

ABSTRACT

ROSE, ELI T. Using Remotely Sensed Indices of Fire Severity and Vegetation Structure to Identify Patterns of Avian Occurrence Following Changes in Fire Management Policy within Great Smoky Mountains National Park. (Under the direction of Dr. Theodore R. Simons).

Fire management policy has the potential to benefit breeding bird species associated with both early succession and fire adapted plant communities. Many of these species are thought to be declining in the southern Appalachian region. Fire management policies within Great Smoky Mountains National Park changed in 1996, allowing managers to incorporate both prescribed and wild fires to achieve habitat management objectives. Over the past 20 years, an increasing amount of fire on the landscape has changed the biological communities within the Park's fire adapted pine-oak forests. I use a combination of field-derived and remotely sensed indices of both fire severity and vegetation structure to quantify changes in patterns of bird occurrence following fire within these habitats.

LandsatTM derived Difference Normalized Burn Ratios provide an index of fire severity by quantifying changes in photosynthetic biomass from before to after a fire. National Park personnel currently use these indices to identify changes in vegetation within the Park. In collaboration with NPS personnel, I developed a rapid assessment tool to evaluate fire severity and contrast this field-based index with Difference Normalized Burn Ratio (DNBR) indices to identify potential strengths and weaknesses of using DNBR to measure fire effects. I developed species occurrence models using Difference Normalized Burn Ratios summarized at four different spatial scales to explore the possibility that species respond to

fire at different spatial scales. Agreement between field derived and Difference Normalized Burn Ratio fire severity indices was lower within the xeric pine-oak forests of the Park than has been shown in other studies. The level of agreement was a function of both the vegetation type and the threshold values used to define fire severity classes. Fire severity influenced patterns of species occurrence all six of the species considered, and my results suggest that different species respond to variation in fire severity at different spatial scales.

One way that variation in fire severity can influence patterns of species occurrence is by altering the structural characteristics of the vegetation. In recent years Light Density and Ranging (LIDAR) has been used to provide an index of the vertical distribution of vegetation present on the landscape. In 2011, the National Park Service acquired discrete return, leaf-off LIDAR products for the Tennessee side of the Park. I compared field-derived estimates of canopy cover for three strata (shrub, midstory, and overstory) with LIDAR derived indices to explore the utility of incorporating leaf-off LIDAR data in models of bird species occurrence. My results suggest that discrete-return LIDAR products acquired during leaf-off conditions can be used to identify broad scale patterns of breeding bird occurrence, especially for species showing strong associations with the upper canopy of coniferous forests.

I modeled occurrence on burned and unburned sites for twenty four bird species to quantify changes associated with the prevalence of fire on the landscape. Overall, thirteen species occurred more frequently on burned sites and two species occurred more frequently on unburned sites. Within burned sites, I developed additional models to identify how patterns of occurrence change with different combinations of fire severity and time since burn.

Sampling points were distributed across a range of fire severities (low to high) and time since burn intervals (two months to twenty eight years). The relative importance of fire severity and time since burn varied with bird species, but both predictors were included in top models for all twenty four species considered. These results provide useful insights for land managers seeking to understand the implications of recent changes in fire management policy in Great Smoky Mountains National Park.

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Using Remotely Sensed Indices of Fire Severity and Vegetation Structure to Identify Patterns
of Avian Occurrence Following Changes in Fire Management Policy within Great Smoky
Mountains National Park

by
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DEDICATION

I dedicate this effort to my parents who have long acknowledged the importance of finding one's own path. Their unwavering support and zest for life has inspired me to dig into life at my own pace and in my own direction, without being too caught up in the expectations and stereotypes that narrow the scope of human experience.

BIOGRAPHY

I am a reluctant wanderer. I spent the first twenty-one years of my life exploring the natural history and geography of San Luis Obispo County, California, where I was born and raised. Two courses at Cuesta Community College set me on my current career trajectory, Environmental Science taught by Nancy Mann, and Principles of Natural History taught by Ron Rupert. These two courses crystalized my desire to better understand the links between everyday human activities and their implications for plant and animal communities. I had always spent most of my free time out-of-doors, exploring the natural history of the Central Coast, but these classes made me want to be a part of the conversation that will ultimately dictate which species thrive and which struggle on a landscape dominated by humans. After earning an Associates of Science from Cuesta, the reluctant wandering began.

From 1996 to 2000, I attended Humboldt State University and earned a Bachelor's degree in Wildlife Biology. The Coast Redwoods offered me entirely new flora and fauna with which to explore and fall in love. I swore I would never leave. Opportunity however, had other plans for me. After taking an opportunity to monitor the success of a program reintroducing the Endangered Puaiohi on Hawaii, I began a love affair with seasonal field work that lasted for more than ten years. This love affair took me from the Pacific Northwest to the Hawaiian Islands, the desert southwest, the intermountain west, and with a little prodding from my now wife, the shores of the Atlantic and the southern Appalachian Mountains. All the while, I struggled between a desire to broaden my horizons by travelling to new places and a desire to dig deeper into ecological questions where I was at the time.

After leading field-crews in the Desert Southwest for more than five years, and wanting to be more effective with my time, I decided I should return to school to further my education.

Ultimately, I ended up here at NCSU, a fortuitous match. Even as I write, the familiar struggle between a desire to broaden my horizons by travelling to new places and a desire to dig deeper into ecological questions in the landscape that I currently call home is rearing its head.

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My graduate experience has been very rewarding, broadening, and filled with many friends, colleagues, and mentors from whom I have learned much. First and foremost, I want to thank my wife, Tracy Borneman, for leading me through this graduate experience both literally and figuratively. Following her to North Carolina is on the top of my list of life's best decisions. Her "Borganizational" skills, keen attention to detail, and voracious appetite for the written language have offered me countless insights when I most needed them. In her I have found an exceptional colleague, a best friend, and an inspiring life partner.

I can't express enough thanks to my advisor and committee. I am grateful to Dr. Ted Simons for giving me this opportunity and providing sound guidance throughout. I have tried to mimic his writing style, diplomacy, and approach to professional discourse as best I could, for these are some of his great strengths. Dr. Jaime Collazo has generously supported me throughout this project, and both he and Dr. Simons have provided the resources for exceptional educational opportunities with some of the top contributors to modern ecological statistics. Among those contributors is Dr. Kenneth Pollock, who has been both patient and persistent in opening my eyes to the complexities of ecological inference. I also want to thank Dr. Alexa McKerrow for her guidance with GIS and remote sensing. After meetings with Alexa I often felt inspired by, and grateful for both her interests and insights.

With most field projects, the physical work is done primarily by undercompensated technicians. I had the good fortune of having some of the best crews that I have yet had the privilege of working with. I can't thank the following people enough for their time, energy,

and contributions: Cynthia Worthington, Laura Childers, Tracy Borneman, April Bartelt, and Daniel Geleynse.

Unsurprisingly, some of the most poignant insights came from the National Park Service personnel that have dedicated their careers to Great Smoky Mountains National Park.

Kristine Johnson and Rob Klein generously donated their time and staff toward this project on many occasions. Bob Dellinger (NPS Fire Effects) assisted with the project full time for nearly a month! His knowledge of the natural history and effects of fire within the Park were indispensable.

I also benefitted greatly from collaborators with the USGS Core Science Analytics Synthesis and Libraries (CSAS&L) program. John Kosovich was instrumental in LIDAR processing and generating products for inclusion in species occurrence models.

The backbone of any project is the administrative support that enables things to move forward. I want to thank Wendy Moore, Susan Marschalk, Meredith Henry, Ruby Valetton, and Martha Reiskind for their attention to detail and knowledge of how things are done in a professional world and here at NCSU.

The financial support for this project came through a collaborative effort between the National Park Service, the USGS National Gap Analysis Program, North Carolina State University, North Carolina Cooperative Fish and Wildlife Research Unit and the Great Smoky Mountains Conservation Association. As with all collaborative efforts the list of people who contributed is not limited to those that are mentioned formally. A big thanks to all involved.

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INTRODUCTION

As land development continues to reduce wildlife habitat (Brown et al. 2010), public land management plays an increasingly important role in conserving wildlife diversity. Great Smoky Mountains National Park (the Park) is one of the largest protected areas in the eastern United States, encompassing more than 211,415 hectares. Recent changes in fire management policy within the Park provide resource managers greater flexibility to use both prescribed burns and controlled wildfires to meet habitat management objectives (NPS fire management plan 1996). This policy shift is, in part, intended to provide resource managers with tools needed to restore fire-adapted xeric pine-oak habitats and their associated fauna. Following the implementation of this policy in 1996, the Park has seen a dramatic increase in the amount of land area subject to both lightning-caused wildfires (Cohen et al. 2007), and prescribed burns (NPS Fire Effects Data 1920-2010). The ecological implications of this change in fire management are not fully understood. Although the National Park Service fire-monitoring program collects long-term information about changes in vegetation composition and structure within the Park, prior to this study, the Park had little information about the effects of fire management actions on bird communities.

From 1996 to 1999 an unprecedented effort to catalogue bird distributions within the Park resulted in more than 74,797 detections of 115 species of birds (Simons and Shriner 2000). In addition to documenting species distributions, these surveys inspired significant contributions toward improving our understanding of the implications of imperfect detection (Alldredge et al. 2007b, Simons et al. 2007), as well as steps toward resolving problems with associated biases (Alldredge et al. 2006, Alldredge et al. 2007a). While this effort provided

highly detailed predictive maps of species distributions within the Park, these maps do not account for ongoing processes of disturbance such as fire.

Breeding birds respond to fire in different ways; positively, negatively, or not at all. The mechanisms behind these responses can be related to foraging opportunities (Pierson et al. 2010), availability of nesting sites or materials (Artman et al. 2001), or predation (Johnson and Temple 1990, Fletcher et al. 2010). Unfortunately, documenting these processes on a landscape-scale is prohibitive. Because many birds have broad species-habitat relationships, measures of land-cover change can provide valuable information about changes in species occurrence over time. Recent research suggests that species occurrence models based on land-cover change can be improved by incorporating information on the processes driving the change (Vallecillo et al. 2009), incorporating information about the spatial scale of the changes (Saab 1999), or by including detailed information about vegetation structure (Gottschalk et al. 2005, Ficetola et al. 2013).

Recent advances in remote-sensing technology are providing unprecedented capacity for identifying patterns of fire severity using Difference Normalized Burn Ratios (DNBR) and vegetation structure using Light Density and Ranging (LIDAR). Within the Park, fire effects personnel regularly use DNBR to produce maps of the extent and severity of fire following both prescribed burns and wildfires. These images help managers assess changes in plant composition following a fire. While DNBR provide coarse grained (30m x 30m) information about fire severity on a landscape (Key and Benson 1999), LIDAR can be used to quantify the vertical distribution of vegetation at a range of spatial scales. The Park acquired LIDAR

in 2011 for terrain mapping, although the information is also useful for measuring changes in vegetation structure.

The objectives of my study were to assess the utility of using both DNBR fire severity and LIDAR vegetation structure indices to identify changes in patterns of bird species occurrence following fire within Great Smoky Mountains National Park. In Chapter 1, I contrast field-derived and remotely sensed estimates of fire severity, and use DNBR to identify patterns of species occurrence at different spatial scales. In Chapter 2, I explore the implications of using LIDAR acquired during leaf-off conditions to make inference about patterns of species occurrence resulting from changes in vegetation structure following fire, and in Chapter 3, I contrast species occurrence between burned and unburned areas and identify patterns of species occurrence associated with variations in fire severity and the time since fire.

STUDY AREA

The study area (Figure 1) consists of low elevation (304-915 meters) pine and oak forests in the western portion of Great Smoky Mountains National Park. The lower elevations of the Park represent a transition zone between northern hardwood and southern pine forests. Prior to fire suppression policies, initiated in the early 1900's, these forests were subject to frequent fire, with return interval estimates ranging from every 2-3 years in Table Mountain Pine dominated stands (DeWeese et al. 2007) to 12.7 years in the xeric pine-oak forests of the western portion of the Park (Harmon 1982). Because the Park has extensive fire history records dating back to before it was chartered by Congress in 1934, the location and timing of most fires occurring in the Park over the last 80 years are known. Following a period of

fire suppression (1940-1996), recent changes in management have led to an increase in both the number and size of fires within the Park (NPS Fire Effects Data 1920-2010, Cohen et al. 2007). Unique variations in fire severity and overlap with previous fires, have created a complex mosaic of fire influenced habitats throughout the park.

I used the Parks detailed fire history, Landsat derived fire severity indices, and LIDAR indices of vegetation structure, to understand changes in patterns of bird species occurrence associated with spatial and temporal patterns of fires in the Park.

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TABLES AND FIGURES

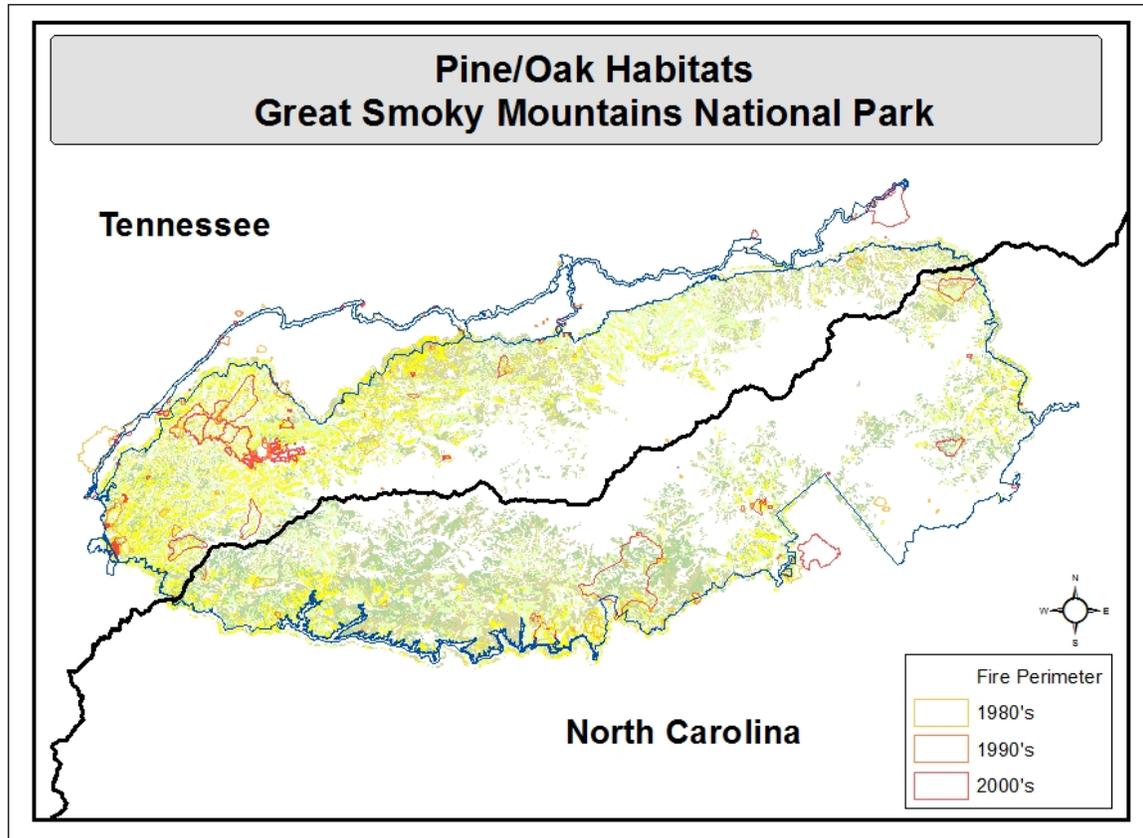


Figure 1.0. Recent changes in fire management policy within Great Smoky Mountains National Park have resulted in an increase in the amount of land area influenced by fire. Historically, frequent fires within the pine and oak habitats of the lower elevations of the Park influenced both the vegetation and bird species assemblages.

