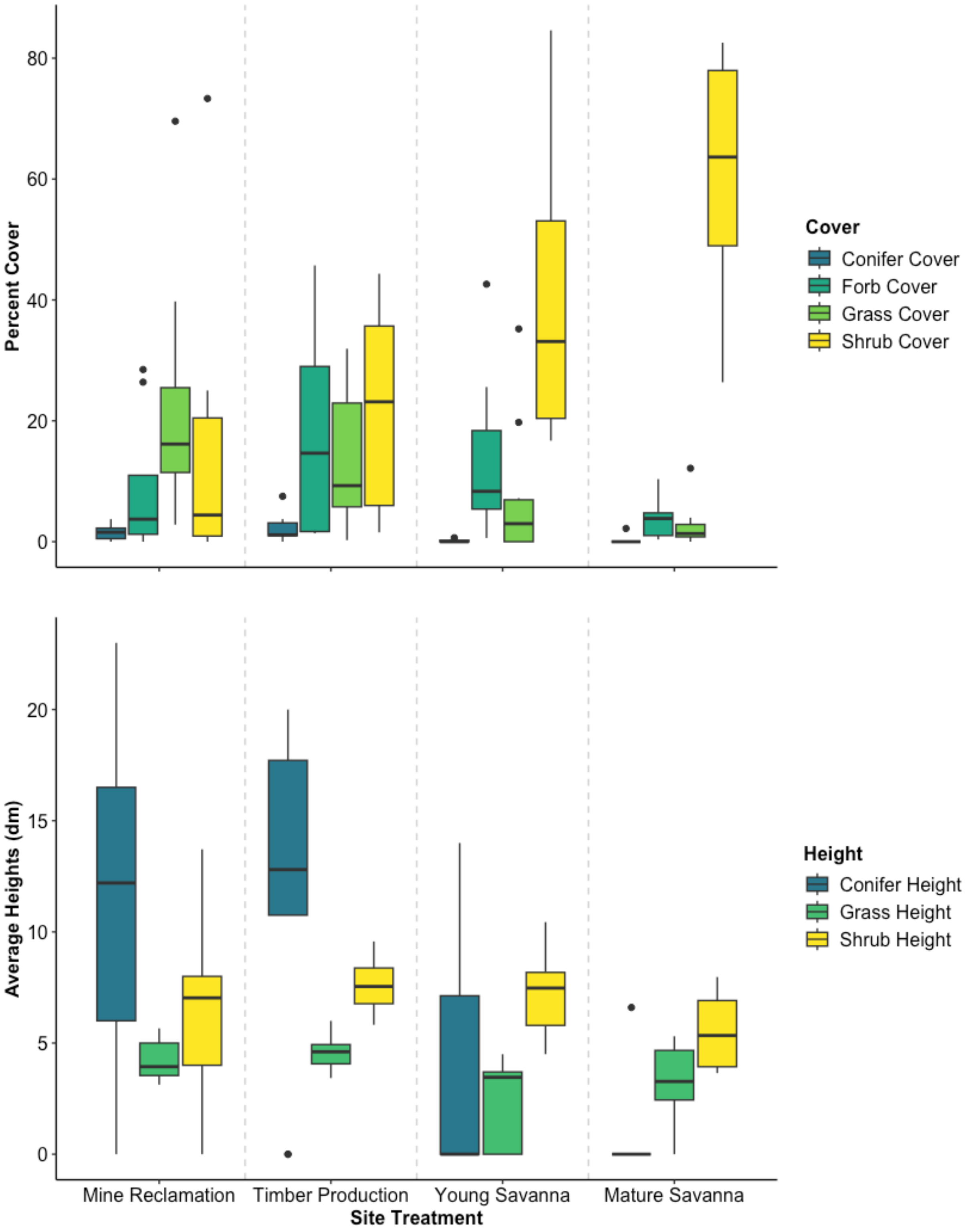
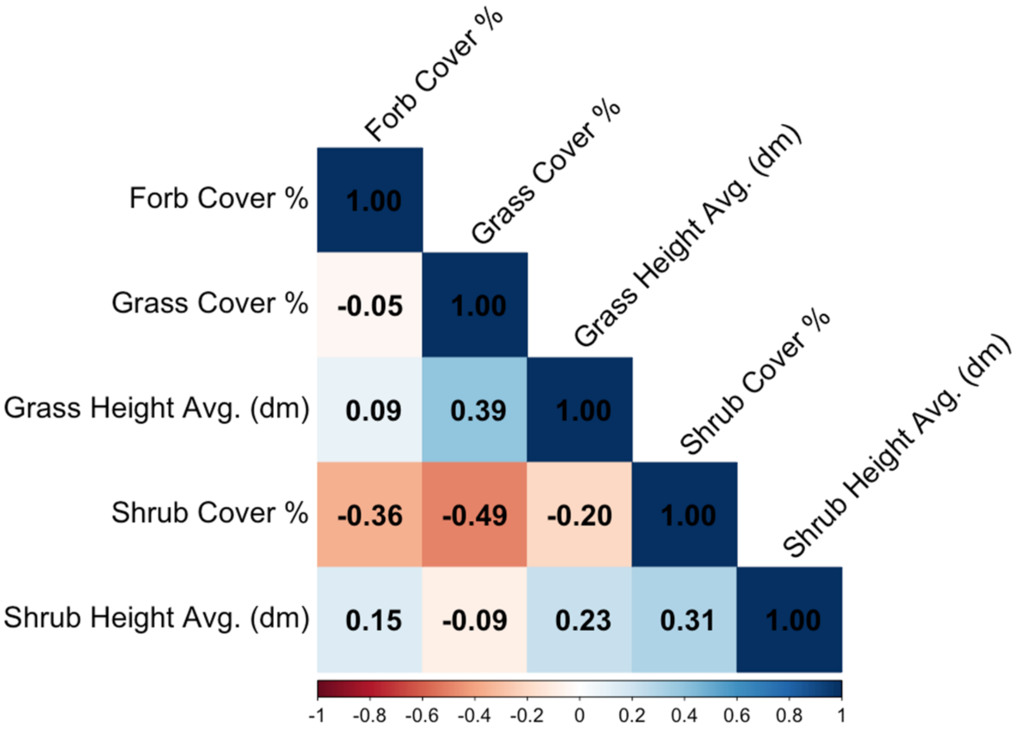

Percent Cover
0
20
40
60
80
Cover
Conifer Cover
Forb Cover
Grass Cover
Shrub Cover
Average Heights (dm)
0
5
10
15
20
Height
Conifer Height
Grass Height
Shrub Height
Mine Reclamation
Timber Production
Young Savanna
Mature Savanna
Site Treatment

Figure 1.5: Percent cover and average heights of understory vegetation cover classes, recorded through line-intercept sampling from May–June 2024 in southeastern Georgia, were summarized across all monitoring points and grouped by site treatment. Percent cover was calculated by summing the lengths (cm) of each vegetation class intercepted along the transects, dividing by the total combined transect length of 80 m, and expressing the result as a percentage (0–100%) for each understory vegetation class at each monitoring point. The planting process of pine trees at the mine reclamation and timber production site treatment resulted in conifer cover and conifer height being highly confounded with site treatment and thus were excluded from further analysis.


Forb Cover %
Grass Cover %
Grass Height Avg. (dm)
Shrub Cover %
Shrub Height Avg. (dm)
1.00
-0.05
1.00
0.09
0.39
1.00
-0.36
-0.49
-0.20
1.00
0.15
-0.09
0.23
0.31
1.00
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1

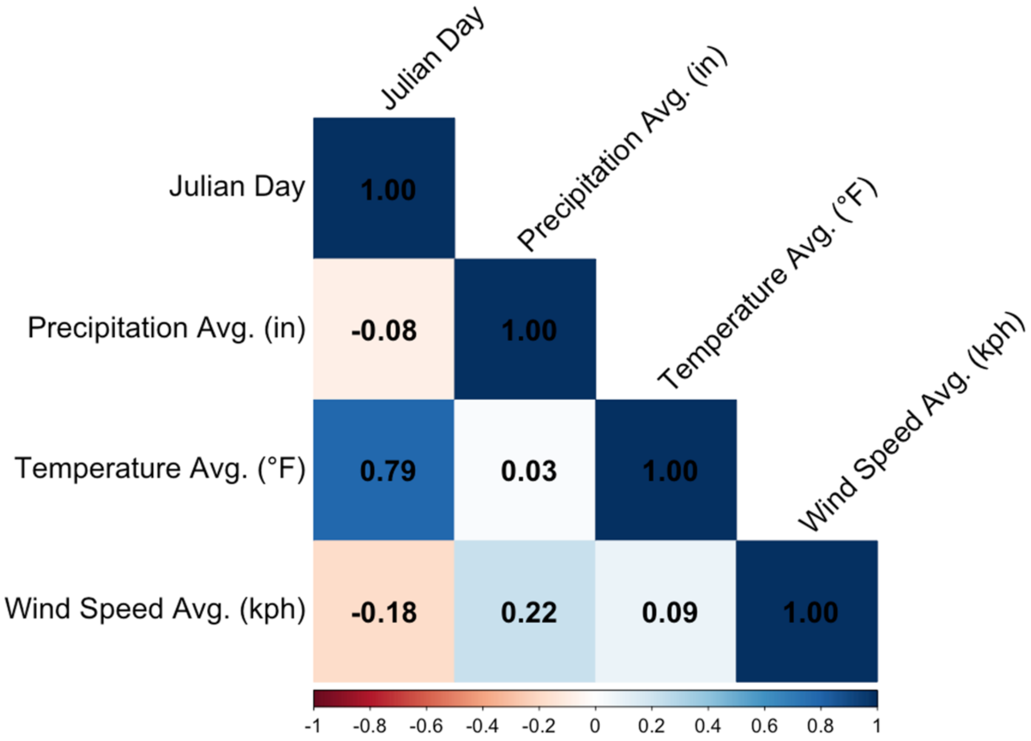

Julian Day
Precipitation Avg. (in)
Temperature Avg. (°F)
Wind Speed Avg. (kph)
1.00
-0.08
1.00
0.79
0.03
1.00
-0.18
0.22
0.09
1.00
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1

Figure 1.6: Correlation matrices for abundance covariates (top panel), forb cover (0–100%), grass cover (0–100%), shrub cover (0–100%), average shrub height (dm), and average grass height (dm)– along with detection covariates (bottom panel), Julian day (0-365), average daily precipitation (in), average daily temperature (°F), and average daily wind speed (kph) used to rule out correlated covariates (|r| ≥ 0.60) from inclusion in relative abundance models. I eliminated average daily temperature was eliminated as a covariate due to being correlated (|r| ≥ 0.60) with Julian day. All covariate data was collected from May–June 2024 in southeastern Georgia.