CHAPTER 1

Normalized Burn Ratio fire-severity indices link ecosystem process with patterns of avian occurrence

ABSTRACT

Remotely-sensed Difference Normalized Burn Ratios (DNBR) provide resource managers with a detailed index of fire severity for the entire footprint of a fire. The ability to link fire severity to species occurrence at a landscape scale can improve our understanding of the effects of fire on vertebrate communities and provide an invaluable management tool. Using fire history information for 28 fires within Great Smoky Mountains National Park, avian point counts, and a combination of both DNBR and field-derived estimates of fire severity, I evaluate the effectiveness of using DNBR to link ecosystem process with patterns of bird occurrence. I found that agreement between field-derived and remotely sensed measures of fire severity (59%) was influenced by vegetation type, being 16-17% stronger at sampling points dominated by deciduous trees than those dominated by conifers. Although field-derived indices of fire severity predicted patterns of species occurrence better than DNBR, for all six species considered, remotely sensed indices provided insights into species-habitat relationships that were not possible using the field-derived fire severity index. Species occurrence patterns for two species associated with early successional habitats were strongest when DNBR values were summarized at large spatial scales, suggesting that these species benefit from larger patches of high severity fire. Two species associated with forest edges and two species associated with contiguous forests showed stronger patterns of species

occurrence at smaller spatial scales. Edge species occurred more frequently with increasing fire severity, suggesting that small forest openings can provide habitat for these species. Species associated with contiguous forests occurred less frequently with increasing fire severity, suggesting that even small patches of high severity fire reduce the frequency of occurrence for these species.

Keywords: difference normalized burn ratio, species occurrence, remote sensing, fire severity, habitat use, birds, spatial scale

INTRODUCTION

Quantifying temporal changes in species occurrence provides important insights into how environmental perturbations affect biodiversity. Whether the goal is documenting distributional shifts associated with global warming, or identifying the effects of local habitat conversion, reliable tools that enable resource managers to quantify changes in species occurrence are needed to make informed management and policy decisions. Since 1972, LandsatTM imagery has been used extensively to capture both spatial and temporal patterns in the spectral characteristics of landscapes across the globe (Pettorelli et al. 2014). Although LandsatTM imagery is applied in a wide variety of conservation and management applications, its ability to capture patterns of avian species occurrence is often limited by a lack of information about the specific processes behind species distribution dynamics (Vallecillo et al. 2009). I explore recent advances in the use of LandsatTM imagery for linking patterns of fire severity to changes in bird occurrence.

In recent years, there has been an increase in both the number of fires and the amount of land area affected by fire within North America (Aldrich et al. 2010, Calkin et al. 2005). The increased prevalence of fire is frequently attributed to a combination of past fire management practices (Romme and Despain 1989), and changing climates (Liu et al. 2013, Pechony and Shindell 2010). The amount of fire on the landscape has broad ecological implications, ranging from changes in vegetation structure to changes in both plant and animal species composition. Moreover, variation in fire severity is often cited as an important determinant of which species persist after a fire (Fontaine et al. 2009, Klaus et al. 2010, Greenburg et al. 2013).

Fire severity is defined as the “degree to which a site has been altered or disrupted by fire” (National Wildfire Coordinating Group 2014) or “the degree of environmental change caused by a fire” (Key and Benson 2006). Although these definitions are broad, efforts to quantify fire severity generally include measurements of the effects of fire on the soil substrate, herbaceous layer, shrub layer, and small and large trees. Quantifying the effects of fire across broad spatial scales is a complex task, and tools for doing so are continually improving.

Recent advances include the use of LandsatTM imagery to assess fire severity in temperate regions of North America (Miller and Thode 2007). One promising tool for assessing severity across the footprint of a fire, is the development of the Difference Normalized Burn Ratio (DNBR), which uses the spectral characteristics of vegetation and mineral soil to quantify changes in vegetation following fire (Key and Benson 2006). This proxy for fire severity can identify patterns of ecological change across large spatial scales. Although agreement between DNBR and ground-based fire severity indices is subject to substantial variation, one recent study showed that agreement between DNBR and ground-based Composite Burned Index fire severity values can be as high as 92% in some forest types (Picotte and Robertson 2011).

The ecological effects of fire are thought to depend largely on interactions among fire severity (Key and Benson 2006, Elliot et al. 2009), fire size (Baker 1993, Key and Benson 2006), the amount of time since burn (Harrod et al. 2000, Elliot et al. 2009, Hurteau et al. 2007), and the taxa of interest (Baker 1993, Elliot et al. 2009). Although most recent studies describe these relationships for plant communities, there is a growing body of literature

linking these patterns to other taxa, including birds (Acquilani et al. 2000, Artman et al. 2005, Fontaine et al. 2009, Greenburg et al. 2007, Haney et al. 2008, Klause et al. 2010, Saab et al. 2005).

In this analysis, I explore the utility of DNBR fire severity indices for linking the effects of fire with patterns of avian species occurrence. I use both field-derived and remotely sensed fire severity indices and avian point counts to: 1) Explore relationships between field-based and remotely sensed DNBR fire severity indices, and to 2) identify the most relevant spatial scale for summarizing DNBR fire severity indices for target species. I develop occupancy models for six bird species; two associated with early succession habitats [Prairie Warbler (*Setophaga discolor*), Yellow-breasted Chat (*Icteria virens*)], two associated with forest edges [Eastern Wood-pewee (*Contopus virens*), Indigo Bunting (*Passerina cyanea*)], and two species known to be sensitive to forest fragmentation [Ovenbird (*Seiurus aurocapilla*), Worm-eating Warbler (*Helmitheros vermivorus*)].

METHODS

Sampling Design

During the 2012, 2013 and 2014 breeding seasons, I identified and surveyed 228 points within recently burned pine and oak habitats in the western portion of the Park. Sampling points were stratified by both fire severity and time since burn (Table 1.1). I used LandsatTM derived Difference Normalized Burn Ratios to quantify fire severity, and grouped time since burn into three categories: 0-5 years, 6-10 years, and 11-28 years. Points were located at least 100m from the fire perimeter within the footprints of 28 recent fires. Each fire

contained between one (Shop Creek 2009) and 30 (Arbutus-Stony 2007) sampling points (Appendix A). All points were placed on upper slopes and ridges to target xeric pine and oak forests of the region, and kept a minimum of 250 meters apart to reduce the influence of spatial autocorrelation.

Fire Severity Indices

Fire terminology corresponds with the National Wildfire Coordinating Group's Glossary of Wildland Fire Terminology (2012). I used Landsat-derived Difference Normalized Burn Ratios as well as field-derived estimates of fire severity to compare field-assessed and remotely sensed estimates of fire severity.

Difference Normalized Burn Ratios

Landsat-based Difference Normalized Burn Ratios (DNBR) provide resource managers with a remotely sensed measure of the change in vegetation resulting from fire (Key and Benson 1999, Epting et al. 2005). This fire severity index is available for most fires that have occurred within the Park since Landsat products became available in 1972. Difference Normalized Burn Ratios are calculated as the difference between the Normalized Burn Ratio (NBR) before and after a fire.

I acquired LandsatTM images from National Park Service personnel and from the USGS Earth Resources Observation and Science Center. I worked with NPS personnel familiar with the fire history of the Park to select and process all LandsatTM scenes. We chose only images without clouds or other atmospheric anomalies overlapping the area of interest. Once representative scenes were chosen, I calculated DNBR fire severity values for all 30m x 30m

grid cells within the scene using ArcMap 10.1. The resulting Difference Normalized Burn Ratios provide a continuous index of the change in vegetation following fire ranging from -2000 to 2000. Summary information for each scene used to calculate DNBR is provided in Appendix A.

Difference Normalized Burn Ratios provide an index of fire severity across the landscape for a continuous 30m x 30m grid, however, species may respond to the effects of fire at different spatial scales. I used the continuous coverage of DNBR indices and the focal mean tool in ArcMap 10.1 to explore the relationship between fire severity and species occurrence at different spatial scales. I summarized DNBR values across four spatial scales; 0.09ha (30m x 30m), 0.81ha (90m x 90m), 2.25ha (150m x 150m), and 4.41ha (210m x 210m) to identify the scale of fire effects most relevant to an individual species.

I used DNBR thresholds developed by NPS fire ecologists within the Park (NPS Thresholds) to stratify sampling points across four discrete fire severity categories. I also used Monitoring Trends in Burn Severity (MTBS) fire severity thresholds to categorize the same sampling points for comparison with both NPS and field-derived indices of fire severity. MTBS thresholds were developed to provide a national standard for summarizing the location, extent, and magnitude of burn severity for all fires occurring within the United States since 1984 (Wildland Fire Leadership Council). Threshold values for both NPS and MTBS are presented in Table 1.2 along with their relationship to field-derived estimates of fire severity.

Field-derived Fire Severity

In addition to remotely sensed threshold indices, I used a field-derived fire severity index for validation and comparison. With the help of National Park Service fire effects personnel, I developed a rapid assessment tool for estimating fire severity during each visit to a sampling point (Appendix B). This index was used to generate a quick visual estimate of fire severity based on tree mortality, duff depth, and char height. The five fire severity categories mirror those derived using MTBS national thresholds for classifying DNBR's and include; Unburned (0), Low (1), Moderate-Low (2), Moderate-High (3), High (4). I recorded field estimates of fire severity during each visit to a sampling point, averaged the scores, and rounded to the nearest whole number to arrive at a final field-based fire severity estimate. Each sampling point was visited a minimum of three times.

Avian Surveys

I used variable circle plot point counts, modified from Reynolds et al. (1980) and Shriner (2001) to identify patterns of bird species occurrence. Each point was visited three times during May and June to estimate breeding bird occurrence and detection probabilities. All birds seen or heard during each ten-minute point count were identified to species and mapped on field data sheets (Appendix C). Prior to initiating a point count, observers recorded date, time, wind speed, temperature and percent cloud cover to account for their influence on detection. Each observer also recorded the habitat type (pine: >75% coniferous, pine-oak: 50% to 75% coniferous, oak-pine: 50% to 75% deciduous, oak: >75% deciduous) within 50 meters of the sampling point.

Data Analysis

Because variation in detection probability can be a source of substantial bias in both density and occupancy estimates (Kissling and Garton 2006, Mackenzie et al. 2006, Simons et al. 2007), I used package single season occupancy models (MacKenzie et al. 2002) to simultaneously estimate species specific detection probabilities and occupancy. These models are available in package “unmarked” (Fiske and Chandler 2011) in the statistical software R, version 15.1 (R Development Core Team 2012). This approach incorporates the probability that a species is present, available, and detected into the resulting species occurrence estimates, allowing us to account for variations in detection rates related to weather, time of day, time of season, or other unknown factors (MacKenzie et al. 2006).

Although variable radius point counts are often used to estimate abundance, I focused on species occurrence because I believe that the assumptions of occupancy sampling are more realistic than those for distance sampling in densely forested habitats. In deciduous forest bird communities, density estimates based on auditory detections can range widely; from 17% to 132% of the actual total (Simons et al. 2007). In part, this reflects how difficult it is to accurately estimate distance from auditory detections. Recent research shows that distance estimation errors increase dramatically beyond approximately 75 meters, depending on singing rate and observer skill (Alldredge et al. 2007). In light of these findings, and in an effort to minimize misidentification and measurement errors, individuals detected beyond 50 meters were not included in these analyses.

I developed occurrence models for each target species using DNBR values summarized at four different spatial scales. I evaluated a conditional model (null model with detection

covariates included) in addition to models including the effects of fire severity at each of the four different spatial scales using an Information Theoretic approach (Burnham et al. 2011). Because the time of day (minutes from sunrise), date, wind speed, cloud cover, and observer were all considered potential sources of detection bias, I included them as detection covariates in all models unless otherwise indicated.

I also explored overall agreement between field-derived and remotely sensed measures of fire severity using the non-parametric, Kendall's Tau-b to quantify agreement between field-derived severity classes and those resulting from both DNBR threshold types. DNBR values were calculated for all unburned points and included in these analyses.

RESULTS

Fire Severity Indices and Thresholds

Overall agreement between field-derived and remotely sensed measures of fire severity across all burned sampling points was 58% and 59% when fire severity was classified using either NPS thresholds (Tau=0.577, DF=227, Z=10.386) or MTBS thresholds (Tau=0.587, DF=227, Z=10.708). The amount of time between the burn and field sampling had little effect on agreement between field-derived and remotely sensed fire severity estimates (Table 1.3). Agreement between the two metrics however, was 17% (NPS) and 16% (MTBS) stronger for deciduous dominated stands (NPS: Tau=0.624, DF=129, Z=8.521. MTBS: Tau=0.632, DF=129, Z=8.708) than it was for pine dominated stands (NPS: Tau=0.447, DF=97, Z=5.104. MTBS: Tau=0.471, DF=97, Z=5.479). Fire severity classes defined by NPS thresholds showed strong agreement with those defined using MTBS thresholds

(Tau=0.945, DF=227, Z=17.140), but were 4% lower in coniferous stands (Tau=0.918, DF=97, Z=10.823) than deciduous (Tau=0.963, DF=130, Z=13.101).

Species Occurrence and Fire Severity Summarized at Different Spatial Scales

During the 2012, 2013, and 2014 breeding seasons, we detected Prairie Warblers, Yellow-breasted Chats, Eastern Wood-peewees, Indigo Buntings, Ovenbirds, and Worm-eating Warblers 19%, 17%, 26%, 76%, 44%, and 45% of the 336 points sampled respectively. Model predictions for overall occupancy state suggest that these estimates are biased low. Predictions for the above species that incorporated covariates on detection (conditional model) were 0.20 ± 0.02 , 0.18 ± 0.02 , 0.34 ± 0.04 , 0.80 ± 0.03 , 0.50 ± 0.03 , and 0.62 ± 0.05 respectively. These predictions emphasize the importance of accounting for the detection process. Occurrence predictions for all species were improved by incorporating measures of fire severity (Table 1.4).

Model results indicate that different species respond to the effects of fire at different spatial scales (Table 1.4 and Figure 1.1). Model predictions for the two species associated with early succession habitats were improved by summarizing fire severity at larger spatial scales (Prairie Warbler: focal mean 150m x 150m, and Yellow-breasted Chat: focal mean 210m x 210m), while predictions for the two species associated with forest edge habitats (Eastern Wood-peewee: focal mean 30m x 30m, and Indigo Bunting: focal mean 30m x 30m) and the two species associated with contiguous forest habitats (Ovenbird: focal mean 90m x 90m, Worm-eating Warbler: focal mean 30m x 30m) were improved by summarizing DNBR fire severity indices at smaller spatial scales.

DISCUSSION

Overall, I found 58% (NPS) and 59% (MTBS) agreement between field-derived and remotely sensed fire severity classes, which is lower than other studies in the Appalachian region. Picotte et al. (2011) found an average of 75% agreement between DNBR and ground-based Composite Burn Index (CBI) fire severity values across a range of southeastern vegetation types. A similar study in deciduous dominated habitats of the southern Appalachians (Wimberly and Reilly 2006) found 71% agreement between DNBR and ground-based CBI values. The higher agreement reported in these studies can be explained in part because both studies used the Composite Burn Index which provides a more rigorous assessment of fire severity. Because our primary focus was linking DNBR fire severity indices to bird occurrence, I chose a more flexible approach which allowed us to assess fire severity up to 28 years after the fire. Interestingly, even over this relatively long time interval agreement between field-derived and remotely sensed classifications varied by less than 5% (Table 1.3).