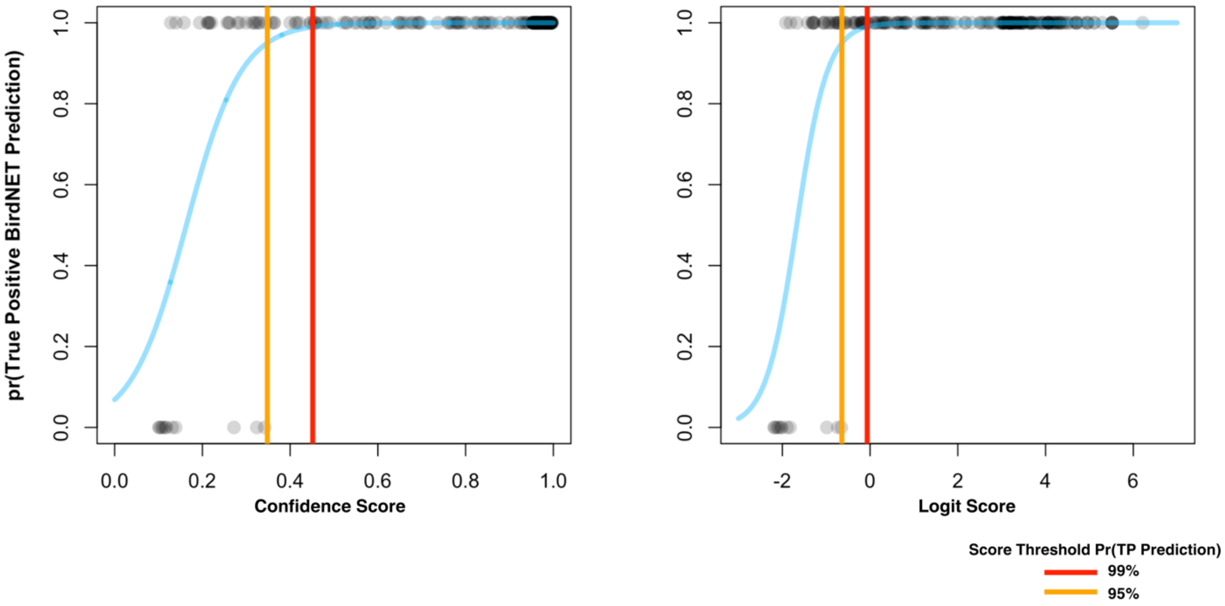


Figure 1.7: Example of a BirdNET confidence score [0.1–1] and logit score [-4–7] threshold for a 99% (red line) and 95% (orange line) probability of a true positive (TP) BirdNET prediction segment calculated from solving a logistic regression model for Prairie Warbler (*Setophaga discolor*) used for validating BirdNET species predictions to reduce probability of including false-positive predictions in analysis. BirdNET data was collected from May–June 2024 in southeastern Georgia.

Species	AIC Null	AIC Conf.	AIC Logit	95% Conf.	99% Conf.	95% Logit	99% Logit	Correct	Total
Bachman's Sparrow	392.92	287.07	238.66	1.21	1.49	5.55	7.57	203	306
Common Nighthawk				NA				208	208
Prairie Warbler	87.97	38.37	36.88	0.35	0.45	-0.64	-0.07	196	207
Common Yellowthroat	23.68	13.73	13.85	0.16	0.21	-1.65	-1.31	165	167
Blue Grosbeak	69.82	29.80	30.84	0.28	0.35	-0.92	-0.44	200	208
Indigo Bunting	24.48	17.12	17.78	0.21	0.32	-1.37	-0.64	202	204
Chuck-will's-widow	14.67	4.00	4.00	0.11	0.11	-2.10	-2.09	207	208
Northern Bobwhite	166.35	71.56	73.14	0.61	0.77	0.65	1.48	180	208

Table 1.1: Akaike's Information Criterion (AIC) scores used to rank score threshold type selection, along with score thresholds for 95% and 99% probability of true positive BirdNET prediction, total correct BirdNET prediction segments, and total BirdNET predictions segments overall for validating BirdNET output for focal species. Based on AIC score rank, either a confidence score [0.1–1] or logit score [-4–7] threshold was used for a 99% probability of true positive BirdNET prediction for every species expect Bachman's Sparrow and Common Nighthawk. A 95% logit score threshold was the only viable threshold for Bachman's Sparrow. All 208 prediction segments sampled for Common Nighthawk were correct, thus logistic regression models would not fit, and no score thresholds were applied. All models were fitted with data collected from May–June 2024 in southeastern Georgia.

RN Model Name	**Abundance Submodel Formula**
Site Treatment + *Vegetation* *(global model)*	~ site treatment + shrub cover + grass cover + forb cover + shrub height + grass height
Site Treatment Only	~ site treatment
Vegetation Only	~ shrub cover + grass cover + forb cover + shrub height + grass height
Null	~ 1

Table 1.2: Covariate formulas for abundance submodels fitted in candidate Royles-Nichols (RN) models used to estimate relative abundance for each focal disturbance-dependent species with the R package ‘*unmarked*’ (v1.4.3, Fiske & Chandler, 2011). Site treatment type (mine reclamation, timber production young savanna, mature savanna) was treated as a factor in abundance submodels for which it was included as a covariate in. While all continuous variables used as abundance covariates (i.e., vegetation variables) were standardized with the ‘*scale*’ function to improve model performance. The detection submodel formula (~ quadratic date + linear date + average daily wind speed + average daily precipitation) was the same for all models and detection covariates were also standardized with the ‘*scale*’ function. The site treatment + vegetation model was treated as the global model, as it included all listed abundance and detection covariates. While the site treatment only and vegetation only models were fitted just with their respective covariates to evaluate the effect of each independently. All models were fitted with data collected from May–June 2024 in southeastern Georgia.

Species	**Model**	***k***	**AIC$_c$**	**ΔAIC$_c$**	**W$_i$**
Bachman's Sparrow	*TV*	14	1386.64	0.00	0.91
	V	11	1391.17	4.53	0.09
	T	9	1434.03	47.39	4.64E-11
	Null	6	1462.35	75.71	3.29E-17
Common Nighthawk	*TV*	14	1440.07	0.00	0.99
	V	11	1449.32	9.24	0.01
	T	9	1459.09	19.02	7.34E-05
	Null	6	1462.99	22.92	1.04E-05
Prairie Warbler	*TV*	14	797.07	0.00	1.00
	T	9	812.61	15.54	0.00
	V	11	837.83	40.76	1.41E-09
	Null	6	880.91	83.84	6.23E-19
Common Yellowthroat	*TV*	14	1375.40	0.00	1.00
	T	9	1395.73	20.33	3.86E-05
	V	11	1405.93	30.53	2.35E-07
	Null	6	1412.09	36.69	1.08E-08
Blue Grosbeak	*TV*	14	1785.72	0.00	0.66
	T	9	1787.10	1.37	0.33
	V	11	1798.34	12.62	0.00
	Null	6	1810.40	24.68	2.91E-06
Indigo Bunting	*T*	9	1325.19	0.00	0.70
	TV	14	1326.90	1.71	0.30
	Null	6	1424.13	98.94	2.30E-22
	V	11	1431.05	105.85	7.25E-24
Chuck-will's-widow	*T*	9	334.05	0.00	0.99
	V	11	342.72	8.67	0.01
	Null	6	348.62	14.57	0.00
	TV	14	350.60	16.55	0.00
Northern Bobwhite	*T*	9	2241.75	0.00	0.89
	TV	14	2245.89	4.14	0.11
	V	11	2259.02	17.27	0.00
	Null	6	2262.89	21.14	2.28E-05

Table 1.3: Royle-Nichols (RN) model selection using Akaike Information Criterion Corrected for a Small Sample Size (AICc) for each disturbance-dependent focal species. Candidate models included: *TV = site treatment + vegetation model (global model), T = treatment only model, V = vegetation only model, and null model* (see Table 1.2). Values for *k* representing the degrees of freedom (i.e., number of covariates) in each model. Along with AICc scores, ΔAICc, and model weight (W_i) values representing rank and certainty in selection between models. The site treatment model + vegetation model was the top model (ΔAICc ≥ 2 over the next best model) for Bachman's Sparrow, Common Nighthawk, Prairie Warbler, and Common Yellowthroat. The site treatment + vegetation model was also designated as the top model for Blue Grosbeak, although there was some uncertainty in model selection (ΔAICc = 1.37), however most model weight was given to the site treatment and vegetation model ($W_i = 0.66$). The treatment only model was the top model (ΔAICc ≥ 2) for Chuck-will's-widow and Northern Bobwhite. And the treatment only model was also designated as the top model for Indigo Bunting, given it had most of the model weight ($W_i = 0.70$) with only slight model uncertainty (ΔAICc = 1.71). The vegetation only and null models were not ranked as top models for any focal species. All models were fitted with data collected from May–June 2024 in southeastern Georgia.

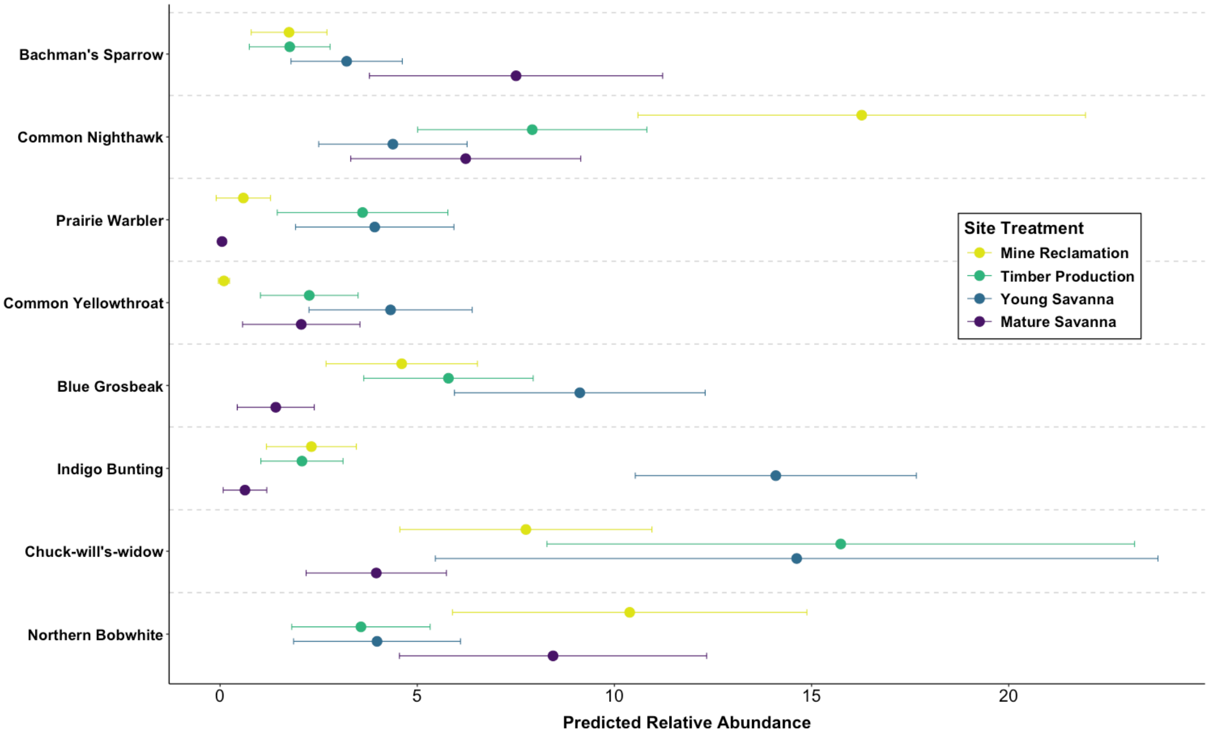


Figure 1.8: Predicted per-monitoring point relative abundance estimates across site treatments for each focal disturbance-dependent species, estimated from single-species, single season Royle-Nichols (RN) models with 95% confidence. Points present the per-monitoring point estimate of relative abundance for each species in a site treatment type, with whiskers indicating the 95% confidence intervals (CIs) around each estimate. Predictions are based on the top model for each species (see Table 1.3). For species where the top model included both site treatment and vegetation, vegetation covariates were held at their mean values to isolate the effect of site treatment on predicted relative abundance. All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