Agreement between field-derived and remotely sensed fire severity increased by 17% (NPS) and 16% (MTBS) at sampling points dominated by deciduous trees compared to those dominated by conifers. These findings corroborate other recent studies showing that DNBR indices vary with vegetation composition (Epting et al. 2005, Picotte and Robertson 2011).

Although DNBR values are influenced by the atmospheric conditions during image acquisition, vegetation type, and changes in vegetation resulting from ecological processes other than fire (Key and Benson 2006), they can be used to quantify fire severity at a variety

of spatial scales. The ability to assess changes in vegetation at multiple spatial scales can provide useful insights into how fire effects scale with patterns of species occurrence.

The fact that we see variation in patterns of species occurrence when DNBR is summarized at different spatial scales is not surprising. Ecologists have long acknowledged how the spatial scale of observation shapes our understanding of species-habitat relationships, but examples of using information from multiple spatial scales to this end are limited. In this study, I summarized DNBR at different spatial scales to explore these relationships in species with different habitat affinities. For example, the optimal scale for predicting the relationship between occurrence and fire severity in early successional species is related to the minimum patch size that the species can exploit. In Figure 1.3, I illustrate this relationship for two species, one that can exploit a small patch of high-severity fire, and one that requires a larger patch of high severity fire. Similarly, the scale that best describes patterns of occurrence for species associated with contiguous forests is indicative of how sensitive they are to forest fragmentation. These patterns have significant implications for using pixel based habitat indices to predict species occurrence or abundance across a landscape. While they suggest that using DNBR or other pixel based indices can result in biased predictions if patch-size is not considered, they also provide a framework for incorporating knowledge of habitat preferences with pixel based indices to explore species-area relationships.

The three species that responded to fire effects at the smallest spatial scale (30m x 30m) include the Eastern Wood-peewee, Indigo Bunting, and Worm-eating Warbler. All three are primarily forest dwelling species. Eastern Wood-peewee and Indigo Bunting are known to select forest edges and small clearings for breeding (Greenburg and Lanham 2000, McIntyre

1985) and neither are thought to be sensitive to forest fragmentation (Kendrick et al. 2013, Robbins et al. 1989). My results corroborate these findings. I found a positive relationship with increasing fire severity for both species, and this relationship was strongest for fire severity at the smallest spatial scale. A stronger relationship between fire severity and species occurrence at small spatial scales indicates that these species exploit small patches of high severity fire, suggesting that these species may be responding to the higher edge-to-area ratios of the smaller patches.

Both Prairie Warblers and Yellow-breasted Chats showed strong occurrence patterns at larger spatial scales. Although both species are often found in recently disturbed forest clearings in the region (Franzreb et al. 2011), prior research suggests that they are both associated with large patches of second growth and early succession habitat (Rodewald and Vitz 2005, McIntyre 1985). High DNBR values at larger scales result from larger patches of high severity fire. The Prairie Warbler showed the strongest relationship when fire severity was summarized at a scale of 150m x 150m suggesting that they are associated with intermediate sized forest clearings. The Yellow-breasted Chat showed the strongest relationship with fire at 210m x 210m suggesting that this species is associated with even larger patches of early successional forest than the Prairie Warbler.

In contrast, both the Worm-eating Warbler and the Ovenbird show a negative relationship with increasing fire severity. Prior research suggests that Worm-eating Warblers are sensitive to forest fragmentation. Robbins et al. (1989) found that occurrence was reduced by 50% when forest patches were smaller than 150 ha. The negative relationship between Worm-eating Warbler occurrence and fire severity at small spatial scales suggests that this

species is sensitive to small patches of high severity fire. While high DNBR values at larger scales indicate larger patches of high severity fire, even small areas exposed to high severity fire may negatively influence this species. Patterns of Ovenbird occurrence are similar to those of the Worm-eating Warbler. Ovenbirds are also found in large tracts of continuous forests (Robbins et al. 1989, Greenburg and Lanham 2000) and our results, as well as those of Klause et al. (2010), show a negative relationship between species occurrence and increasing fire severity. Improved predictions at a slightly larger scale for Ovenbirds (90m x 90m) than for Worm-eating Warblers (30m x 30m) suggests that they are less sensitive to small patches of high severity fire than Worm-eating Warblers.

Although both forest type and the threshold values influenced the agreement between field derived and remotely sensed indices, including information on DNBR fire severity improved model predictions for all six of the species I considered. This suggests that DNBR is a useful tool for identifying changes in species occurrence within the xeric pine-oak forests of Great Smoky Mountains National Park. The extent to which DNBR can be used to link ecological process with patterns of species occurrence on other landscapes or in other regions is unknown. I encourage other researchers to explore potential applications of these metrics to modeling species-habitat relationships for other species and landscapes.

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TABLES AND FIGURES

Table 1.1. Sampling points in burned areas (228) were stratified by fire severity (using DNBR and the NPS Thresholds) and time-since-burn, in xeric pine-oak forests of the western portion of the Park.

| | 0-5 years | 6-10 years | 11-30 years |
|--------------------------|------------------|-------------------|--------------------|
| Unburned – Low Severity | 5 | 22 | 25 |
| Low – Moderate Severity | 23 | 21 | 24 |
| Total Low | 28 | 43 | 49 |
| Moderate – High Severity | 24 | 22 | 27 |
| High Severity | 15 | 12 | 8 |
| Total High | 39 | 34 | 35 |

Table 1.2. Fire severity classes defined using both field-derived and remotely sensed indices. Severity classes were defined for remotely sensed DNBR fire severity indices using thresholds developed within Great Smoky Mountains National Park (NPS Thresholds) and those defined using Monitoring Trends in Burn Severity (MTBS) national standards.

| Severity Class | Field Class | NPS Thresholds* | MTBS Thresholds |
|--------------------------|--------------------|------------------------|------------------------|
| Unburned | 0 | NA | < 100 |
| Low Severity | 1 | < 79 | 100 to 269 |
| Low – Moderate Severity | 2 | 80 to 269 | 270 to 439 |
| Moderate – High Severity | 3 | 270 to 549 | 440 to 659 |
| High Severity | 4 | > 550 | > 660 |

*NPS thresholds include both Unburned and Low Severity in the same class

Table 1.3. Kendal’s Tau B results showing the agreement between field-derived and remotely sensed fire severity classes.

| Time Since Burn | NPS thresholds | MTBS thresholds |
|------------------------|---------------------------|---------------------------|
| Within five years | Tau=0.625, DF=67, Z=5.974 | Tau=0.588, DF=67, Z=5.785 |
| Six to ten years | Tau=0.579, DF=77, Z=6.016 | Tau=0.597, DF=77, Z=6.251 |
| More than ten years | Tau=0.592, DF=84, Z=6.425 | Tau=0.614, DF=84, Z=6.733 |

Table 1.4. Model selection results evaluating the relationship between fire severity and occurrence are presented for six species: two species that have been shown to be sensitive to forest fragmentation (Ovenbird, Worm-eating Warbler), two species that exploit forest openings (Eastern Wood-peewee, Indigo Bunting), and two species that are found in early succession habitats (Prairie Warbler, Yellow-breasted Chat). Models evaluated include Landsat-derived DNBR fire severity values summarized at four spatial scales (30m², 90m², 150m², and 210m²).

| Species | Model | nPars | AIC | AICwt | State Estimate ± SE |
|----------------------|---------------------------|-------|---------|-------|-----------------------------|
| Prairie Warbler | p(#), psi(dNBR_150mx150m) | 14 | 487.83 | 0.61 | intercept: -1.78 ± 0.19 |
| | p(#), psi(dNBR_90mx90m) | 14 | 489.13 | 0.32 | fire severity: 1.37 ± 0.19 |
| | p(#), psi(dNBR_210mx210m) | 14 | 492.23 | 0.07 | |
| | p(#), psi(dNBR_30mx30m) | 14 | 499.21 | 0.00 | |
| Yellow-breasted Chat | p(#), psi(dNBR_210mx210m) | 14 | 460.92 | 0.49 | intercept: -1.87 ± 0.20 |
| | p(#), psi(dNBR_150mx150m) | 14 | 461.04 | 0.46 | fire severity: 1.40 ± 0.23 |
| | p(#), psi(dNBR_90mx90m) | 14 | 465.49 | 0.05 | |
| | p(#), psi(dNBR_30mx30m) | 14 | 473.85 | 0.00 | |
| Eastern Wood-peewee | p(#), psi(dNBR_30mx30m) | 14 | 704.23 | 0.44 | intercept: -0.68 ± 0.20 |
| | p(#), psi(dNBR_90mx90m) | 14 | 704.59 | 0.37 | fire severity: 0.80 ± 0.21 |
| | p(#), psi(dNBR_150mx150m) | 14 | 706.59 | 0.14 | |
| | p(#), psi(dNBR_210mx210m) | 14 | 708.54 | 0.05 | |
| Indigo Bunting | p(#), psi(dNBR_30mx30m) | 14 | 1207.13 | 0.97 | intercept: 2.05 ± 0.37 |
| | p(#), psi(dNBR_90mx90m) | 14 | 1214.42 | 0.03 | fire severity: 1.69 ± 0.45 |
| | p(#), psi(dNBR_150mx150m) | 14 | 1219.11 | 0.00 | |
| | p(#), psi(dNBR_210mx210m) | 14 | 1223.73 | 0.00 | |
| Ovenbird | p(#), psi(dNBR_90mx90m) | 14 | 967.65 | 0.79 | intercept: -0.02 ± 0.15 |
| | p(#), psi(dNBR_150mx150m) | 14 | 971.42 | 0.12 | fire severity: -0.97 ± 0.17 |
| | p(#), psi(dNBR_30mx30m) | 14 | 972.16 | 0.08 | |
| | p(#), psi(dNBR_210mx210m) | 14 | 976.18 | 0.01 | |
| Worm-eating Warbler | p(#), psi(dNBR_30mx30m) | 14 | 1004.96 | 0.86 | intercept: 0.49 ± 0.22 |
| | p(#), psi(dNBR_90mx90m) | 14 | 1008.75 | 0.13 | fire severity: -0.92 ± 0.19 |
| | p(#), psi(dNBR_150mx150m) | 14 | 1013.91 | 0.01 | |
| | p(#), psi(dNBR_210mx210m) | 14 | 1017.36 | 0.00 | |

All models include observer, date, time since sunrise, wind speed, cloud cover, and temperature as covariates on detection.

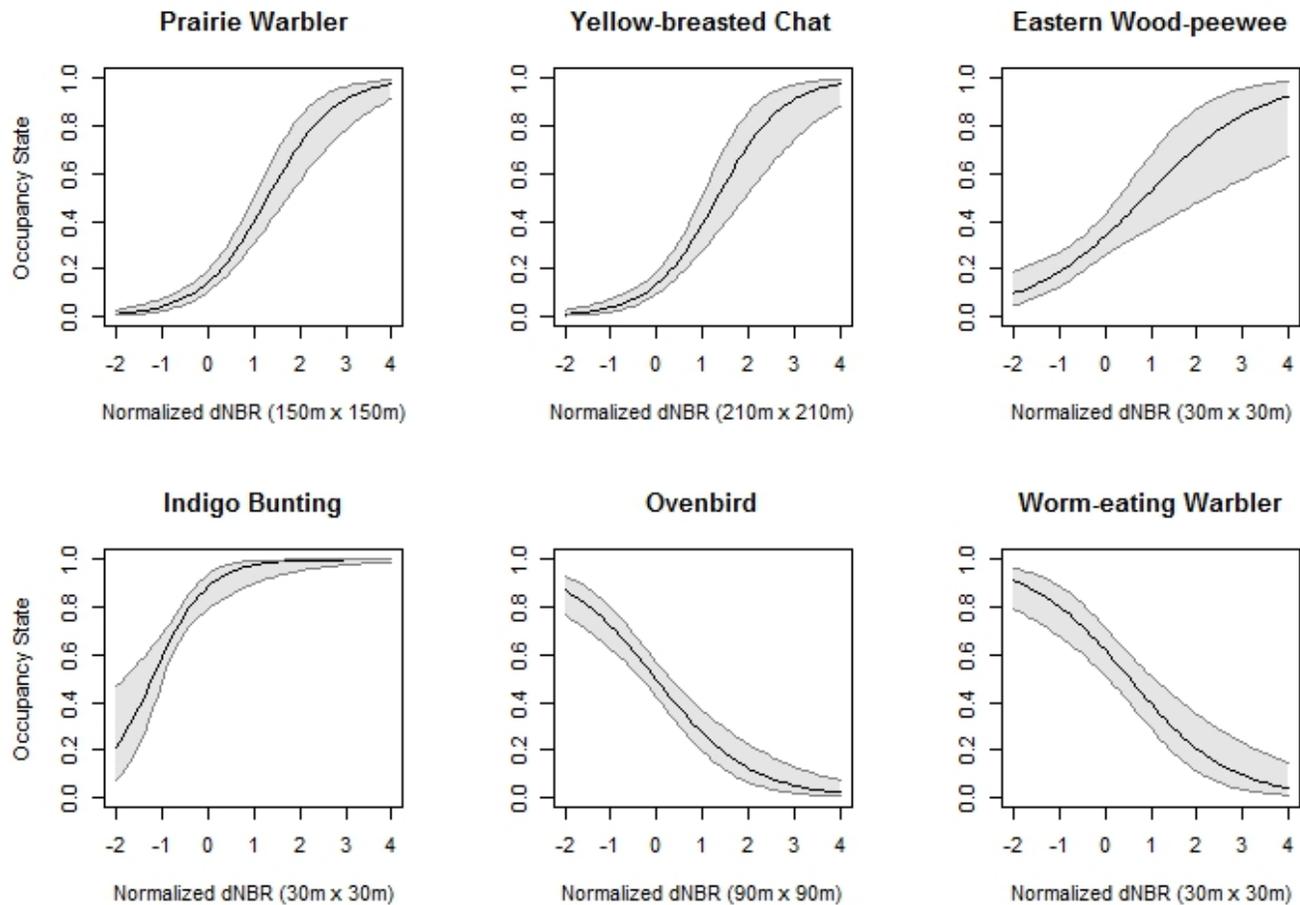
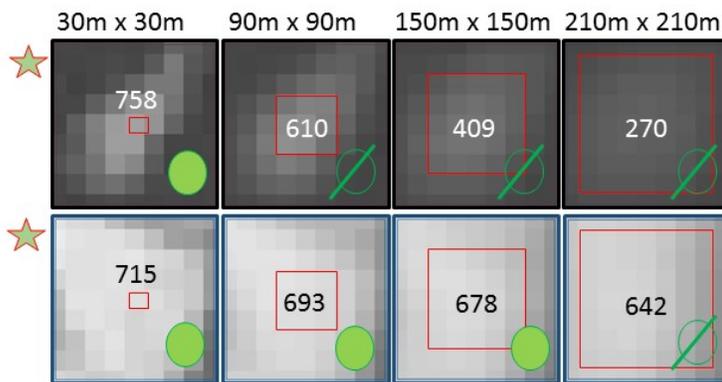
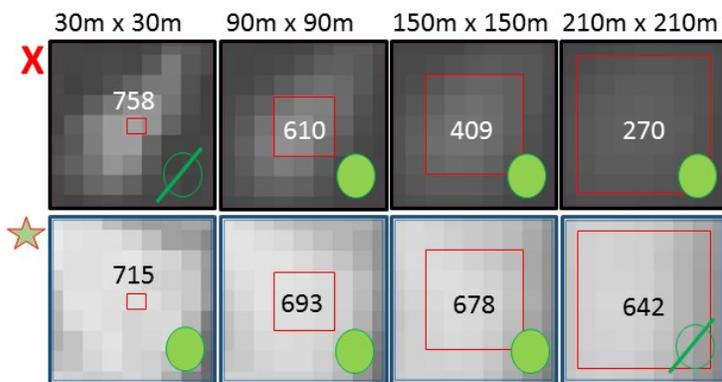


Figure 1.1. Changes in species occurrence with increasing fire severity, predictions from the top model. Predictions incorporate DNBR fire severity indices summarized at the spatial scale included in parentheses.