Species	**Top Model**	**χ^2**	***p*-value**	***c*-hat**
Bachman's Sparrow	TV	7.42E+15	1	0.1
Common Nighthawk	TV	5.97E+16	0.505	0.87
Prairie Warbler	TV	8.73E+15	0.05	1.56
Common Yellowthroat	TV	1.09E+17	0.109	1.52
Blue Grosbeak	TV	2.93E+17	0.008	4.15
Indigo Bunting	T	8.57E+16	0.214	1.49
Chuck-will's-widow	T	1.12E+17	0.084	2.95
Northern Bobwhite	T	1.11E+18	0	15.46

Table 1.4: Mackenzie and Bailey's Goodness-of-Fit test results used to evaluate model fit to the observed data for Royle-Nichols (RN) top models by disturbance-dependent bird species (see Table 1.3). Each top model was assessed using a Chi-square (χ^2) test, with corresponding *p*-values, and *c*-hat value. Each species model ran for 1,000 bootstrap simulations to stabilize Chi-square estimates, ensuring robust goodness-of-fit evaluation across all tested models. A relatively low Chi-square value paired with a high *p*-value (≥ 0.05) suggested good model fit, indicating that the observed relative abundance patterns align well with those predicted by the model. Conversely, relatively high Chi-square values and lower p-values (close to 0) suggested lack of model fit, as seen for species such as Northern Bobwhite and Blue Grosbeak. The *c*-hat values were also used to evaluate potential over-dispersion in models: values near 1 imply a good fit with no substantial over-dispersion, whereas values ≥ 4 suggest severe model overdispersion, seen again for Northern Bobwhite and Blue Grosbeak, possibly due to missing covariates that were potentially important for predicting patterns of relative abundance for these species, but were beyond what was measured and included in models. A relatively low *c*-hat

value (0.1) for Bachman's Sparrow may suggest under-dispersion, potentially indicating that relevant covariates were missing from the model, leading to inflated standard errors (SEs) for parameter estimates and possibly masking true effects. All RN models tested were fitted with data collected from May–June 2024 in southeastern Georgia.

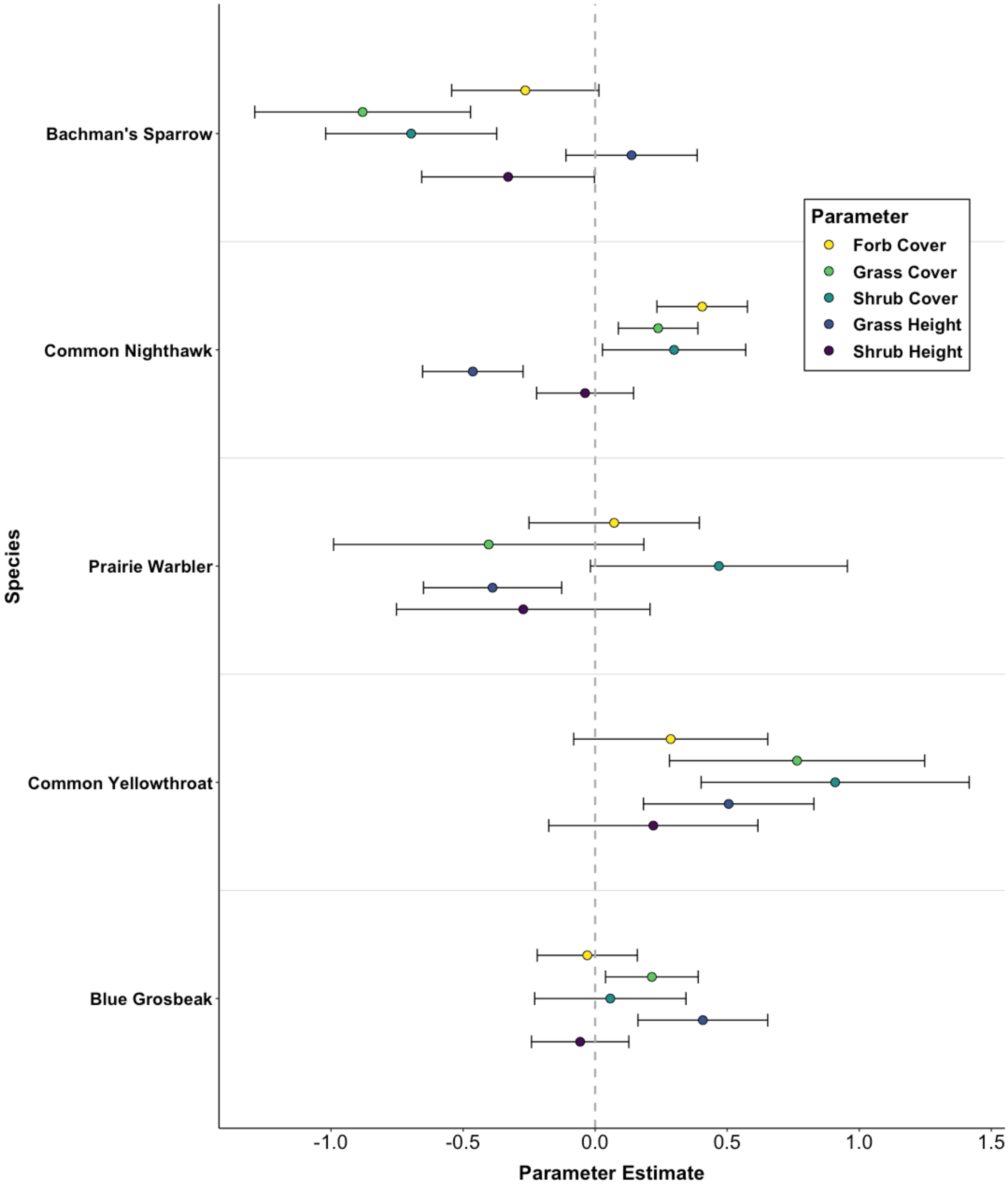

Bachman's Sparrow
Common Nighthawk
Prairie Warbler
Common Yellowthroat
Blue Grosbeak
Species
Parameter
Forb Cover
Grass Cover
Shrub Cover
Grass Height
Shrub Height
-1.0
-0.5
0.0
0.5
1.0
1.5
Parameter Estimate

Figure 1.9: Parameter estimates from single-species Royle-Nichols (RN) models for the effects of forb cover, grass cover, shrub cover, grass height, and shrub height on relative abundance for species where the site treatment + vegetation RN model was the top model. Each point represents the raw parameter estimate for each vegetation covariate’s (i.e., parameter) effect on species relative abundance, and whiskers indicate the 95% confidence intervals around each parameter estimate. All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

Species	VIF	Covariate	Covariate Type
Bachman’s Sparrow	3.85	Mature savanna	Abundance
	2.98	Young savanna	Abundance
	2.18	Timber Production	Abundance
	2.97	Shrub Cover	Abundance
	1.71	Grass Cover	Abundance
	1.64	Forb Cover	Abundance
	2.45	Shrub Height	Abundance
	1.72	Grass Height	Abundance
	1.10	Quadratic Date	Detection
	1.03	Linear Date	Detection
	1.10	Wind Speed	Detection
	1.03	Precipitation	Detection
Common Nighthawk	3.24	Mature savanna	Abundance
	3.40	Young savanna	Abundance
	1.53	Timber Production	Abundance
	3.89	Shrub Cover	Abundance
	2.12	Grass Cover	Abundance
	1.95	Forb Cover	Abundance
	2.16	Shrub Height	Abundance
	2.45	Grass Height	Abundance
	1.09	Quadratic Date	Detection
	1.04	Linear Date	Detection
	1.09	Wind Speed	Detection
	1.04	Precipitation	Detection
Prairie Warbler	1.26	Mine Reclamation	Abundance
	1.08	Mature savanna	Abundance
	2.26	Timber Production	Abundance
	5.28	Shrub Cover	Abundance
	2.25	Grass Cover	Abundance
	2.60	Forb Cover	Abundance
	2.31	Shrub Height	Abundance
	2.36	Grass Height	Abundance
	1.27	Quadratic Date	Detection
	1.28	Linear Date	Detection
	1.07	Wind Speed	Detection
	1.02	Precipitation	Detection
Common Yellowthroat	1.12	Mine Reclamation	Abundance

	2.76	Mature savanna	Abundance
	1.69	Timber Production	Abundance
	4.99	Shrub Cover	Abundance
	3.93	Grass Cover	Abundance
	2.59	Forb Cover	Abundance
	1.50	Shrub Height	Abundance
	1.62	Grass Height	Abundance
	1.09	Quadratic Date	Detection
	1.03	Linear Date	Detection
	1.09	Wind Speed	Detection
	1.03	Precipitation	Detection
Blue Grosbeak	1.76	Mature savanna	Abundance
	2.20	Young savanna	Abundance
	1.76	Timber Production	Abundance
	2.62	Shrub Cover	Abundance
	1.95	Grass Cover	Abundance
	1.42	Forb Cover	Abundance
	1.65	Shrub Height	Abundance
	1.65	Grass Height	Abundance
	1.11	Quadratic Date	Detection
	1.03	Linear Date	Detection
	1.11	Wind Speed	Detection
	1.03	Precipitation	Detection
Indigo Bunting	1.59	Mature savanna	Abundance
	3.35	Young savanna	Abundance
	2.52	Timber Production	Abundance
	2.52	Shrub Cover	Abundance
	2.16	Grass Cover	Abundance
	1.34	Forb Cover	Abundance
	1.62	Shrub Height	Abundance
	1.41	Grass Height	Abundance
	1.06	Quadratic Date	Detection
	1.01	Linear Date	Detection
	1.07	Wind Speed	Detection
	1.02	Precipitation	Detection
Chuck-will’s-widow	3.98	Mature savanna	Abundance
	3.36	Young savanna	Abundance
	1.86	Timber Production	Abundance
	3.44	Shrub Cover	Abundance
	2.05	Grass Cover	Abundance