A) Can exploit small patch of high severity fire (>650 DNBR)



B) Requires a large patch of high severity fire (>650 DNBR)



- ★ Species is present ● Correctly informs model predictions
- ✗ Species is absent ●/ Misinforms model predictions

Figure 1.2. Summarizing DNBR fire severity indices at different spatial scales can inform species-habitat relationships. Above, I explore the relationship between patch size (small patch: boxes outlined in black, large patch: boxes outlined in blue), fire severity (lighter pixels represent higher severity fire), the scale at which DNBR indices are summarized (30, 90, 150 and 210 meters) and species occurrence, using two theoretical species (A&B). The numbers (focal mean value) indicate the DNBR value of the central pixel when summarized across all pixels within the red box. The DNBR value in small patches will be substantially lower when summarized at larger spatial scales. If a range of patch sizes are considered, DNBR summarized at the smallest spatial scale will correctly inform model predictions most frequently for species that can exploit small patches of high-severity fire (A). Summarizing DNBR at small spatial scales can misinform the model for small patches with high-severity fire when modeling a species that requires larger patches of high-severity fire to successfully colonize a recently burned area (B, upper left box). With replicates representing a range of patch sizes, a single scale will best inform the model (in this example both 90m and 150m share the same support).

CHAPTER 2

Using discrete-return leaf-off LIDAR to identify patterns of breeding bird occurrence

ABSTRACT

Discrete-return leaf-off LIDAR data provide detailed information about the vertical structure of vegetation across a landscape. These products are widely available, and can be used to model patterns of bird occurrence at large spatial scales. I contrasted both field and LIDAR derived indices of vegetation cover for three strata in southern Appalachian xeric pine-oak forests. Agreement between indices was stronger in the upper canopy ($R^2=0.57$) than in midstory ($R^2=0.32$) or shrub layers ($R^2=0.04$). In addition, agreement was stronger at sites dominated by coniferous trees ($R^2=0.54$) than those dominated by deciduous trees ($R^2=0.38$). I also compared the utility of both field and LIDAR derived indices of vegetation cover for making inferences about patterns of breeding bird occurrence. I developed bird species occurrence models using both indices and compared the resulting predictions. Differences in agreement between indices translated to moderate agreement between species occurrence predictions. My results suggest that discrete-return leaf-off LIDAR data can be used to identify broad scale patterns of breeding bird occurrence, but its utility may be limited to species with strong associations with variation in upper canopy, rather than shrub cover. Using LIDAR-derived metrics of vegetation structure for modeling forest bird species occurrence may result in biased predictions associated with variation in canopy position and vegetation type.

Keywords: LIDAR, species occurrence, remote sensing, vegetation structure, canopy position, birds

INTRODUCTION

Light Detection and Ranging (LIDAR) is at the forefront of remote sensing advances that are improving our understanding of environmental change. Its ability to capture patterns in vegetation structure across the landscape promises to provide unprecedented capacity for species-habitat relationships at large spatial scales. Gottschalk et al. (2005), reviewed more than 120 recent papers using remote sensing for bird applications, and suggest that linking specific vegetation structure characteristics to species of interest will improve upon models derived from reflectance-based satellite imagery. Ficitola et al. (2013) compared models from multiple remote sensing sources, and found that LIDAR-derived vegetation structure indices outperform those based on reflectance imagery alone. Although LIDAR has proven effective for modeling patterns of occurrence and abundance for a growing number of species (Garabedian et al. 2014, Goetz et al. 2013, Bradbury et al. 2005, Hagar et al. 2014), LIDAR data quality can vary depending on how and when they are acquired. LIDAR data are currently available for portions of 9 countries and 27 U.S. states (National Elevation Dataset, 3D Elevation Program), and most of this data was acquired during leaf-off conditions using discrete-return technology. This presents some obvious challenges for understanding habitat associations of birds that breed during leaf-on conditions.

Similarly, although discrete-return LIDAR uses the amount of time it takes the energy to return to the sensor (typically 3-5 returns from a single pulse) to capture height information, it is limited by the range measurement resolution, effectively the minimum vertical target discrimination distance (Ussyshkin and Theriault 2011). Therefore, the resulting vertical arrangement of pulse returns is a combination of both the vegetation structure and the

inherent structure of the pulse returns, which is imposed by the range measurement resolution. Although full waveform sensors capture additional structural information using the continuous distribution of energy returning from each laser pulse, most National LIDAR Dataset products have been acquired using discrete-return technology. Efforts to model the entire waveform of vegetation structure from discrete-return LIDAR are informing new methods for capturing the entire vegetation structure (Ussyshkin and Theriault 2011). In this chapter, I explore the utility of Fractional Cover metrics derived from discrete-return LIDAR data (Morsdorf et al. 2006) for modeling patterns of species occurrence in breeding forest songbirds.

I contrast remotely sensed estimates of vegetation cover derived from LIDAR with those derived from field observations, and contrast species occurrence predictions generated using the two methods. My objectives are to: 1) quantify the agreement between field-derived estimates of vegetation cover and LIDAR-derived estimates of Fractional Cover and 2) explore agreement between species occurrence predictions modeled using both leaf-off Fractional Cover and leaf-on field-derived estimates of vegetation cover.

METHODS

Sampling Design

During the 2012, 2013 and 2014 breeding seasons (15 April – 30 June), I identified and surveyed 285 sampling points within pine and oak habitats of the western portion of Great Smoky Mountains National Park (also the Park) for use in these analyses. This represents a subset of the points included in Chapter 1 and includes only points within the footprint of the

Tennessee LIDAR acquisition that did not have any evidence of disturbance from the time of data acquisition to field sampling. These include 95 sampling points placed in locations with no record of fire since the Park's establishment in 1934, and 190 sampling points in burned areas. I used LandsatTM derived Difference Normalized Burn Ratios to quantify fire severity, and grouped time since burn into three categories: 0-5 years, 6-10 years, and 11-28 years (Table 2.1) to capture a broad range of vegetation structures. Points in burned areas were located at least 100m from the fire perimeter within the footprints of 28 recent fires. Each fire contained between one (Shop Creek 2009) and 30 (Arbutus-Stony 2007) sampling points (Appendix A). All points were placed on upper slopes and ridges to target xeric pine and oak forests of the region, and kept a minimum of 250 meters apart to reduce the influence of spatial autocorrelation.

Field-derived vegetation structure indices

During each visit to a sampling point, observers visually estimated the percent canopy cover for three strata (shrub cover: 0-2meters, midstory cover: 2-10m, and overstory cover: >10m). During analysis I averaged these canopy cover estimates across the three visits to reduce the effects of possible observer bias. In addition to visual cover estimates, I took photographs of the vegetation directly overhead during leaf-off conditions (March 2014) for comparison with LIDAR-derived indices. The resulting estimates of both percent canopy cover (shrub, midstory, and overstory) and proportion canopy closure (photographs) were compared with LIDAR-derived estimates of Fractional Cover.

LIDAR-derived Vegetation Structure Indices

LIDAR acquisition flights covering the study area were flown during leaf-off conditions from the 15th of February to the 30th of April 2011. Data acquisition was funded by the American Recovery and Reinvestment Act of 2009, and collected by the Center for Remote Sensing and Mapping Science, University of Georgia and Photo Science, Inc. in a joint effort. LIDAR data were collected in accordance with the specifications of the USGS Grant Program Announcement #10HQPA0014 for proposal #NM-ARRA-0073. Specific details of the acquisition can be found in Jordan et al. (2011).

The classified .LAS files received from the vendor contained unclassified pulse returns from both power lines and airline condensation trails. To ensure accuracy, and to derive summary information about the vertical distribution of returns, collaborators with the USGS Core Science Analytics Synthesis and Libraries (CSAS&L) program performed additional processing of the classified .LAS files provided by the vendor. That processing was done using a combination of ArcGIS 10.1 and Global Mapper 14.1 software to check for and remove outliers, preview data, and build vertical return profiles.

I then summarized first return heights, binned to 1m intervals above the ground, using R version 15.1 (R Development Core Team 2012) to provide estimates of Fractional Cover (Morsdorf et al. 2006) for overstory (above 10m), midstory (2-10m), shrub layer (0-2m), and vegetation above 2m (Table 2.2).

Avian Surveys

I used variable circle plot point counts, modified from Reynolds et al. (1980) and similar to those conducted by Shriner (2001) to survey the avian community in xeric pine-oak forests of the Park. Each point was visited three times during May and June to estimate the probability that an observer would detect each species if it was present. During each visit observers conducted ten-minute point counts, mapping the location and distance to each individual bird and species detected. Counts were recorded on data sheets in the field (Appendix C), and transcribed into a Microsoft Access™ database.

Data Analysis

Photographs taken during point visits were converted to binary images using ImageJ software version 1.47v to calculate the proportion of canopy closure at each sampling point. Each image was carefully inspected to ensure that vegetation and sky were accurately converted to black and white respectively, and that glare or poor image quality did not introduce unwanted variation. I used linear regression (lm, base package “stats”) in program R version 15.1 (R Development Core Team 2012) to quantify agreement between both field-derived and LIDAR-derived estimates of canopy closure and cover. I report R squared values, F statistics, and p-values for all linear regression models.

Because variation in detection probability can be a source of substantial bias in both density and occupancy estimates (Kissling and Garton 2006, Mackenzie et al. 2006, Simons et al. 2007), I used package single season occupancy models (MacKenzie et al. 2002) to simultaneously estimate species specific detection probabilities and occupancy. These models are available in package “unmarked” (Fiske and Chandler 2011) in the statistical

software R, version 15.1 (R Development Core Team 2012). This approach incorporates the probability that a species is present, available, and detected into the resulting species occurrence estimates, allowing us to account for variations in detection rates related to weather, time of day, time of season, or other unknown factors (MacKenzie et al. 2006).

Although variable radius point counts are often used to estimate abundance, I focused on species occurrence because I believe that the assumptions of occupancy sampling are more realistic than those for distance sampling in densely forested habitats. In deciduous forest bird communities, density estimates based on auditory detections can range widely; from 17% to 132% of the actual total (Simons et al. 2007). In part, this reflects how difficult it is to accurately estimate distance from auditory detections. Recent research shows that distance estimation errors increase dramatically beyond approximately 75 meters, depending on singing rate and observer skill (Alldredge et al. 2007). In light of these findings, and in an effort to minimize misidentification errors, individuals detected beyond 50 meters were not included in analyses herein.

I developed occurrence models for each target species using a combination of overstory, midstory, and shrub cover derived from both field measurements and LIDAR imagery. In addition to a single model incorporating vegetation structure estimates from these two sources, I evaluated both null (no covariates on detection or occupancy) and conditional (all covariates are included on detection, but none on occupancy) models using an Information Theoretic approach.

Because the time of day (minutes from sunrise), date, wind speed, cloud cover, and observer were all considered potential sources of detection bias, I included them as detection covariates in all models unless otherwise indicated.

RESULTS

Agreement between LIDAR and Field derived Indices of Vegetation Structure

Overall agreement between Fractional Cover above 2m and estimates of closure derived from photos taken during leaf-off conditions was 42% ($R^2=0.42$, $F=56.59$, $DF=76$, $P=0.00$), and was 16% higher in coniferous dominated forests ($R^2=0.54$, $F=36.81$, $DF=30$, $P=0.00$) than in predominately deciduous forests ($R^2=0.38$, $F=28.88$, $DF=44$, $P=0.00$) (Figure 2.1, Vegetation).

Despite both seasonal, and methodological differences in data collection, agreement between estimates of overstory fractional cover (LIDAR: leaf-off) and percent cover (Field: Leaf-on) was 57% ($R^2=0.57$, $F=377.9$, $DF=284$, $P=0.00$). Estimates were similar for sampling points dominated by deciduous trees ($R^2=0.59$, $F=224.7$, $DF=154$, $P=0.00$) and coniferous trees ($R^2=0.60$, $F=192.1$, $DF=128$, $P=0.00$) (Figure 2.1, Overstory). Overall, agreement between midstory indices ($R^2=0.32$, $F=137.6$, $DF=284$, $P=0.00$) was 25% lower than it was for overstory indices (Figure 2.1, Midstory). This lack of agreement was most noticeable at sample points dominated by deciduous trees ($R^2=0.17$, $F=33.31$, $DF=154$, $P=0.00$), but it was also seen at points dominated by conifers ($R^2=0.48$, $F=117.5$, $DF=128$, $P=0.00$). LIDAR-derived estimates of shrub cover were even lower still ($R^2=0.04$, $F=13.4$, $DF=283$, $P=0.00$), with little to no agreement in both deciduous dominated ($R^2=0.10$, $F=17.96$, $DF=153$,

P=0.00) and coniferous dominated ($R^2=0.00$, $F=0.47$, $DF=128$, $P=0.49$) forests (Figure 2.1, Shrub).

Vegetation Structure and Species Occurrence

Field-derived estimates of canopy cover outperformed LIDAR-derived estimates of fractional cover for all four species (Table 2.3). Despite differences in the predictive ability of the two methods, the sign of the parameter estimate and the parameters identified as significant were the same in most cases (Table 2.4). All models for the two species associated with early successional habitats indicate significant negative responses to increasing overstory and midstory cover. Although models of occurrence for the two species associated with contiguous forests generally indicate a positive relationship with vegetation cover, the sign of the parameter estimate for the shrub layer is not consistent across the different indices. In addition, the model using LIDAR-derived indices of midstory cover showed a significant positive association with Worm-eating Warbler occurrence, while the model using field-derived estimates did not show a significant association.

Predictions from both models (LIDAR-derived: leaf-off, and Field-derived: leaf-on) indicate 50% ($R^2=0.50$, $F=279.5$, $DF=283$, $P=0.00$), 48% ($R^2=0.48$, $F=266.0$, $DF=283$, $P=0.00$), 53% ($R^2=0.53$, $F=325.1$, $DF=283$, $P=0.00$), and 51% ($R^2=0.51$, $F=299.8$, $DF=283$, $P=0.00$) agreement between the two methods for Prairie Warbler, Yellow-breasted Chat, Ovenbirds, and Worm-eating Warblers respectively (Figure 2.2).

DISCUSSION

Overall, both methods of characterizing vegetation cover show moderate agreement and the resulting species occurrence predictions indicate similar patterns for the species considered. These results highlight two important potential sources of bias when discrete-return leaf-off LIDAR is used to make inferences about relationships between vegetation structure and bird occurrence. These results suggest that both canopy position (shrub, midstory, overstory), and vegetation type (deciduous or coniferous) can influence estimates of Fractional Cover.

The agreement between field-derived and LIDAR-derived estimates was stronger for measurements taken higher in the canopy. Agreement was greatest above 10m in height (overstory: 57%), decreased for estimates of cover between 2 and 10m (midstory: 32%), and further decreased for estimates of cover below 2m in height (shrub: 4%). Because Fractional Cover is derived solely from first returns, it contains more information about the upper layers of the canopy. In densely forested areas, such as Great Smoky Mountains National Park, the majority of first returns come from the upper canopy. I would expect LIDAR acquisition during leaf-off conditions to reduce this effect because there is less leaf area in the upper canopy. The fact that agreement between LIDAR-derived and field-derived estimates in the shrub layer was slightly better for deciduous (10%) than it was for coniferous (0%) forests provides some support for this idea. On the contrary, I might expect the opposite effect during leaf-on conditions, as there would be more leaf area in the upper canopy of deciduous forests. Interestingly, during leaf-on conditions, Riano et al. (2004) found just that, agreement between field-derived and LIDAR-derived percentage of canopy hits (similar to

Fractional Cover, but they used all pulse returns) was stronger in oak than in pine forests.

Another LIDAR metric commonly related to field measurements is maximum canopy height.

Estimates of canopy height from LIDAR use the highest pulse returns (generally first returns)

and agreement with field-derived metrics can be quite strong (Wasser et al. 2013, leaf-on:

$R^2=0.90$, leaf-off: $R^2=90$).

Ecologists have long recognized the link between vegetation structure and patterns of species occurrence (MacArthur and MacArthur 1961, Recher 1969). Although it is not always clear

why a species is associated with specific structural characteristics, some species show

stronger associations with vegetation cover than others. I identified two species that have

strong associations with early successional vegetation and two species that have strong

associations with contiguous forests. In this study, species occurrence models using either

percent cover (field-derived) or Fractional cover (LIDAR-derived) identified the same trends,

and in most cases the same level of significance. This suggests that Fractional Cover

provides enough information to identify broad scale changes in species occurrence for

species that have strong associations with vegetation cover. The possibility of making

erroneous inferences from LIDAR-derived vegetation structure indices however, is likely

greater for species without such strong habitat associations.

One of the challenges of using LIDAR-derived measures of vegetation structure to model

patterns of species occurrence is identifying the relationship between pulse return

information and the specific vegetation structure characteristic of interest. Because LIDAR

pulse return information can be summarized in a wide variety of ways (Evans et al. 2009,

Hudak et al. 2008), a clear understanding of potential sources of bias (such as canopy

position and vegetation type) is important for interpreting patterns of species occurrence. Although both field and LIDAR-derived metrics identify strong patterns of occurrence for all four species, my results indicate model agreement is only between 48-53% (Figure 2.2). The agreement between predictions is limited in part, by variation imposed by using discrete-return leaf-off LIDAR, that is, variation associated with both canopy position and vegetation type.

I used four species that have strong habitat associations with known vegetation structure characteristics to evaluate the utility of LIDAR-derived indices of vegetation structure for modeling patterns of species occurrence. My results show a moderate relationship between field and LIDAR-derived indices of vegetation structure in addition to a moderate relationship between species occurrence predictions derived from each, but they also illustrate the importance of understanding potential sources of bias. I show that discrete-return LIDAR acquired during leaf-off conditions can be successfully used to identify patterns of species occurrence across a range of canopy cover conditions, but suggest that their use should be approached with caution, and include assessment of potential sources of bias.

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TABLES AND FIGURES

Table 2.1. Sampling points in burned areas (190) were stratified by fire severity (using DNBR and the NPS Thresholds) and time-since-burn, within xeric pine-oak forests of the western portion of the Park. An additional 90 sampling points were placed in unburned areas.

| | 0-5 years | 6-10 years | 11-30 years |
|--------------------------|-----------|------------|-------------|
| Unburned – Low Severity | 5 | 22 | 14 |
| Low – Moderate Severity | 15 | 21 | 22 |
| Total Low | 20 | 43 | 36 |
| Moderate – High Severity | 19 | 22 | 21 |
| High Severity | 9 | 12 | 8 |
| Total High | 28 | 34 | 29 |

Table 2.2. Vegetation structure indices acquired from field observations and derived from LIDAR. I derived Fractional Cover using the equations presented on the right.

| Structural Attribute (Field) | Structural Attribute (LIDAR) | Calculation (LIDAR) |
|---------------------------------|---|---|
| Overstory Percent Cover | Overstory Fractional Cover | $\frac{\# FR \text{ above } 10m}{\# \text{ of pulses}}$ |
| Midstory Percent Cover | Midstory Fractional Cover | $\frac{\# FR \text{ between } 2 \text{ and } 10m}{\# \text{ of pulses} - \# FR \text{ above } 10m}$ |
| Shrub Percent Cover | Shrub Fractional Cover | $\frac{(\#FR < 2m) - \# FR_{Ground \text{ Returns}}}{\# \text{ of pulses} - \# FR \text{ above } 2m}$ |
| Photo Closure | Vegetation Above 2m Fractional Cover | $\frac{\# FR \text{ above } 2m}{\# \text{ of pulses}}$ |

FR = First Returns

Table 2.3. Model selection results indicating the relative performance of field-derived indices of vegetation cover and LIDAR-derived Fractional Cover (FC) indices when used to predict species occurrence. Models were developed for two species associated with early succession habitats (ES) and two species associated with contiguous forests (CF).

| Species | Model | nPars | AIC | AICwt |
|------------------------------------|--|--------------|------------|--------------|
| Prairie Warbler ^{ES} | p(#), psi(overstory + midstory + shrub) | 16 | 407.50 | 1.00 |
| | p(#), psi(overstory ^{FC} + midstory ^{FC} + shrub ^{FC}) | 16 | 430.65 | 0.00 |
| | p(#), psi(.) | 13 | 492.81 | 0.00 |
| Yellow-breasted Chat ^{ES} | p(#), psi(overstory + midstory + shrub) | 16 | 400.49 | 0.59 |
| | p(#), psi(overstory ^{FC} + midstory ^{FC} + shrub ^{FC}) | 16 | 401.23 | 0.41 |
| | p(#), psi(.) | 13 | 458.98 | 0.00 |
| Ovenbird ^{CF} | p(#), psi(overstory + midstory + shrub) | 16 | 833.77 | 1.00 |
| | p(#), psi(overstory ^{FC} + midstory ^{FC} + shrub ^{FC}) | 16 | 866.89 | 0.00 |
| | p(#), psi(.) | 13 | 890.28 | 0.00 |
| Worm-eating Warbler ^{CF} | p(#), psi(overstory + midstory + shrub) | 16 | 840.76 | 0.96 |
| | p(#), psi(overstory ^{FC} + midstory ^{FC} + shrub ^{FC}) | 16 | 847.18 | 0.04 |
| | p(#), psi(.) | 13 | 877.63 | 0.00 |

All models include observer, date, time since sunrise, wind speed, cloud cover, and temperature as covariates on detection.

Table 2.4. Parameter estimates for models incorporating both field-derived and LIDAR-derived estimates of vegetation structure. Although indices differ in both acquisition season and methodology, parameter estimates indicate the same trend in most cases.

| Species | Parameter | ¹Percent Cover Model (Field: Leaf-on) | ²Fractional Cover Model (LIDAR: Leaf-off) |
|----------------------|------------------|---|---|
| Prairie Warbler | intercept | 4.17 ± 1.33 | 3.01 ± 0.76 |
| | overstory cover | -6.92 ± 1.21 (-)* | -3.74 ± 0.98 (-)* |
| | midstory cover | -5.42 ± 1.18 (-)* | -6.64 ± 1.33 (-)* |
| | shrub cover | -0.61 ± 0.75 (0) | -1.25 ± 1.52 (0) |
| Yellow-breasted Chat | intercept | 2.49 ± 0.98 | 2.82 ± 0.72 |
| | overstory cover | -5.91 ± 0.96 (-)* | -4.90 ± 1.03 (-)* |
| | midstory cover | -2.32 ± 0.83 (-)* | -4.70 ± 1.14 (-)* |
| | shrub cover | -1.07 ± 0.88 (0) | -2.33 ± 1.70 (0) |
| Ovenbird | intercept | -3.11 ± 0.88 | -1.95 ± 0.51 |
| | overstory cover | 4.32 ± 0.68 (+)* | 2.48 ± 0.65 (+)* |
| | midstory cover | 2.27 ± 0.78 (+)* | 2.38 ± 0.82 (+)* |
| | shrub cover | 0.03 ± 0.75 (0) | -1.24 ± 1.23 (0) |
| Worm-eating Warbler | intercept | -1.71 ± 1.06 | -3.07 ± 0.78 |
| | overstory cover | 4.11 ± 0.87 (+)* | 3.57 ± 1.09 (+)* |
| | midstory cover | 1.74 ± 0.87 (0) | 4.41 ± 1.56 (+)* |
| | shrub cover | -0.82 ± 0.94 (0) | 0.55 ± 1.16 (0) |

¹Parameter estimates for the model using field-derived percent cover: p(#), psi(overstory + midstory + shrub)

²Parameter estimates for the model using LIDAR-derived Fractional Cover: p(#), psi(overstory^{FC} + midstory^{FC} + shrub^{FC})

* $P(> |Z|) \leq 0.05$

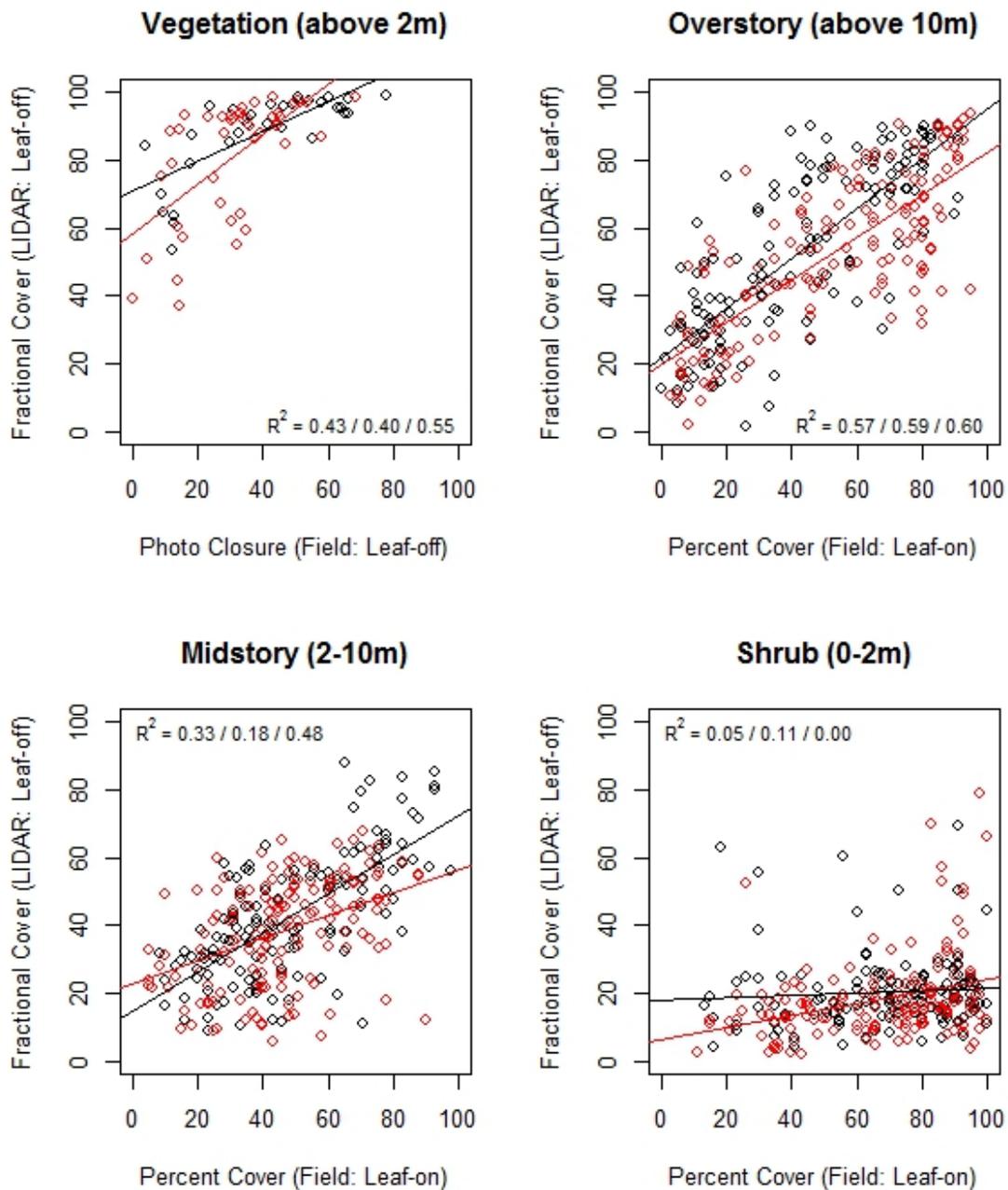


Figure 2.1. Overall agreement between field-derived (digital photographs) and LIDAR-derived indices of vegetation cover (top left) for deciduous (red) and coniferous (black) dominated forests. LIDAR-derived indices showed stronger agreement with field-derived estimates of canopy cover in the overstory (top right) than in either the midstory (bottom left) or shrub layers (bottom right). R^2 values are presented for “overall / deciduous / coniferous” agreement.

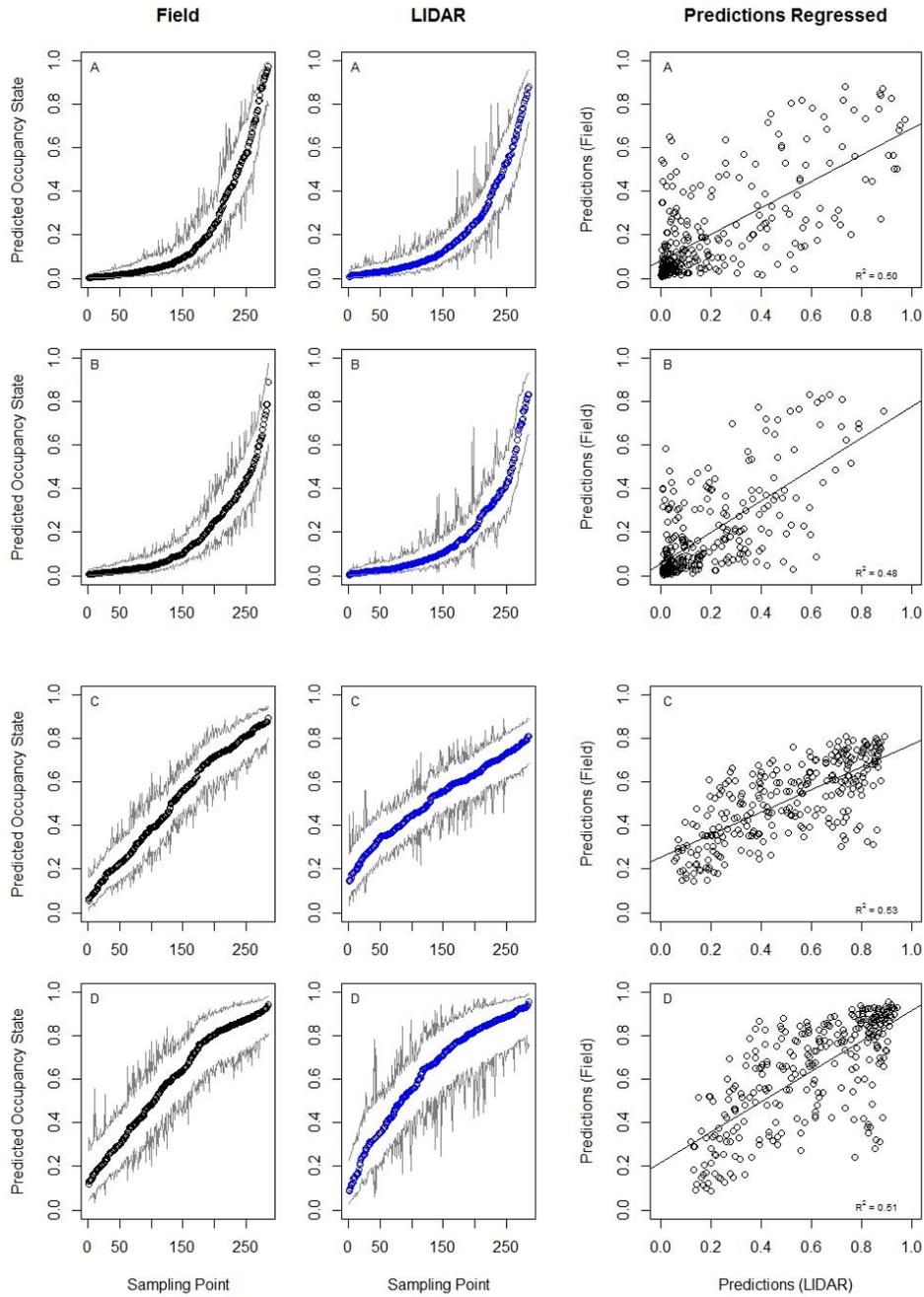


Figure 2.2. Species occurrence predictions and 95% confidence intervals, generated using field-derived percent vegetation cover (left) and LIDAR-derived Fractional Cover (center), for points sampled within Great Smoky Mountains National Park. Agreement between predictions under each model for each species (right). Results for the Prairie Warbler (A), Yellow-breasted Chat (B), Ovenbird (C), and Worm-eating Warbler (D).