	1.68	Forb Cover	Abundance
	2.17	Shrub Height	Abundance
	2.47	Grass Height	Abundance
	1.14	Quadratic Date	Detection
	1.15	Linear Date	Detection
	1.06	Wind Speed	Detection
	1.07	Precipitation	Detection
Northern Bobwhite	3.50	Mature savanna	Abundance
	1.99	Young savanna	Abundance
	1.41	Timber Production	Abundance
	4.33	Shrub Cover	Abundance
	1.97	Grass Cover	Abundance
	1.69	Forb Cover	Abundance
	2.33	Shrub Height	Abundance
	1.83	Grass Height	Abundance
	1.12	Quadratic Date	Detection
	1.04	Linear Date	Detection
	1.12	Wind Speed	Detection
	1.03	Precipitation	Detection

Table 1.5: Variance Inflation Factor (VIF) values for abundance and detection covariates from the global (i.e., site treatment + vegetation) Royle-Nichols (RN) models for all disturbance-dependent species. The factor ‘Mine Reclamation’ was the model intercept for all species expect Common Yellowthroat and Prairie Warbler, as low relative abundance estimates for these species in the mine reclamation treatment caused inflated VIF values between treatment covariates. The ‘Young Savanna’ factor was used as the model intercept for these two species instead. All VIF values for abundance submodels were < 5, and all detection submodel VIF values were < 2, indicating no major issues with multicollinearity between covariates in global RN models. All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

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Chapter 2: Influence of Autonomous Recording Unit (ARU) Survey Effort on Songbird Relative Abundance Estimates from Royle-Nichols Models

Abstract

Passive acoustic monitoring with autonomous recording units (ARUs) can enable efficient monitoring of avian populations. Royle-Nichols (RN) models may be well suited for estimating abundance or relative abundance from ARU detection/non-detection data; as repeated surveys can easily be conducted with ARUs. Yet, optimal survey effort using these methods remains unexplored. Using ARU data from four site treatments in southeastern Georgia, I assessed how survey frequency and mean cumulative detection probability influenced estimates for Blue Grosbeak (*Passerina caerulea*) and Bachman's Sparrow (*Peucaea aestivalis*) from May–June 2024. A baseline dataset of 50 daily surveys was subsampled into reduced frequencies: 25 surveys every 2nd day, 17 every 3rd day, 13 every 4th day, 8 every 7th day, and 5 every 10th day. RN models were fitted to each subsample. Abundance estimates decreased with subsampling, showing survey frequency arbitrarily influences estimates and RN models should be viewed as relative, not absolute, abundance estimates. However, the specific order of relative abundance across site treatments remained consistent for both species during subsampling, indicating RN models can still reliably infer effects across sites. Mean cumulative detection probability decreased with subsampling yet remained >70% for both species. Subsampling reduced precision in relative abundance estimates for both species; particularly for Bachman's Sparrow, emphasizing species-specific sensitivity to survey effort. However, subsampling every 2nd day or every 3rd day resulted in moderate losses of precision (≤ 34%) for both species, suggesting reduced survey frequency may be a viable strategy for efficient data collection depending on species detectability and study goals.

Introduction

Passive acoustic monitoring with Autonomous Recording Units (ARUs) is rapidly becoming adopted by the field of avian conservation and ecology (Gibb et al., 2019; Hoefer et al., 2023; Shonfield & Bayne, 2017; Sugai et al., 2019; Wood, Klinck, et al., 2021). ARU surveys can be conducted at spatial and temporal scales infeasible with traditional methods (i.e., trained surveyors conducting point count or line-transect surveys) through the deployment of programable ARUs set to record soundscapes simultaneously in the field (Darras et al., 2018; Gibb et al., 2019). ARUs are also becoming increasingly affordable, empowering widespread population monitoring at a fraction of the cost to using trained surveyors (Darras et al., 2018; Shonfield & Bayne, 2017). Moreover, recent machine-learning classifiers that automatically annotate ARU data (i.e., produce lists of species identifications from vocalizations within recordings) decrease the human-effort involved in post-processing (Kahl et al., 2021; Lapp et al., 2023; Van Doren et al., 2024). Analyses using ARU data have been successful in measuring bird occupancy by converting acoustic data collected across sites and dates to binary detection/non-detection histories with repeated surveys/visits (Clement et al., 2022; Cole et al., 2022; Knight et al., 2022; Metz & Pease, 2024; Wood et al., 2019).

Despite these advancements, estimating avian species abundance with established modeling methods (e.g., distance sampling models, N-mixture models) using ARU data remains challenging due to complications in measuring distances of individuals (Yip et al., 2020) or determining counts of individuals from audio recordings or machine-learning classifier output (Doser et al., 2021; Fiss et al., 2024; Pérez-Granados & Traba, 2021). Being able to estimate differences in species abundance with ARU data across spatially discrete units (e.g., sites) and time (e.g., surveys, seasons) is desirable, even if only indices of relative abundance, as it can offer insights into the population trends or habitat use of a species with greater detail than occupancy alone (Kéry & Royle, 2015). Studies have explored various methods to overcome challenges in estimating abundance with ARU data including integrating acoustic data into spatial capture-recapture models (Efford et al., 2009), using point-count data in an integrated modeling approach (Doser et al., 2021), and using call rate estimations for abundance or relative abundance approximations (Borker et al., 2014; Pérez-Granados et al., 2021; Pérez-Granados & Traba, 2021). However, these methods tend to require experience with custom model building programs (e.g., JAGS; Plummer, 2003) or other supplemental data (e.g., point-counts), limiting their widespread application.

An adapted occupancy model framework, the Royle-Nichols (hereafter RN) model, is a promising approach for estimating bird abundance using detection/non-detection data alone (Royle & Nichols, 2003). RN models share many assumptions with the classic occupancy model including population closure, monitoring point and survey independence, equal detectability of individuals within a survey (i.e., same rate rates of vocalizations), and no false-positive detections (MacKenzie et al., 2002). Most importantly, RN models extend this framework by linking the relationship between detection probability and abundance. Thus, RN models leverage heterogeneity in detection probabilities across spatially discrete units and time to infer species abundance. This feature makes RN models particularly well-suited for binary detection/non-detection data collected with ARUs (Fiss et al., 2024; Royle & Nichols, 2003; Strebel et al., 2021).

Still, RN models fitted with ARU data may not reliably estimate absolute or ‘true’ abundance if the effective survey area for a sampling point is unknown or varies across monitoring points (Fiss et al., 2024). Nevertheless, its ability to provide differences in relative abundance for a species across spatially discrete units and time can offer valuable insights capable of informing management and monitoring efforts. Moreover, RN models are appealing in that they can be easily fitted in the Program R package '*unmarked*' (Fiske & Chandler, 2011; R Core Team, 2024) without requiring experience with other custom model-building programs. Fiss et al. (2024) recently demonstrated RN models fitted with ARU data in '*unmarked*' provide similar estimates of abundance when compared to other abundance models fitted with both ARU and point-count data. Furthermore, they reported RN models fitted with ARU data had greater precision (e.g., smaller standard errors [SEs]) in abundance estimates compared to RN models fitted with point count data. This greater precision in abundance estimates could be attributed to the increased survey effort and higher cumulative detection probability (the probability of detecting a target species once across all spatially discrete units and surveys) provided by ARUs compared to traditional methods (e.g., point counts) (Doser et al., 2021; Fiss et al., 2024; Knight et al., 2022).

Passive acoustic monitoring with ARUs can be conducted intensively— over weeks, months, or even continuously— often at a daily survey frequency (Gibb et al., 2019). Yet, the benefits of conducting daily surveys over a large temporal scale in the context of RN models and estimating relative abundance with high precision remains unexplored. Thus, an important question remains: at what point do these benefits of multiple repeated surveys saturate in terms of abundance estimation and precision? This question is important because passive acoustic monitoring studies must balance the trade-offs between robust data collection and computational and data storage limitations. Even with the use of machine-learning classifiers to automatically identify species in recordings, the immense amount of data (multiple terabytes) that can be collected with ARUs pose a challenge for monitoring in terms of data storage and post-processing (Blumstein et al., 2011; Sugai et al., 2019). This is especially limiting for projects that lack specialized computational resources such as high-performance computing and high-volume data storage systems.

Reducing the survey effort by programming ARUs to record intermittently (e.g., every few days or once a week instead of daily) increases the feasibility of post-processing and data storage. However, this reduction comes at the potential cost of sacrificing a higher cumulative detection probability and loss in precision for abundance estimates. Using a consecutive 50-day dataset as a baseline and post hoc subsampled datasets representing reduced survey frequencies, I aimed to investigate how survey effort and mean cumulative detection probability influence the output and precision of relative abundance estimates in RN models. To accomplish this, I evaluated differences in RN model parameter estimates across four sites in southeastern Georgia representing a distinct land-use or management type (mine reclamation, timber production, young savanna, and mature savanna) for two breeding songbirds; Blue Grosbeak (*Passerina caerulea*) and Bachman's Sparrow (*Peucaea aestivalis*). Both songbird species vocalize readily to defend breeding territories, producing a reliable acoustic signal for detection if available. They are also both considered disturbance-dependent species and commonly associated with the post-disturbance upland pine (*Pinus* spp.) habitats throughout my study area in the southeastern Coastal Plain region of Georgia (Dunning et al., 2020; Lowther & Ingold, 2020). Yet, Bachman's Sparrows are considered an uncommon species and nearly exclusively found in pine savanna habitat, whereas Blue Grosbeaks are comparatively a common species found in a larger variety of post-disturbance habitats; thus, I hypothesized that relative abundance estimates for Bachman's Sparrows may be more sensitive to reductions in survey frequency than Blue Grosbeak.