CHAPTER 3

Avian response to fire severity and time since burn in low elevation pine-oak habitats of Great Smoky Mountains National Park

ABSTRACT

Recent changes in fire management policy within Great Smoky Mountains National Park have resulted in an increase in the prevalence of fire within Park boundaries. This increase in fire has broad ecological implications for both plant and animal communities. I combine avian point counts in burned and unburned areas with remote sensing indices of fire severity to infer temporal changes in bird occurrence for up to twenty eight years following fire. Using hierarchical linear models that account for the possibility of a presence at a site when no individuals are detected, I developed species occurrence models for twenty four species. Thirteen species were significantly more prevalent within burned areas, while two species occurred were significantly less prevalent in unburned areas. Within burned areas, the top occurrence model for each species included fire severity, time since burn, or both, suggesting that fire influenced species occurrence patterns for all twenty four species modeled. In addition, temporal patterns of occurrence varied substantially among sampling points with different levels of fire severity. These results provide insights into how the bird community in Great Smoky Mountains National Park may be changing in response to recent changes in fire management policy.

Keywords: Great Smoky Mountains National Park, difference normalized burn ratio, species occurrence, fire severity, habitat use, birds, spatial scale, time since fire

INTRODUCTION

Recent changes in the fire management policy within Great Smoky Mountains National Park (also the Park) have broad implications for its plant and animal communities. Within the Park, fire is an important source of disturbance, potentially driving population changes for many bird species. Historic accounts suggest that some species associated with xeric pine-oak forests have declined during the 20th century (Northern Bobwhite: Stupka 1963, Red-headed Woodpecker: Stupka 1963, Red-cockaded Woodpecker: Nicholson 1997), these declines coincide with a period of fire suppression. The absence of Red-cockaded Woodpeckers in the Park after 1985 is notable. Breeding colonies within the xeric pine-oak forests of the western portion of the Park were reported from 1935 – 1985 (Dimmick et al. 1980, Fleetwood 1936, Stupka 1963, Tanner 1965). Red-cockaded Woodpecker nesting colonies depend on mature yellow pine stands, open understory and mid-canopy, and frequent low severity fire (Ligon et al. 1986). These habitats declined within the Park during the era of fire suppression. In recent years, fire management paradigms have changed nationally, and current management policy within the Park uses both prescribed and wild fires to meet management objectives. This policy has resulted in an increase in the amount of land area subject to both prescribed burns (NPS Fire Effects Data 1920-2010) and wildfires (Cohen et al. 2007), the extent to which recent fires have influenced bird communities in the region is poorly understood.

Throughout the 18th and 19th centuries, fire was a regular part of the southern Appalachian landscape, with an estimated fire return interval of 9-13 years in yellow-pine forests (Flatley et al 2013, Harmon 1982), and 2-3 years in habitats dominated by Table Mountain Pine

(DeWeese 2007). Regular fire maintained an overstory of fire tolerant Shortleaf (*Pinus echinata*), Table Mountain (*Pinus pungens*), and Virginia (*Pinus virginiana*) pines, along with a unique avian community. With the Weeks Act of 1911 and the Clarke-McNary Act of 1924 federal funds became available for fighting fire. Active fire suppression within the Park began around 1940 and resulted in a reduction in fire frequency (LaForest 2012, Flatley et al. 2013). The subsequent era of fire suppression (~1940 to 1996) encouraged the establishment of shade tolerant Red Maples (*Acer rubrum*), Black Gums (*Nyssa sylvatica*), and White Pines (*Pinus strobus*), altering both plant and animal communities within the region (Harrod et al. 2000). Prompt fire suppression remained the dominant fire management strategy until the late 1990's when the ecological ramifications of this practice became more broadly understood. In 1996, changes in fire management policy began to give managers greater flexibility to allow wildfires to burn and to use prescribed burns for achieving management objectives (NPS Fire Management Plan 1996).

Although few studies within the southern Appalachians address the influence of fire on birds, research is beginning to inform management decisions and provide insights into the effects of fire on bird communities of the region (Klause et al. 2010, Greenburg et al. 2007, Greenburg et al. 2013). Within the lower elevation pine-oak forests of the western portion of the park, there remains much to be discovered about the effects of fire on bird communities. The Parks detailed fire history records combined with recent changes in management, provide a unique opportunity to complement existing research by linking long-term fire history with patterns of species occurrence within this unique ecosystem.

To contribute to our understanding of bird responses to fire in the region, I combine remotely sensed measures of fire severity (DNBR) and repeated avian point counts to develop occurrence models that can help managers understand long-term changes in patterns of species occurrence within the Park. Specifically, I 1) contrast species occurrence in recently (within 28 years) burned areas with occurrence in areas that have not burned since the establishment of the Park (more than 70 years), and 2) identify patterns of species occurrence that incorporate the effects of fire severity and time since burn at spatial scales relevant to each bird species.

METHODS

During the 2012, 2013 and 2014 breeding seasons, I identified and surveyed 336 points within pine and oak habitats of the western portion of the Park (Figure 1). I placed 108 sampling points in locations with no record of fire since the Park's establishment in 1934, and 228 sampling points in burned areas, stratified by both fire severity and time since burn (Figure 3.1). I used LandsatTM derived Difference Normalized Burn Ratios (DNBR) to quantify fire severity, and stratified time since burn across three categories: 0-5 years, 6-10 years, and 11-28 years. Sampling points in burned areas were located at least 100m from the fire perimeter within the footprints of 28 recent fires. The footprint of each fire contained between one (Shop Creek 2009) and 30 (Arbutus-Stony 2007) sampling points (Appendix A). All points were placed on upper slopes and ridges in an effort to target xeric pine and oak forests of the region, and kept a minimum of 250 meters apart to reduce the influence of spatial autocorrelation.

Quantifying the bird community

To quantify the bird community, I used variable circle plot point counts, modified from Reynolds et al. (1980) and similar to those conducted by Shriner (2001). Each sampling point was visited three times between 1st May and the 30th June within a single breeding season, generally by different observers. To increase the chances of encountering singing birds, all points were surveyed between sunrise and 10:00 am and performed during fair weather. Point counts were not done during rain or periods of high wind (wind speeds >15 miles per hour). During each visit, an observer performed a single ten minute point count, and mapped all birds detected on a data sheet (Appendix C). Each ten minute count was broken into three 200 second intervals to facilitate comparison with past data collected within the Park. Movement of birds detected during each time interval, and evidence of counter-singing were noted using multi-colored pens.

Quantifying fire severity

As the amount of fire on the landscape has increased in recent years, quantifying the effects of fire has become increasingly important. In Chapter 1, I used advances in the application of LandsatTM imagery to assess variations in fire severity within the Park. Landsat-derived Difference Normalized Burn Ratios can provide resource managers with a remotely sensed measure of the change in vegetation resulting from fire (Key and Benson 2006). This fire severity index is available for most fires that have occurred within the Park since Landsat products became available in 1972. Difference Normalized Burn Ratios are calculated as the difference between the Normalized Burn Ratio before and after a fire, using a ratio of the

peak reflectance of vegetation and mineral soil. Difference Normalized Burn Ratios are routinely used within the Park to assess landscape scale effects of fire on the vegetation.

Data Analysis

I used single season occupancy models (MacKenzie et al. 2002), to incorporate all three components of the detection process (probability a species is present, available, and detected) in the resulting estimates of species occurrence. I used R version 15.1 (R Development Core Team 2012) for all analyses, and the “unmarked” package (Fiske and Chandler 2011) to develop all occupancy models. Observations of individuals were restricted to those detected within 50m of the observer unless otherwise indicated. In some instances the plot radius was unrestricted to allow sufficient detections to develop models for rare or wide ranging species that would otherwise have too few observations.

I used a four step approach to maximize the number of species analyzed. First, I used all 336 points to get an overall detection rate and to identify the most important covariates influencing the detection process for each species. Next, using all 336 sampling points, I quantified species occurrence at unburned and burned sampling points. Third, I restricted the data to the 228 burned points in order to identify the appropriate spatial scale for summarizing fire severity indices for each species. Finally, I used the restricted dataset to quantify changes in species occurrence across the range of fire severity and time since burn on my sites.

Using an information theoretic approach, I evaluated models including the additive influence of all possible combinations of observer, date, time since sunrise, wind speed, percent cloud

cover, and temperature to identify detection covariates relevant for each species. The covariates identified in the top model were then included in all further analyses for each species.

In the second step, again using all 336 sampling points, I develop a model for each species that included both the relevant detection covariates (identified in the first step) and a binary indicator for sites that burned (1) and those that didn't (0). This provided estimates of species occurrence at both burned and unburned sampling points. While this approach indicates which species occur more frequently in burned or unburned areas, it does little to inform the ecological process that drives these patterns. The next two steps compared sampling points in burned areas to explore these patterns in greater detail.

In Chapter 1, I developed five models of species occurrence using DNBR fire severity indices summarized at four different spatial scales to understand the relationship between patterns of fire and patterns of species occurrence. DNBR imagery is produced as a raster with 30m x 30m pixels. These pixels were summarized using focal mean tools in ARCGIS. I evaluated DNBR fire severity products at three additional scales (90m x 90m, 150m x 150m, 210m x 210m). I evaluated all models using an information theoretic approach, and used the spatial scale identified in the top model in all further analyses for each species.

Lastly, I develop occurrence models incorporating both DNBR fire severity indices and the amount of time that lapsed since the most recent fire (time since burn), to identify temporal changes in species occurrence following fires that burned at different severities. Again, I used an information theoretic approach to identify the top model from a set of six incorporating all possible combinations of fire severity (summarized at the spatial scale most

relevant for each species) and time since burn. The model set included the conditional model (the null model with detection covariates), along with the effects of fire severity, the amount of time since burn, and their additive effects, in addition to models incorporating a quadratic term for time since burn. Parameter estimates from models contributing to a cumulative weight of 75% were averaged to determine the final occurrence predictions for each species. Unless otherwise noted, I consider the effects of a given parameter to be significant if twice the standard error of the estimate did not overlap zero for one or more of the models contributing to 75% of the cumulative weight.

RESULTS

We detected 81 species (Appendix D) during 1008 point counts (three visits to each of 336 sampling points). I developed species occurrence models for twenty four species. One or more covariates influencing the detection process was included in the top model for all but one species (Figure 3.2). Including observer, date, wind speed, cloud cover, temperature, or time of day did not improve predictions for the Eastern Bluebird. Predicted occupancy state at burned and unburned sampling points within the park are also included in Figure 3.2.

Overall, thirteen species occurred more frequently in burned areas, nine species showed no difference, and two species occurred less frequently in burned areas (Figure 3.1).

While only fifteen species show differences between burned and unburned points, they all appear to be influenced by fire in some way (Figures 3.3). In all cases, models incorporating fire severity, time since burn, or both, outperformed the conditional model. In addition, one or more models contributing to an overall 75% cumulative weight contained both fire

severity and time since burn for all twenty four species, though their relative importance and the strength of the effect varied (Table 3.2). The quadratic effects of time were also included in one or more models contributing to 75% cumulative weight for twenty species (Table 3.2).

Within burned areas, some species occur more frequently immediately following fire regardless of its severity (Carolina Wren, Eastern-wood Pewee, Red-headed Woodpecker), while others occur more frequently only after high severity (American Goldfinch, Blue-gray Gnatcatcher, Brown-headed Cowbird, Eastern Bluebird, Eastern Towhee, Mourning Dove, Northern Cardinal, Northern Flicker, Pine Warbler, Prairie Warbler, Yellow-breasted Chat) or low severity (Blue-headed Vireo, Northern Parula, Ovenbird, Worm-eating Warbler) fires (Figures 3.3, Appendix E).

In addition to changes in occupancy resulting from variable fire severity, some species showed strong changes in frequency of occurrence with the amount of time since burn. Brown-headed Cowbirds, Eastern Bluebirds, Eastern Wood-pewee, Prairie Warbler, Red-headed Woodpeckers, and Yellow-breasted Chats all occurred less frequently as time since burn increased, while Worm-eating Warblers occurred more frequently with increasing time since burn (Figures 3.3, Appendix E).

DISCUSSION AND MANAGEMENT IMPLICATIONS

The effect of fire on birds is highly variable, and it depends on complex species-habitat relationships. Fire can increase the number of available snags for cavity nesters (Saab et al. 2009), decrease the leaf-litter available to conceal ground nests (Greenburg et al. 2007), and create forest openings that benefit species associated with early succession habitats (Artman

et al. 2005). Although quantifying fire severity and time since burn cannot identify the direct effects of fire on a given bird species, it can help us understand landscape-scale patterns of species occurrence that logistical constraints might otherwise prohibit.

In general, our understanding of the long-term influences of fire on birds is limited. Few studies attempt to identify patterns of bird occurrence or abundance following fire for more than 3-5 years (Greenburg et al. 2013, Watson et al. 2012). Watson et al. (2012) however, suggest that, for some species, patterns of bird occurrence following fire can change continually for more than 20 years. Within the southern Appalachian region, long-term (> 10 years) trends in species occurrence following fire have not previously been considered. By looking at species occurrence across fires that burned as many as 28 years prior to our surveys, we can begin to see signals of bird community succession in the pine-oak forests of Great Smoky Mountains National Park.

These patterns are seen most clearly following high severity fires. Peak occupancy occurs almost immediately after high severity fire for some species (Brown-headed Cowbird, Carolina Wren, Eastern Wood-pewee, Indigo Bunting, and Red-headed Woodpecker), while some species increase to peak frequencies over a period of five to ten years following fire (American Goldfinch, Blue-gray Gnatcatcher, Eastern Towhee, Mourning Dove, Prairie Warbler and Yellow-breasted Chat). Eastern Bluebirds only persist for about ten years following high severity fire, Prairie Warblers and Yellow-breasted Chats persist at peak frequencies for about fifteen years after the highest severity fires, while species like American Goldfinch and Mourning Dove occur at peak frequencies for more than twenty years.

Patterns of occurrence are more subtle for low severity fires, with some species showing delayed responses to fire. Within the Park, Hooded Warblers and Worm-eating Warblers increase in frequency for up to fifteen years following low severity fire. Greenburg et al. (2007) found that Hooded Warbler and Worm-eating Warbler densities declined temporarily following fuel reduction treatments that included fire, then increased. Their results suggest that declines within the first two years following treatment were associated with the loss of tall shrub cover (Hooded Warbler) and decreases in leaf litter depth (Hooded Warbler and Worm-eating Warbler). Presumably, as the shrub layer returns Hooded Warblers (shrub nesters) will have more nesting habitat available, while the accumulation of leaf litter provides more nest concealment for ground nesting Worm-eating Warblers.

My approach used spatial variation in occurrence across sampling points exposed to fire at different time intervals to infer temporal changes in species occurrence following fire. The extensive fire history information available within the Park, combined with the long-term collection of satellite images available through the Landsat Program made this approach feasible. My results illustrate the complexity of understanding how birds respond to fire because of biases associated with the size and spatial arrangement of the fires on the landscape. I attempted to minimize the effects of these biases by restricting sampling points to upper slopes and ridges within xeric pine-oak habitats. In addition, I included multiple fires from any given time period. The use of DNBR as an index of fire severity is another possible source of variation. Although DNBR can provide an index of fire severity for any given location within the footprint of a fire, agreement between the index and field-derived measures of fire severity is subject to a number of potential sources of bias (Key and Benson

1999, Picotte 2011, Chapter 2). Nevertheless, DNBR was the most reliable index of fire severity available for the temporal period and spatial extent of my study.

Although my results provide insights into current patterns of species occurrence for the twenty four modeled species, data were insufficient to model the other fifty eight species encountered during our surveys. Some species were not encountered frequently enough, while others were encountered too frequently to use occurrence as an informative metric. Similarly, species that range widely or aggregate in large groups during the breeding season were not included, as these behaviors grossly violate the assumption of occupancy models (MacKenzie et al. 2006).

Fire has previously been shown to influence species richness and diversity in the southern Appalachian region (Klaue et al. 2010, Greenburg et al. 2007). Current theory describing these patterns suggest that increases in environmental heterogeneity (often induced by fire) result in increased bird species diversity (Roth 1976, Tews et al. 2004, Fuhlendorf et al. 2006). While I do not address questions of species diversity, my results do suggest that certain species will benefit from the spatial and temporal habitat changes induced by fire. In other words, the composition of species present on the landscape is subject to variation with fire severity, its extent, and the amount of time since a fire has burned.

The benefits of using frequent low severity fires to induce increases in species diversity, are thought to be limited compared to the benefits of high severity fire (Artman et al. 2005, Klaus et al. 2005, Klaus et al. 2010). Within the Park however, even low severity fires often contain patches of high severity fire. These small patches of high severity fire can provide habitat for many early succession species. Although I do not address patch size specifically,

the scale at which patterns of fire severity (DNBR) most effectively predicted species occurrence is directly related to a species habitat requirements. Early succession species that are most likely to benefit from large patches of high severity fire include those that show the strongest relationships with fire severity at larger spatial scales (Chapter 1). These species include Blue-gray Gnatcatchers, Mourning Doves, Prairie Warblers and Yellow-breasted Chats. Further research is needed to better understand the implications of the spatial arrangement of fire-induced habitats on birds.

My results provide a starting point for understanding how fire management decisions influence bird species distributions and abundance in Great Smoky Mountains National Park. By understanding long-term patterns of bird response to variation in fire severity at different spatial scales, managers can begin to make informed decisions about how fire policy influences multiple members

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TABLES AND FIGURES

Table 3.1. Covariates included in the top detection model and the probability of occurrence (95% CI lower, 95% CI upper) for sampling points without fire since prior to 1940 and points that burned one or more times since 1986.

| Species Code | Top Detection Covariates | Unburned | Burned |
|---------------------|---|--------------------------|--------------------------|
| ACFL ^{NR} | p(WindSpeed+Temperature) | 0.14 (0.08, 0.25) | 0.11 (0.06, 0.18) |
| AMGO ^{NR} | p(Date) | 0.54 (0.35, 0.71) | 0.84 (0.52, 0.96) |
| BGGN | p(Observer+Time+WindSpeed+CloudCover+Temperature) | 0.23 (0.11, 0.40) | 0.63 (0.37, 0.83) |
| BHCO ^{NR} | p(Temperature) | 0.05 (0.01, 0.15) | 0.19 (0.11, 0.32) |
| BHVI | p(Observer+Date+Time) | 0.74 (0.58, 0.86) | 0.61 (0.50, 0.70) |
| BLJA ^{NR} | p(Observer+Date+WindSpeed+CloudCover) | 0.71 (0.54, 0.84) | 0.89 (0.71, 0.97) |
| CARW | p(Observer+Date) | 0.58 (0.44, 0.71) | 0.82 (0.68, 0.90) |
| EABL | p(.) | 0.04 (0.01, 0.12) | 0.24 (0.16, 0.34) |
| EATO | p(WindSpeed+Temperature) | 0.14 (0.09, 0.23) | 0.67 (0.59, 0.74) |
| EAWP | p(Date) | 0.08 (0.04, 0.17) | 0.45 (0.35, 0.54) |
| GCFL ^{NR} | p(Observer+Time+WindSpeed+Temperature) | 0.27 (0.14, 0.45) | 0.27 (0.16, 0.42) |
| HOWA | p(Observer+Date+WindSpeed+Temperature) | 0.74 (0.67, 0.81) | 0.77 (0.65, 0.86) |
| INBU | p(Observer+CloudCover+Temperature) | 0.61 (0.51, 0.70) | 0.89 (0.83, 0.93) |
| MODO ^{NR} | p(Observer+Time+WindSpeed+CloudCover+Temperature) | 0.39 (0.25, 0.56) | 0.71 (0.51, 0.86) |
| NOCA | p(WindSpeed+Temperature) | 0.22 (0.11, 0.38) | 0.32 (0.20, 0.49) |
| NOFL ^{NR} | p(Observer+WindSpeed) | 0.57 (0.41, 0.71) | 0.78 (0.61, 0.89) |
| NOPA | p(Date+Temperature) | 0.21 (0.11, 0.36) | 0.30 (0.19, 0.44) |
| OVEN | p(Observer+Date+CloudCover) | 0.37 (0.30, 0.45) | 0.81 (0.67, 0.90) |
| PIWA | p(Date) | 0.48 (0.37, 0.60) | 0.59 (0.50, 0.67) |
| PRAW | p(Date+CloudCover) | 0.01 (0.00, 0.07) | 0.29 (0.23, 0.35) |
| RHWO ^{NR} | p(Temperature) | 0.05 (0.01, 0.18) | 0.52 (0.30, 0.74) |
| WEWA | p(Observer+WindSpeed) | 0.54 (0.44, 0.63) | 0.78 (0.60, 0.89) |
| YBCH | p(WindSpeed) | 0.02 (0.00, 0.08) | 0.26 (0.20, 0.32) |
| YTWA | p(Observer+Date+Time+WindSpeed+CloudCover) | 0.67 (0.48, 0.82) | 0.63 (0.49, 0.74) |

^{NR} To improve model performance, observations for this species were not restricted to detections within 50m of the observer. Occurrence estimates for these species will inherently be higher than those from observations restricted to 50m and should not be compared across species.

Table 3.2. Summary of AIC results for top models relating species occurrence to combinations of fire severity (fire) and time since burn (time). Models contributing to 75% of the cumulative model weight were averaged for final occurrence predictions, and are included herein. Fire-time models are developed using the 228 sampling points in burned areas only.

| Species Code | Model | nPars | AIC | AICwt | Cumulative Weight |
|--------------------|---|-------|--------|-------|-------------------|
| ACFL ^{NR} | p(#), psi(*fire severity _{90x90} + time ^q) | 7 | 179.08 | 0.49 | 0.49 |
| | p(#), psi(*fire severity _{90x90}) | 5 | 180.04 | 0.31 | 0.80 |
| | p(#), psi(*fire severity _{90x90} + time) | 8 | 181.24 | 0.17 | 0.97 |
| AMGO ^{NR} | p(#), psi(*fire severity _{90x90} + *time ^q) | 6 | 659.02 | 0.52 | 0.52 |
| | p(#), psi(time) | 4 | 660.35 | 0.27 | 0.79 |
| | p(#), psi(time ^q) | 5 | 662.29 | 0.10 | 0.89 |
| BGGN | p(#), psi(fire severity _{210x210} + time ^q) | 15 | 476.53 | 0.70 | 0.70 |
| | p(#), psi(fire severity _{210x210} + time) | 14 | 480.00 | 0.12 | 0.82 |
| | p(#), psi(*fire severity _{210x210}) | 13 | 480.67 | 0.09 | 0.91 |
| BHCO ^{NR} | p(#), psi(*fire severity _{90x90} + *time) | 5 | 231.42 | 0.57 | 0.57 |
| | p(#), psi(*fire severity _{90x90} + time ^q) | 6 | 232.38 | 0.35 | 0.93 |
| | p(#), psi(*fire severity _{90x90}) | 4 | 237.45 | 0.03 | 0.96 |
| BHVI | p(#), psi(*fire severity _{150x150} + time ^q) | 13 | 667.42 | 0.71 | 0.71 |
| | p(#), psi(*fire severity _{150x150} + *time) | 12 | 669.21 | 0.29 | 1.00 |
| | p(#), psi(*fire severity _{150x150}) | 11 | 680.41 | 0.00 | 1.00 |
| BLJA ^{NR} | p(#), psi(*time) | 12 | 832.28 | 0.46 | 0.46 |
| | p(#), psi(time ^q) | 13 | 833.73 | 0.22 | 0.68 |
| | p(#), psi(fire severity _{30x30} + time) | 13 | 834.04 | 0.19 | 0.87 |
| CARW | p(#), psi(*time) | 10 | 783.34 | 0.51 | 0.51 |
| | p(#), psi(fire severity _{210x210} + *time) | 11 | 785.16 | 0.21 | 0.72 |
| | p(#), psi(time ^q) | 11 | 785.25 | 0.20 | 0.92 |
| EABL | p(#), psi(*fire severity _{90x90} + *time ^q) | 5 | 306.98 | 0.95 | 0.95 |
| | p(#), psi(*fire severity _{90x90} + *time) | 4 | 313.18 | 0.04 | 1.00 |
| | p(#), psi(time ^q) | 4 | 318.89 | 0.00 | 1.00 |
| EATO | p(#), psi(*fire severity _{90x90} + *time ^q) | 7 | 806.79 | 0.94 | 0.94 |
| | p(#), psi(*fire severity _{90x90} + *time) | 6 | 812.73 | 0.05 | 0.99 |
| | p(#), psi(*fire severity _{90x90}) | 5 | 814.86 | 0.01 | 1.00 |
| EAWP | p(#), psi(fire severity _{90x90} + *time) | 5 | 565.08 | 0.31 | 0.31 |
| | p(#), psi(fire severity _{90x90} + time ^q) | 6 | 565.21 | 0.29 | 0.60 |
| | p(#), psi(*time) | 4 | 565.48 | 0.26 | 0.86 |
| GCFL ^{NR} | p(#), psi(*time ^q) | 13 | 265.20 | 0.59 | 0.59 |
| | p(#), psi(fire severity _{30x30} + *time ^q) | 14 | 267.49 | 0.22 | 0.81 |
| | p(#), psi(.) | 11 | 269.11 | 0.10 | 0.91 |
| HOWA | p(#), psi(*fire severity _{210x210} + time) | 13 | 864.29 | 0.48 | 0.48 |
| | p(#), psi(*fire severity _{210x210} + time ^q) | 14 | 866.20 | 0.18 | 0.66 |
| | p(#), psi(*fire severity _{210x210}) | 12 | 866.78 | 0.14 | 0.79 |
| INBU | p(#), psi(*fire severity _{30x30} + *time) | 12 | 791.23 | 0.73 | 0.73 |
| | p(#), psi(*fire severity _{30x30} + time ^q) | 13 | 793.23 | 0.27 | 1.00 |
| | p(#), psi(*time) | 11 | 802.71 | 0.00 | 1.00 |

Table 3.2 Continued

| Species Code | Model | nPars | AIC | AICwt | Cumulative Weight |
|--------------------|--|-------|--------|-------|-------------------|
| MODO ^{NR} | p(#), psi(*fire severity _{150x150} + *time ^q) | 15 | 603.25 | 0.71 | 0.71 |
| | p(#), psi(*fire severity _{150x150}) | 13 | 605.76 | 0.20 | 0.92 |
| | p(#), psi(*fire severity _{150x150} + time) | 14 | 607.76 | 0.07 | 0.99 |
| NOCA | p(#), psi(*fire severity _{30x30}) | 5 | 322.34 | 0.54 | 0.54 |
| | p(#), psi(fire severity _{30x30} + time) | 6 | 323.43 | 0.31 | 0.85 |
| | p(#), psi(*fire severity _{30x30} + time ^q) | 7 | 325.12 | 0.13 | 0.98 |
| NOFL ^{NR} | p(#), psi(*fire severity _{210x210}) | 10 | 744.81 | 0.55 | 0.55 |
| | p(#), psi(*fire severity _{210x210} + time) | 11 | 745.95 | 0.31 | 0.86 |
| | p(#), psi(*fire severity _{210x210} + time ^q) | 12 | 747.54 | 0.14 | 1.00 |
| NOPA | p(#), psi(*fire severity _{210x210} + *time) | 6 | 338.20 | 0.46 | 0.46 |
| | p(#), psi(*fire severity _{210x210} + time ^q) | 7 | 339.02 | 0.30 | 0.76 |
| | p(#), psi(*fire severity _{210x210}) | 5 | 341.02 | 0.11 | 0.87 |
| OVEN | p(#), psi(*fire severity _{90x90} + *time ^q) | 13 | 550.71 | 0.95 | 0.95 |
| | p(#), psi(*fire severity _{90x90} + *time) | 12 | 556.77 | 0.04 | 0.99 |
| | p(#), psi(*fire severity _{90x90}) | 11 | 560.14 | 0.01 | 1.00 |
| PIWA | p(#), psi(*fire severity _{210x210}) | 4 | 741.40 | 0.54 | 0.54 |
| | p(#), psi(*fire severity _{210x210} + time) | 5 | 742.98 | 0.25 | 0.79 |
| | p(#), psi(*fire severity _{210x210} + time ^q) | 6 | 744.72 | 0.10 | 0.89 |
| PRAW | p(#), psi(*fire severity _{150x150} + *time ^q) | 7 | 433.73 | 0.82 | 0.82 |
| | p(#), psi(*fire severity _{150x150} + *time) | 6 | 436.77 | 0.18 | 1.00 |
| | p(#), psi(*fire severity _{150x150}) | 5 | 457.80 | 0.00 | 1.00 |
| RHWO ^{NR} | p(#), psi(*time ^q) | 5 | 377.47 | 0.58 | 0.58 |
| | p(#), psi(fire severity _{30x30} + *time ^q) | 6 | 378.63 | 0.32 | 0.90 |
| | p(#), psi(fire severity _{30x30} + *time) | 5 | 381.43 | 0.08 | 0.98 |
| WEWA | p(#), psi(*fire severity _{30x30} + *time) | 11 | 620.44 | 0.62 | 0.62 |
| | p(#), psi(*fire severity _{30x30} + time ^q) | 12 | 622.18 | 0.26 | 0.88 |
| | p(#), psi(*fire severity _{30x30}) | 10 | 623.72 | 0.12 | 1.00 |
| YBCH | p(#), psi(*fire severity _{210x210} + *time ^q) | 6 | 402.67 | 0.98 | 0.98 |
| | p(#), psi(*fire severity _{210x210} + *time) | 5 | 410.18 | 0.02 | 1.00 |
| | p(#), psi(*fire severity _{210x210}) | 4 | 419.44 | 0.00 | 1.00 |
| YTWA | p(#), psi(fire severity _{210x210} + *time ^q) | 15 | 618.28 | 0.53 | 0.53 |
| | p(#), psi(*time ^q) | 14 | 619.10 | 0.35 | 0.88 |
| | p(#), psi(*fire severity _{210x210}) | 13 | 622.52 | 0.06 | 0.94 |

* This term has a significant effect (2*SE of the estimate does not overlap zero).