Methods

Study Area

All sites were established across the lower Coastal Plain region of southeastern Georgia in Charlton, Folkston, and Brantley counties in 2024 (Figure 1.1). Upland pine habitat chosen for sites was characterized by relatively flat topography with acidic, poorly drained, and predominantly sandy texture soils. I categorized four distinct site treatment types (also referred to as sites): mine reclamation, timber production, young savanna, and mature savanna (Figure 1.2). Both the mine reclamation (following heavy mineral surface mining; Pirkle et al., 2013; U.S. Geological Survey, 2018) and timber production site contained stands of intensively managed loblolly pine (*Pinus taeda*), typically ≤ 5 m in height, and planted ~2–8 years ago. The mine reclamation site was previously used for timber production prior to mining and reclamation efforts were focused on restoring the mined land back for timber production. Therefore, overall site preparation and management practices for the mine reclamation site was analogous to the timber production site (i.e., only difference is mined vs. unmined). Site preparation for both site treatment types followed a common approach for short-rotation, even-aged management of pine stands in the Southeastern United States (Schultz, 1997).

The young savanna site treatment contained stands of longleaf pine *(Pinus palustris)* planted ~ 7 years ago. Longleaf pine stands were typically ≤ 5 m in height, and stands were managed with prescribed fire every 2–3 years to inhibit hardwood stand competition and promote desired understory characteristics (*Georgia DNR Altamaha Corridor Management Plan*, 2021). The mature savanna site was selected in stands of second-growth (~50-years-old) longleaf pine savanna with a stand basal area of 40–70 square feet per acre and managed with prescribed fire every 2–3 years to maintain the structural characteristics of pine savanna habitat (U.S. Fish

& Wildlife Service, 2006). More details on study area and differences in site treatment can be found in *Chapter 1 Study Area*.

Monitoring Design

I established 9 mine reclamation monitoring points for passive acoustic monitoring, censusing all available land for this site treatment type. Thereafter, I established 9 monitoring points at the timber production site, 10 monitoring points in the young savanna site at Sansavilla WMA, and 8 monitoring points in the mature savanna site at Okefenokee NWR for a roughly even distribution of monitoring points across site treatments. Every monitoring point had an ARU deployed to record acoustic data of bird vocalizations. All ARUs were placed in the center of a 225 m radius buffer from other ARUs (monitoring points) to avoid recording the same birds and minimize recordings from birds outside of treatment areas. However, there were two monitoring points that overlapped and some buffer radii extended outside of treatment areas (Figure 1.3). SongMeter Minis and SongMeter Mini 2s produced by Wildlife Acoustics Inc. (Maynard, MA, USA) were deployed to record throughout the breeding bird season from 03 May–21 June in 2024. All ARUs were secured to a t-post 1.5 m off the ground and equipped with 2 omnidirectional microphones recording in stereo at a sampling rate of 44100 Hz with 18 dB of channel gain. Every ARU was configured to record daily with the same schedule (Figure 1.4). I set ARUs to record daily for 20 minutes before sunrise in addition to 3 minute intervals every hour from 1 hour before sunrise to 4 hours after sunrise; then record again for 20 minutes after sunset in addition to 3 minute intervals every hour to 3 hours after sunset. Altogether, 67 minutes of acoustic data were recorded daily at each monitoring point in 2024.

BirdNET Processing and Validation

I annotated acoustic data with BirdNET, a research platform developed by Cornell Lab of Ornithology and Chemnitz University of Technology that provides deep neural network machine-learning algorithms to annotate recordings of bird vocalizations (v1.2.0, Kahl et al., 2021). BirdNET produced output for each audio file with a series of species predictions for all potential species identified along with a confidence score. Comparing BirdNET output with manual validation (i.e., human listens and annotates a subset of recordings) is an important step in evaluating performance of BirdNET predictions to avoid including false positives in models (Cole et al., 2022; Pérez-Granados, 2023b; Ware et al., 2023; Wood & Kahl, 2024). I followed the guidelines in Wood & Kahl, 2024 for generating species-specific BirdNET score thresholds through manual validation with BirdNET prediction segments and their associated confidence scores. More details on BirdNET processing and validation can be found in *Chapter 1 Methods*.

Abundance Models

I estimated abundance by fitting single-season, single-species RN models with the R package 'unmarked' (v1.4.3, Fiske & Chandler, 2011) for Blue Grosbeak and Bachman's Sparrow. I filtered BirdNET predictions by date and monitoring point from 03 May – 21 June 2024, which created a detection/non-detection matrix across monitoring points with 50 daily surveys for each species across the breeding season (Figure 2.1). I created correlation matrices (Figure 1.6) for abundance covariates, forb cover (0–100%), grass cover (0–100%), shrub cover (0–100%), average shrub height (dm), and average grass height (dm)– along with detection covariates, Julian day (0-365), average daily precipitation (in), average daily temperature (°F), and average daily wind speed (kph) to rule out correlated covariates ($|r| \geq 0.60$) for inclusion in models. I eliminated average daily temperature as it was correlated ($|r| \geq 0.60$) with Julian day.

Precipitation was not included in models as it only contained 0s for some subsampled datasets and a covariate with constant values would cause model convergence failure. See *Chapter 1 Methods* for details on covariate data collection. Site treatment type was treated as a factor in abundance submodels. All continuous variables used as abundance covariates (i.e., vegetation variables) were standardized with the 'scale' function to improve model performance. The detection submodel formula (~ quadratic date + linear date + average daily wind speed) was the same for all models and detection covariates were also standardized with the 'scale' function. The site treatment + vegetation model was treated as the global model, as it included all listed abundance and detection covariates (Table 1.2). For the site treatment + vegetation model (global model), I used the 'vif' function to calculate Variance Inflation Factor (VIF) values between covariates in both submodels as a final check for multicollinearity. I then compared Akaike Information Criterion Corrected for a Small Sample Size (AICc) scores from the '*AICcmodavg*' R package (v2.3.3, Marc J. Mazerolle, 2023) from candidate RN models and selected top models (see Table 2.2).

Post Hoc Subsampling

I subsampled the baseline (everyday) dataset with 50 consecutive surveys five times equally across all monitoring points to simulate various reduced survey frequencies in 2-, 3-, 4-, 7-, and 10-day intervals from 03 May – 21 June, which created datasets representing surveys being conducted across all monitoring points every 2nd day, every 3rd day, every 4th day, every 7th day, and every 10th day (Figure 2.2). All datasets had identical within day recording schedules and BirdNET post-processing (Figure 1.4; Table 1.1.). The baseline (everyday) dataset consisted of 50 surveys– producing 2,010 hours of audio (~1,215 GB). The every 2nd day dataset consisted of 25 surveys– producing 1,005 hours of audio (~608 GB). The every 3rd day consisted of 17 surveys– 683 hours of audio (~413 GB). The every 4th day dataset consisted of 13 surveys– producing 522 hours of audio (~316 GB). The every 7th day dataset consisted of 8 surveys – producing 322 hours of audio (~194 GB). The every 10th day consisted of 5 surveys– producing 201 hours of audio (~122 GB). All subsampled datasets were re-fitted to the same RN top models as the baseline dataset.

Measuring Precision of Relative Abundance Estimates

I used the coefficient of variation (CV) for relative abundance estimates as a standardized measure of precision across different datasets for both species. To calculate the mean CV for relative abundance estimates in each dataset, I first determined the site treatment-level CVs for each site treatment type. I did this by dividing the SE, by the predicted relative abundance estimate for that site treatment. These site treatment-level CVs provided a standardized measure of variability relative to the predicted mean for each site treatment. Finally, I averaged the site treatment-level CVs across all site treatments within each dataset to produce the mean CV for relative abundance estimates. This ensured differences in survey effort and precision are compared on a consistent scale across datasets.

Results

Model Selection

The site treatment model + vegetation model was the top model (ΔAICc ≥ 2 over the next best model) for Bachman’s Sparrow with the baseline (everyday) dataset (table 2.2). The site treatment + vegetation model was also designated as the top model for Blue Grosbeak, although there was some uncertainty in model selection (ΔAICc = 0.94), however most model weight was given to the site treatment and vegetation model ($W_i = 0.61$). All VIF values for abundance submodels were < 3, and all detection submodel VIF values were < 2, indicating no major multicollinearity between categorical (i.e., site treatment factors) and continuous covariates in global RN models.

Model Estimates

All models fitted with the baseline and subsampled datasets successfully converged and produced predictive per-sampling point estimates of relative abundance across site treatments for Blue Grosbeak and Bachman's Sparrow. The baseline dataset with 50 consecutive surveys produced predicted per-monitoring point estimates of relative abundance across site treatment for Blue Grosbeak in order of highest to lowest (Table 2.3): young savanna ($\widehat{N} = 8.20 \pm 1.49$), timber production ($\widehat{N} = 5.16 \pm 1.02$), mine reclamation, and mature savanna ($\widehat{N} = 1.38 \pm 0.50$) site treatments. And the baseline dataset with 50 consecutive surveys produced predicted relative abundance estimates for Bachman's Sparrow across site treatment in order of highest to lowest (Table 2.4): mature savanna ($\widehat{N} = 7.21 \pm 1.90$), young savanna ($\widehat{N} = 2.84 \pm 0.68$), timber production ($\widehat{N} = 1.75 \pm 0.53$), and mine reclamation ($\widehat{N} = 1.68 \pm 0.49$).

Although the absolute value of abundance estimates decreased as survey frequency was reduced in subsampled datasets, the pattern of relative abundances estimates between site treatments remained consistent across all models (Figure 2.3). For example, in the every 10th day dataset, the relative abundance estimates for Blue Grosbeak were lower overall (e.g., young savanna: $\widehat{N} = 5.92 \pm 2.56$; timber production: $\widehat{N} = 1.50 \pm 0.67$) but still followed the same ranking of site treatments as the baseline dataset. Similarly, for Bachman's Sparrow, the every 10th day dataset showed a reduction in the absolute value of relative abundance estimates while maintaining the same treatment-specific order.

Estimates of mean cumulative detection probability ($\hat{P}$) decreased with reduced survey frequency for both species (Figure 2.4). For Bachman's Sparrow, $\widehat{P}$ ranged from 0.99 ± 5.00E-03 in the baseline dataset to 0.72 ± 0.04 in the every 10th day dataset, representing a 27% decrease in mean cumulative detection probability. This decrease was less pronounced for Blue Grosbeak, whereby mean cumulative detection probabilities ranged from practically complete detectability at 1.00 ± 1.00E-04 in the baseline dataset to 0.88 ± 2.62E-02 in the every 10th day dataset, resulting in only a 12% decrease. Furthermore, most subsampled datasets exhibited only slight declines in $\widehat{P}$ from the baseline (every 2nd day [0.2%], every 3rd day [0.6%], every 4th day [2%], and every 7th day [3%]).

The reduction in survey frequency and mean cumulative detection probability overall reduced the precision or mean CV for relative abundance estimates of both species, yet the extent of precision loss differed between Bachman's Sparrow and Blue Grosbeak (Figure 2.5). For Blue Grosbeak, the mean CV increased from 0.24 in the baseline (everyday) dataset to 0.50 in the every 10th day dataset, reflecting a 108% reduction in precision from the baseline. Although, intermediate datasets such as every 2nd day and every 3rd day exhibited moderate declines in precision from the baseline with only 20% and 34% loss in precision respectively. In contrast, mean CVs for Bachman's Sparrow displayed a steeper decrease in precision with subsampled datasets. The mean CV was 0.34 in the baseline dataset and 0.62 in the every 10th day dataset, corresponding to a 128% loss in precision from the baseline. Yet, once again intermediate datasets showed moderate loss in precision with reduced sampling, producing a 26% loss in precision from the baseline for the every 2nd day dataset and 32% for the every 3rd day dataset.

Discussion

Although the absolute value of relative abundance estimates often decreased with subsampling, my results suggest that RN models are effective at capturing patterns of relative abundances estimates across site treatments, even with reduced survey effort. In my study, the specific order of relative abundance estimates across four site treatments remained consistent for both species, from the baseline dataset throughout all subsampled datasets. There is uncertainty and contention surrounding if RN models produce ‘actual’ or absolute abundance estimates (Fiss et al., 2024; Kéry & Royle, 2016a; Royle & Nichols, 2003). My results suggest that survey frequency arbitrarily influences these estimates, as there was considerable variation in treatment-specific abundance estimates across subsampled datasets. This indicates that RN models likely only provide relative measures of abundance, and caution should be used when interpreting these estimates as measures of true abundance. Nevertheless, these estimates maintained their treatment-specific order and still provided valuable insights into how site treatment is driving differences in relative abundance for both species (see *Chapter 1 Results and Discussion* for details).

Mean cumulative detection probabilities remained relatively high for Blue Grosbeak ($\hat{P} = \geq 0.88$) and Bachman’s Sparrow ($\hat{P} = \geq 0.72$), even in the most subsampled dataset (e.g., surveys occurring once every 10-days). This could simply be due to the survey effort being much higher than what is traditionally conducted with point count surveys (typically only 2-3 surveys) for songbirds, even at the lowest subsampling (5 surveys, once every 10 days) with ARUs, further highlighting the utility of passive acoustic monitoring (Duchac et al., 2020; Fiss et al., 2024; Knight et al., 2022; Ralph et al., 1995). Though, for Bachman’s Sparrow, mean cumulative detection probability had a more pronounced decrease with survey effort than Blue Grosbeak, suggesting higher survey frequencies may be needed to improve detection probabilities (≥ 70%) for Bachman's Sparrow. But these results may also indicate that availability for detection was high for these species during the breeding season (both species frequently vocalize to defend territories), reducing the impact of survey frequency on mean cumulative detection probability. In contrast, species with low availability for detection due to cryptic behavior (e.g., reduced vocal activity) may exhibit more variation in cumulative detection probabilities across different survey efforts (Diefenbach et al., 2007; Nichols et al., 2009). In such cases, survey frequency could have a more pronounced impact on mean cumulative detection probability, as lower availability increases the likelihood of missed detections.

My results demonstrate that reducing survey frequency and mean cumulative detection probability can lead to a loss of precision in relative abundance estimates. This finding aligns with the understanding that cumulative detection probability contributes to improved precision in abundance estimates (Doser et al., 2021; Kéry & Royle, 2015; Strebel et al., 2021; Yamaura et al., 2016). Reduced survey frequency and mean cumulative detection probability resulted in a loss of precision in relative abundance estimates for both species; however, the extent of precision loss was greater across subsampling for Bachman's Sparrow, the less common species found in a narrower range of post-disturbance habitats, typically pine savannas regularly managed with prescribed fire (Dunning et al., 2020). This highlights a need to account for species-specific sensitivity to reduced survey effort during study design. Yet, intermediate subsampling (every 2nd day, every 3rd day) only resulted in moderate losses of precision for both species, indicating reducing survey frequency could be a viable strategy for more efficient data collection depending on the target species and study goals.

Future studies could utilize CV estimates, which standardize the expression of precision loss from less survey effort, to conduct power analyses. This approach could help determine optimal sampling frequencies needed to achieve the desired precision for specific research questions when using RN models and ARUs. And further research will be needed to fully understand how species-specific availability for detection influences the relationship between cumulative detection probability, optimal survey effort, and the precision of parameter estimates in RN models. Yet, given my model's effectiveness at capturing patterns of relative abundance estimates in all datasets, with only moderate losses in precision with less frequent surveys, studies focused on breeding songbirds that vocalize frequently may take advantage of a more efficient survey frequency (once every other day or few days) without sacrificing substantial precision in estimating relative abundance from RN models.

This is advantageous for many passive acoustic monitoring programs that are limited by computational limits in post-processing and high-volume data storage, or programs that wish to maximize the scale of monitoring both spatially (e.g., hundreds of monitoring points) and temporally (e.g., multiple seasons) in an efficient yet robust manner. Ultimately, monitoring design (including survey frequency) will depend on each acoustic monitoring program's goals and budgetary constraints. If programs also wish to evaluate bird species richness and diversity across sites with ARU data, there would likely be additional benefit to intensive survey frequencies that were not considered for my goals in estimating species abundance (Ware et al., 2023; Wimmer et al., 2013; Wood, Kahl, et al., 2021). My ARUs only recorded 67 minutes a day, creating file sizes in .wav format of ~675 MB/day. The baseline dataset produced ~34 GB/50 days and ~1.25 TB/50 days for all 36 monitoring points. This level of data collection may be manageable for programs with desktops that have typical performance metrics (8-core CPUS, 16-24 GB RAM) and external hard drives or cloud-based storage. The future is promising for ever-more efficient data storage and post-processing too, as developers continue to roll-out more efficient versions of machine-learning classifiers, file format efficiency increases, and large-volume data storage solutions become more robust and widespread.

Figures

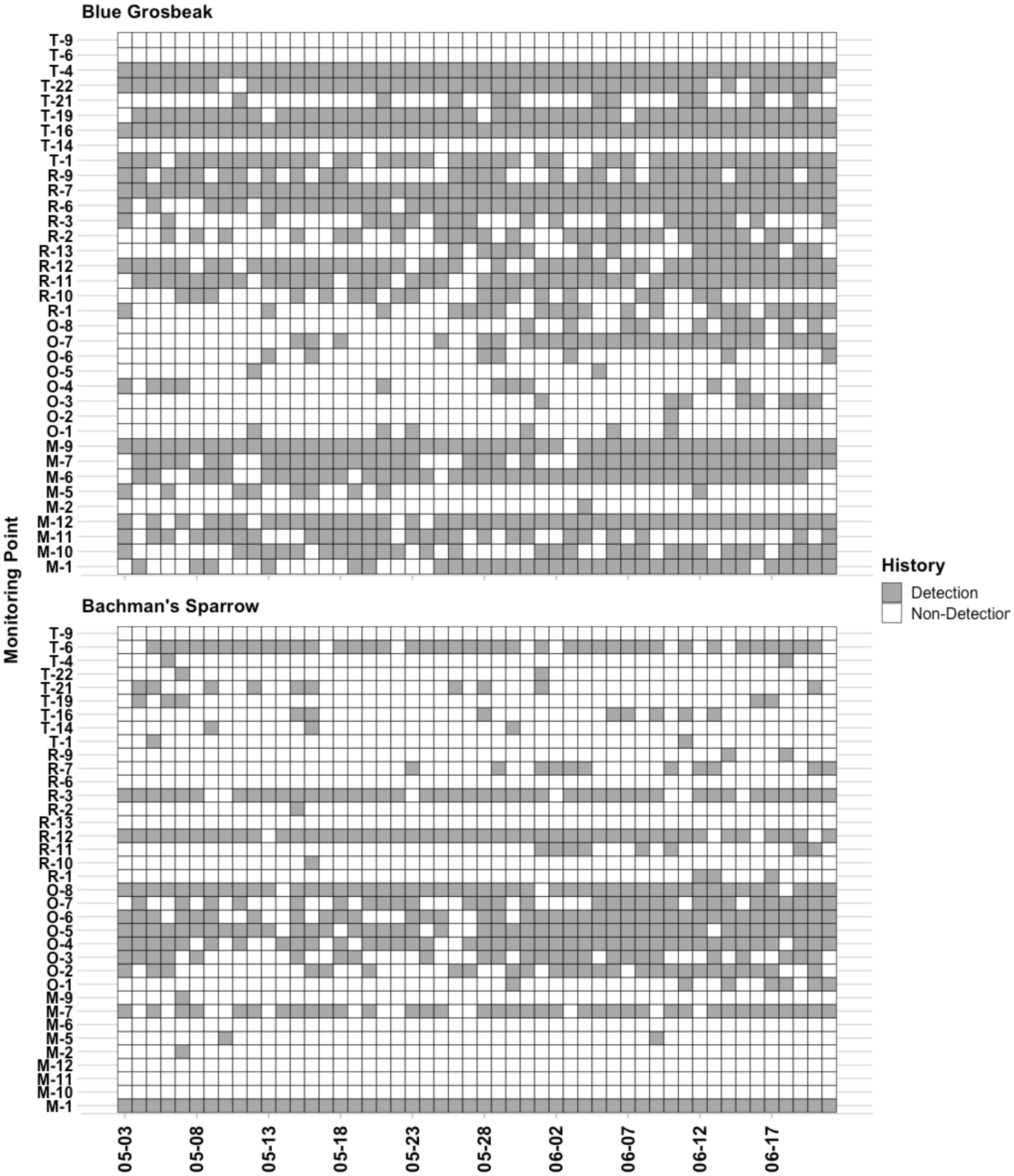
Blue Grosbeak
Bachman's Sparrow
Monitoring Point
T-9
T-6
T-4
T-22
T-21
T-19
T-16
T-14
T-1
R-9
R-7
R-6
R-3
R-2
R-13
R-12
R-11
R-10
R-1
O-8
O-7
O-6
O-5
O-4
O-3
O-2
O-1
M-9
M-7
M-6
M-5
M-2
M-12
M-11
M-10
M-1
05-03
05-08
05-13
05-18
05-23
05-28
06-02
06-07
06-12
06-17
History
Detection
Non-Detectior

Figure 2.1: Complete detection/non-detection histories from the baseline 50-day dataset for both Blue Grosbeak and Bachman’s Sparrow across all 36 monitoring points. Passive acoustic monitoring surveys with Autonomous Recording Units (ARUs) occurred across monitoring points in each site representing a distinct land-use or management type from 03 May–21 June 2024 in southeastern Georgia. Monitoring points labelled along the y-axis correspond to the site treatment type (“T” = timber production, “M” = mine reclamation , “R” = young savanna, and “O” = mature savanna). Blue tiles indicate a detection that day, and white tiles indicate a non-detection for the given species, monitoring point, and date. All subsampled dataset’s detection/non-detection histories were created from this baseline detection/non-detection history.

Species	**Model**	***k***	**AIC$_c$**	**ΔAIC$_c$**	**W$_i$**
Blue Grosbeak	*TV*	13	1593.95	0.00	0.61
	T	8	1594.90	0.94	0.38
	V	10	1604.38	10.42	0.00
	Null	5	1614.05	20.09	0.00
Bachman's Sparrow	*TV*	13	1220.14	0.00	0.92
	V	10	1224.91	4.77	0.08
	T	8	1264.82	44.67	0.00
	Null	5	1291.14	70.99	0.00

Table 2.2: Royle-Nichols (RN) model selection using Akaike Information Criterion Corrected for a Small Sample Size (AICc) for Blue Grosbeak and Bachman's Sparrow fitted with the baseline (everyday) dataset. Candidate models included: *TV = site treatment + vegetation model (global model), T = treatment only model, V = vegetation only model, and null model* (see Table 2.1). Values for *k* representing the degrees of freedom (i.e., number of covariates) in each model. Along with AICc scores, ΔAICc, and model weight (W$_i$) values representing rank and certainty in selection between models. The site treatment model + vegetation model was the top model (ΔAICc ≥ 2 over the next best model) for Bachman's Sparrow. The site treatment + vegetation model was also designated as the top model for Blue Grosbeak, although there was uncertainty in model selection (ΔAICc = 0.94), however most model weight was given to the site treatment and vegetation model (W$_i$ = 0.61). The vegetation only and null models were not ranked as top models for any focal species. All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

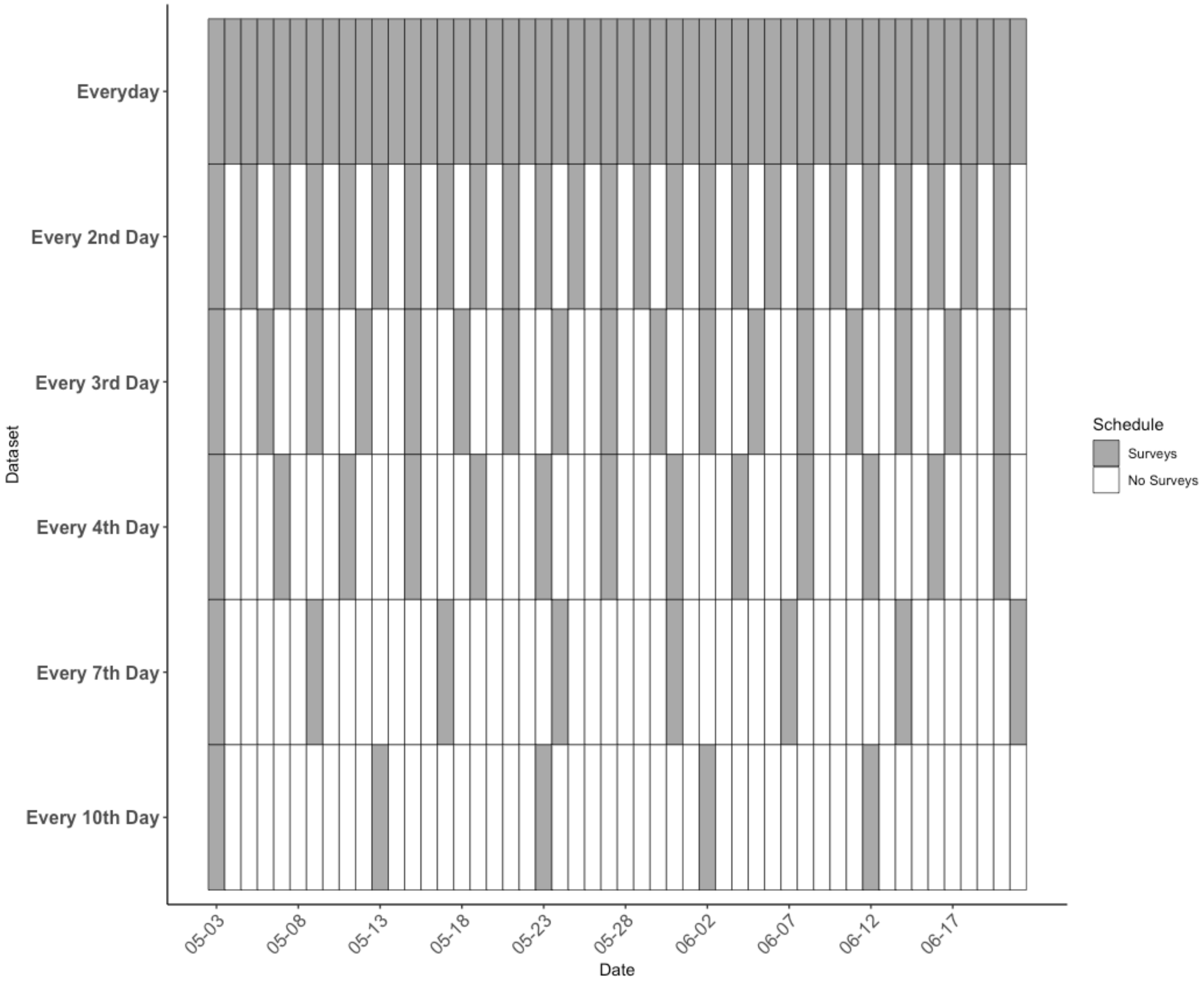
Everyday
Every 2nd Day
Every 3rd Day
Every 4th Day
Every 7th Day
Every 10th Day
Dataset
05-03
05-08
05-13
05-18
05-23
05-28
06-02
06-07
06-12
06-17
Date
Schedule
Surveys
No Surveys

Figure 2.2: The baseline dataset survey frequency with 50 surveys occurring every consecutive day from 03 May – 21 June 2024 (top row) in southeastern Georgia and the post hoc subsampled datasets created from it. Subsampling was done 5 times equally across all monitoring points to simulate various reduced sampling frequencies in 2-, 3-, 4-, 7-, and 10-day intervals starting on 03 May. All datasets had the same within day recording schedules (Figure 1.4) and were processed with BirdNET. The everyday dataset consisted of 50 surveys– producing 2,010 hours of audio (~1,215 GB). The every 2nd day dataset consisted of 25 surveys– producing 1,005 hours of audio (~608 GB). The every 3rd day consisted of 17 surveys– 683 hours of audio (~413 GB). The every 4th day dataset consisted of 13 surveys– producing 522 hours of audio (~316 GB). The every 7th day dataset consisted of 8 surveys – producing 322 hours of audio (~194 GB). The every 10th day consisted of 5 surveys– producing 201 hours of audio (~122 GB).

Dataset	**Treatment**	$\widehat{N}$	$\widehat{N}$ **SE**	$\widehat{P}$	$\widehat{P}$ **SE**
Everyday	Young Savanna	8.20	1.49	0.99	1.00E-04
	Timber	5.16	1.02		
	Mine	3.95	0.88		
	Mature Savanna	1.38	0.50		
Every 2nd Day	Young Savanna	6.35	1.44	0.99	1.60E-03
	Timber	3.94	0.95		
	Mine	2.86	0.79		
	Mature Savanna	1.06	0.43		
Every 3rd Day	Young Savanna	5.40	1.41	0.99	3.20E-03
	Timber	2.90	0.80		
	Mine	2.67	0.82		
	Mature Savanna	0.85	0.38		
Every 4th Day	Young Savanna	6.45	1.79	0.98	9.10E-03
	Timber	3.25	0.92		
	Mine	2.33	0.77		
	Mature Savanna	0.79	0.37		
Every 7th Day	Young Savanna	4.65	1.52	0.97	1.18E-02
	Timber	2.53	0.84		
	Mine	2.33	0.90		
	Mature Savanna	1.19	0.56		
Every 10th Day	Young Savanna	5.92	2.56	0.88	2.62E-02
	Timber	1.5041	0.67		
	Mine	0.96	0.52		
	Mature Savanna	0.69	0.41		

Table 2.3: Ordered predicted relative abundance ($\widehat{N}$) estimates from Royle-Nichols (RN) models for Blue Grosbeak across site treatments (young savanna, timber, mine, mature savanna), and their standard errors ($\widehat{N}$ SE), mean cumulative detection probability ($\widehat{P}$) across all monitoring points and their standard errors ($\widehat{P}$ SE). Estimates are reported for each dataset that represents reduced sampling frequencies from the baseline dataset (everyday) fitted with the same top RN model (see table 2.2). All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

Dataset	**Treatment**	$\hat{N}$	$\hat{N}$ **SE**	$\hat{P}$	$\hat{P}$ **SE**
Everyday	Mature Savanna	7.21	1.90	0.99	5.00E-03
	Young Savanna	2.84	0.68		
	Timber	1.75	0.53		
	Mine	1.68	0.49		
Every 2nd Day	Mature Savanna	4.39	1.56	0.96	1.47E-02
	Young Savanna	1.84	0.55		
	Timber	1.48	0.50		
	Mine	0.94	0.36		
Every 3rd Day	Mature Savanna	6.02	2.02	0.91	0.03
	Young Savanna	1.92	0.60		
	Timber	1.19	0.46		
	Mine	0.87	0.35		
Every 4th Day	Mature Savanna	4.43	1.88	0.92	0.03
	Young Savanna	1.18	0.44		
	Timber	0.97	0.43		
	Mine	0.95	0.41		
Every 7th Day	Mature Savanna	2.57	1.38	0.81	0.04
	Young Savanna	0.78	0.36		
	Timber	0.55	0.31		
	Mine	0.36	0.23		
Every 10th Day	Mature Savanna	2.11	1.35	0.72	0.04
	Young Savanna	0.71	0.37		
	Timber	0.57	0.36		
	Mine	0.50	0.34		

Table 2.4: Ordered predicted relative abundance ($\hat{N}$) estimates from Royle-Nichols (RN) models for Bachman's Sparrow across site treatments (mature savanna, young savanna, timber, mine), and their standard errors ($\hat{N}$ SE), mean cumulative detection probability ($\hat{P}$) across all monitoring points and their standard errors ($\hat{P}$ SE). Estimates are reported for each dataset that represents reduced sampling frequencies from the baseline dataset (everyday) fitted with the same top RN model (see table 2.2). All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

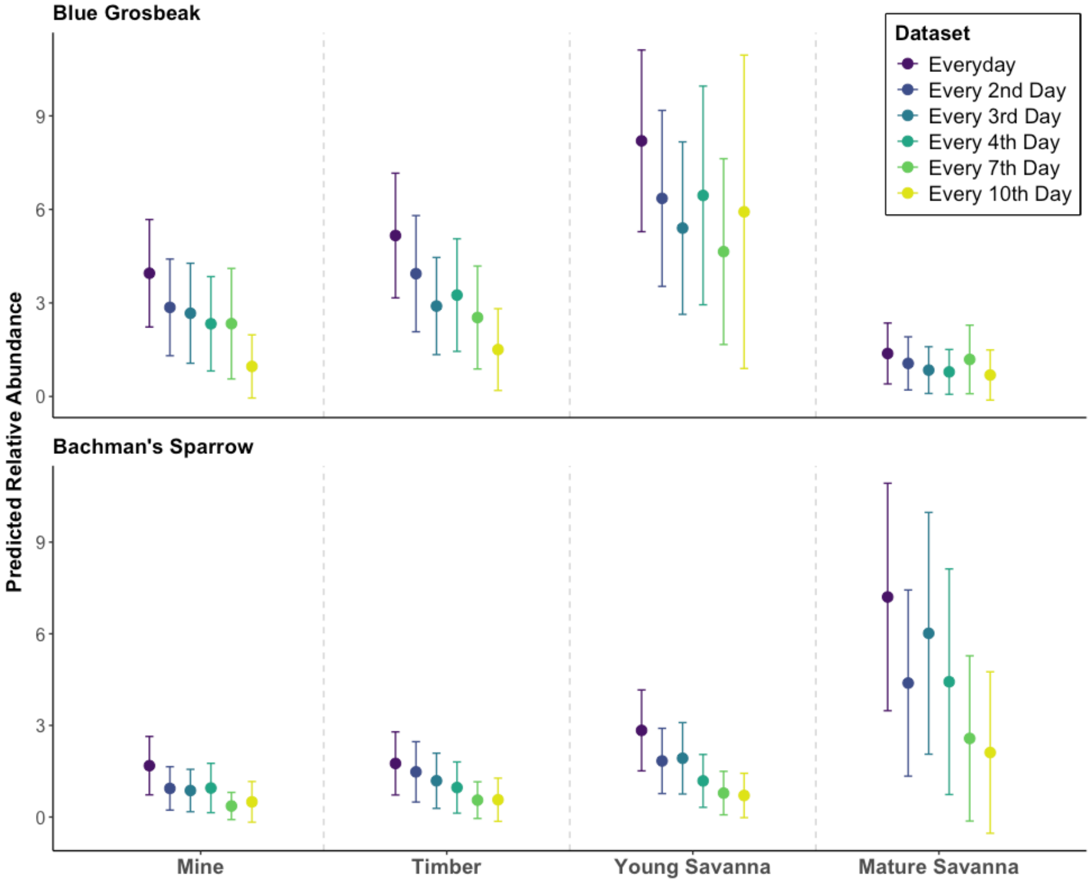

Figure 2.3: Predicted relative abundance estimates from Royle-Nichols (RN) models for Blue Grosbeak and Bachman's Sparrow from the baseline (everyday) dataset and 5 different subsampled datasets representing reduced sampling frequencies (see figure 2.2). Points present the per-monitoring point estimate of relative abundance for each species and site treatment type, along with whiskers representing the 95% confidence interval around each estimate. All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

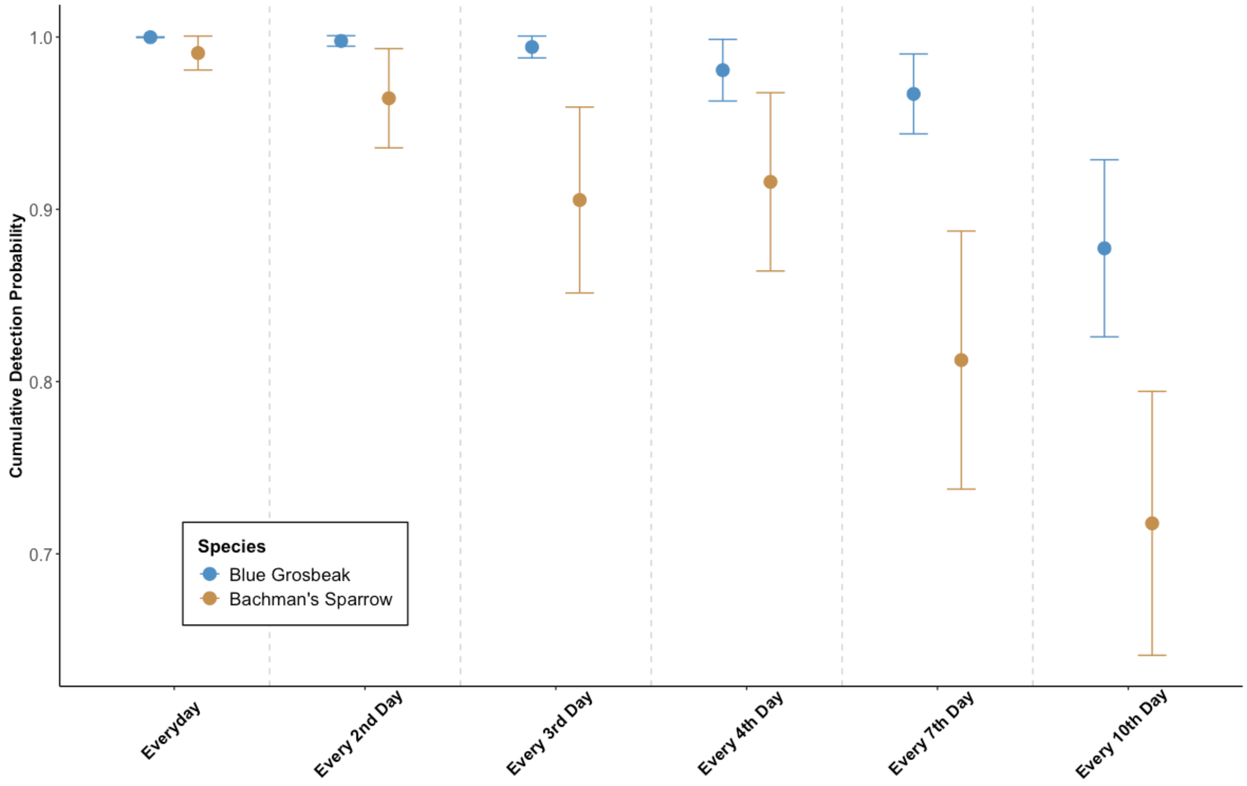

Figure 2.4: Mean cumulative detection probability estimates from Royle-Nichols (RN) models for Blue Grosbeak and Bachman's Sparrow across baseline (everyday) and subsampled datasets representing reduced daily survey frequencies (see figure 2.2). Points present the mean cumulative detection probability for a species and whiskers represent the 95% confidence interval surrounding the estimate. Mean cumulative detection probability estimates were calculated by averaging monitoring point-level estimates of cumulative detection probability across all monitoring points for each dataset. All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

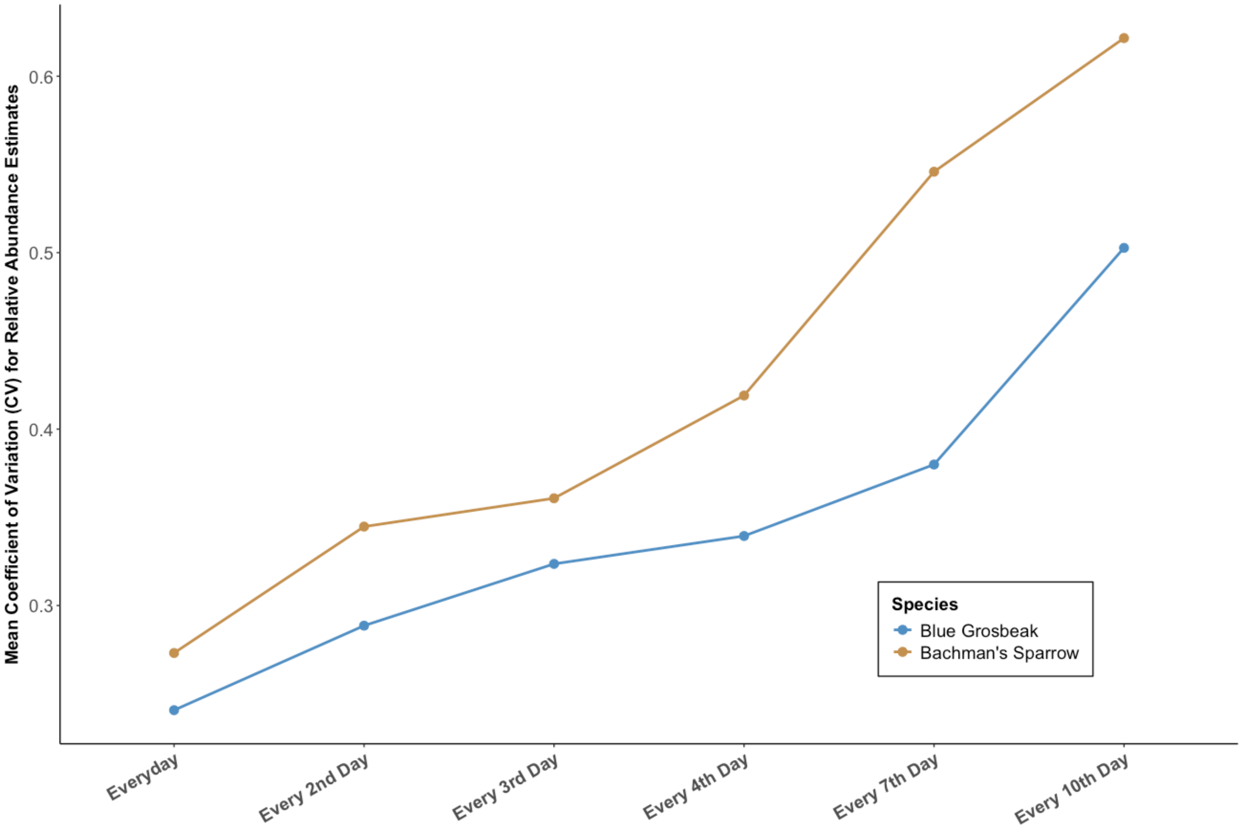

Figure 2.5 The mean coefficient of variation (CV) for relative abundance estimates, calculated from Royle-Nichols (RN) models, was used as a standardized measure of precision across baseline (everyday) and subsampled datasets representing reduced survey frequencies (see Figure 2.2) for both Blue Grosbeak and Bachman’s Sparrow. The treatment-level CVs for each site treatment were determined first. This was done by dividing the SE over the predicted relative abundance estimate for that site treatment. Finally, treatment-level CVs across all site treatments were averaged within each dataset to produce the mean CV for relative abundance estimates across datasets. All RN models were fitted with data collected from May–June 2024 in southeastern Georgia.

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