^q A quadratic term is included for this covariate.

See Table 3.1 for top detection covariates included in models for each species.

^{NR} To improve model performance, observations for this species were not restricted to detections within 50m of the observer.

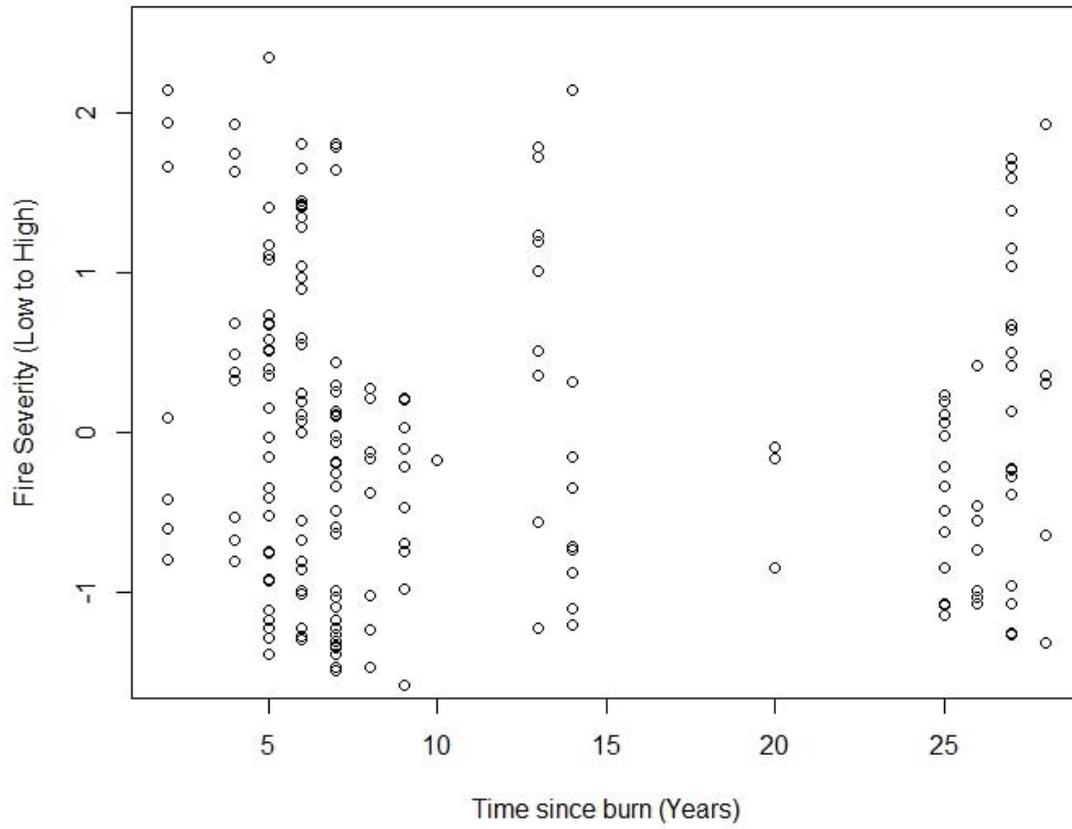


Figure 3.1. Distribution of sampling points across possible combinations of fire severity and time since burn.

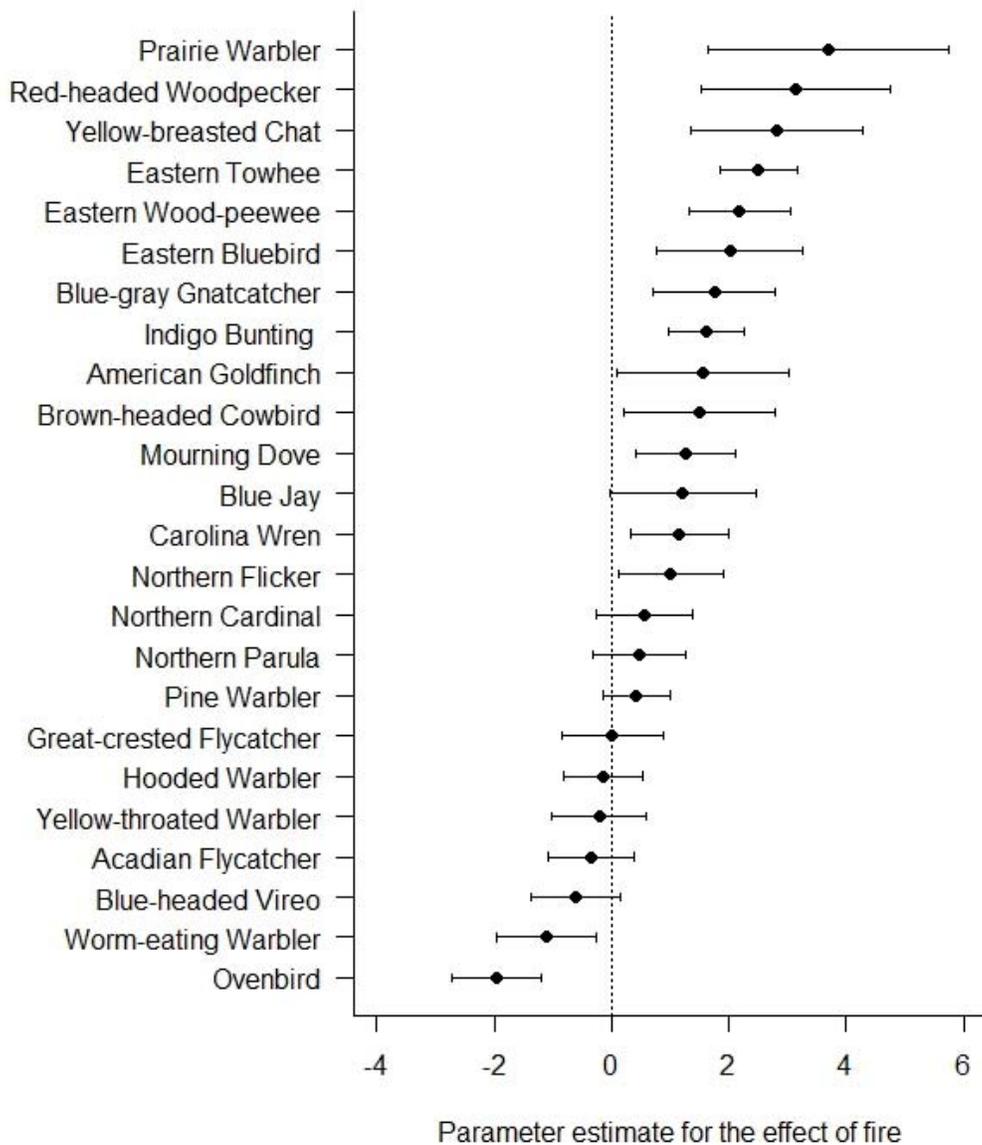
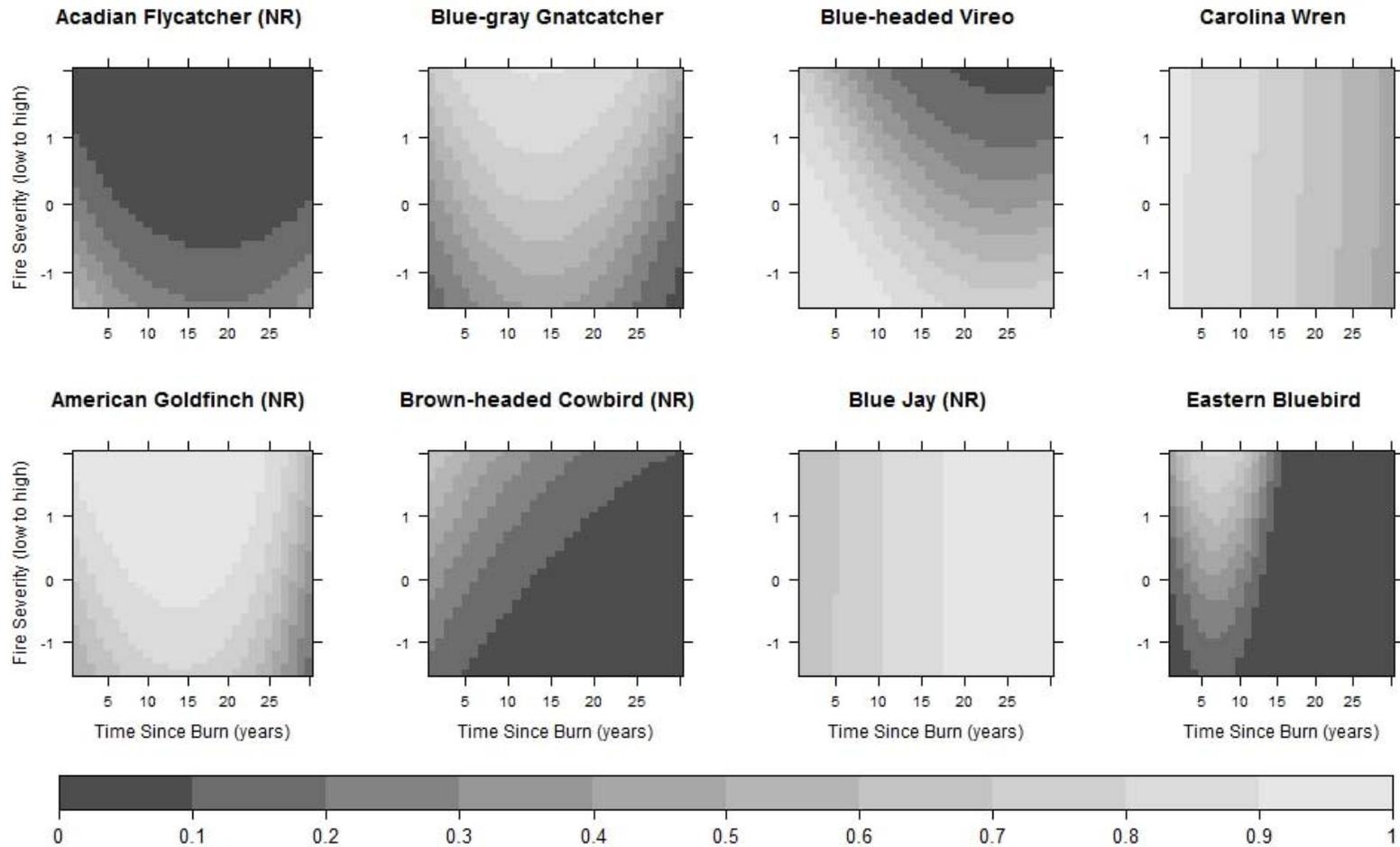
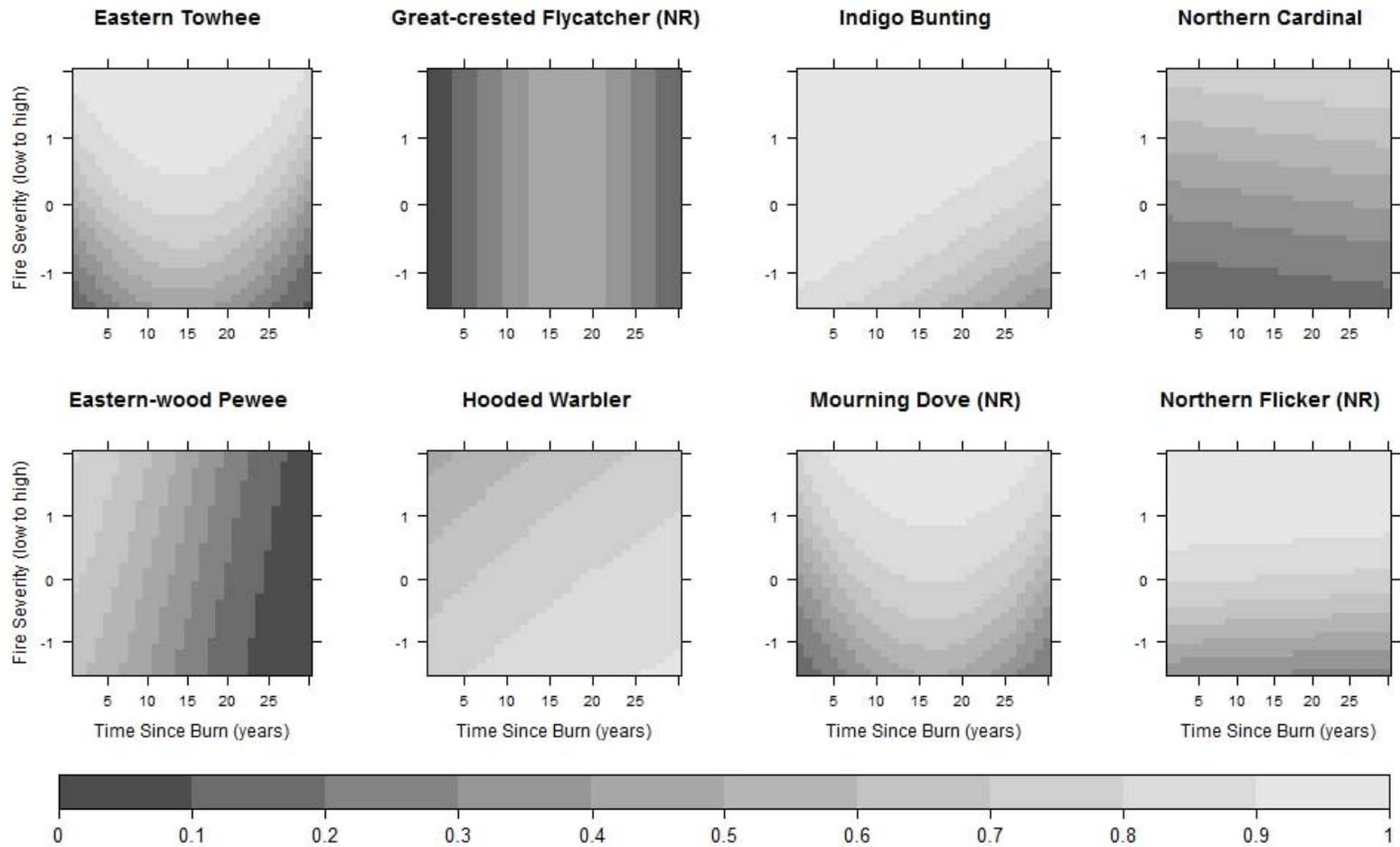
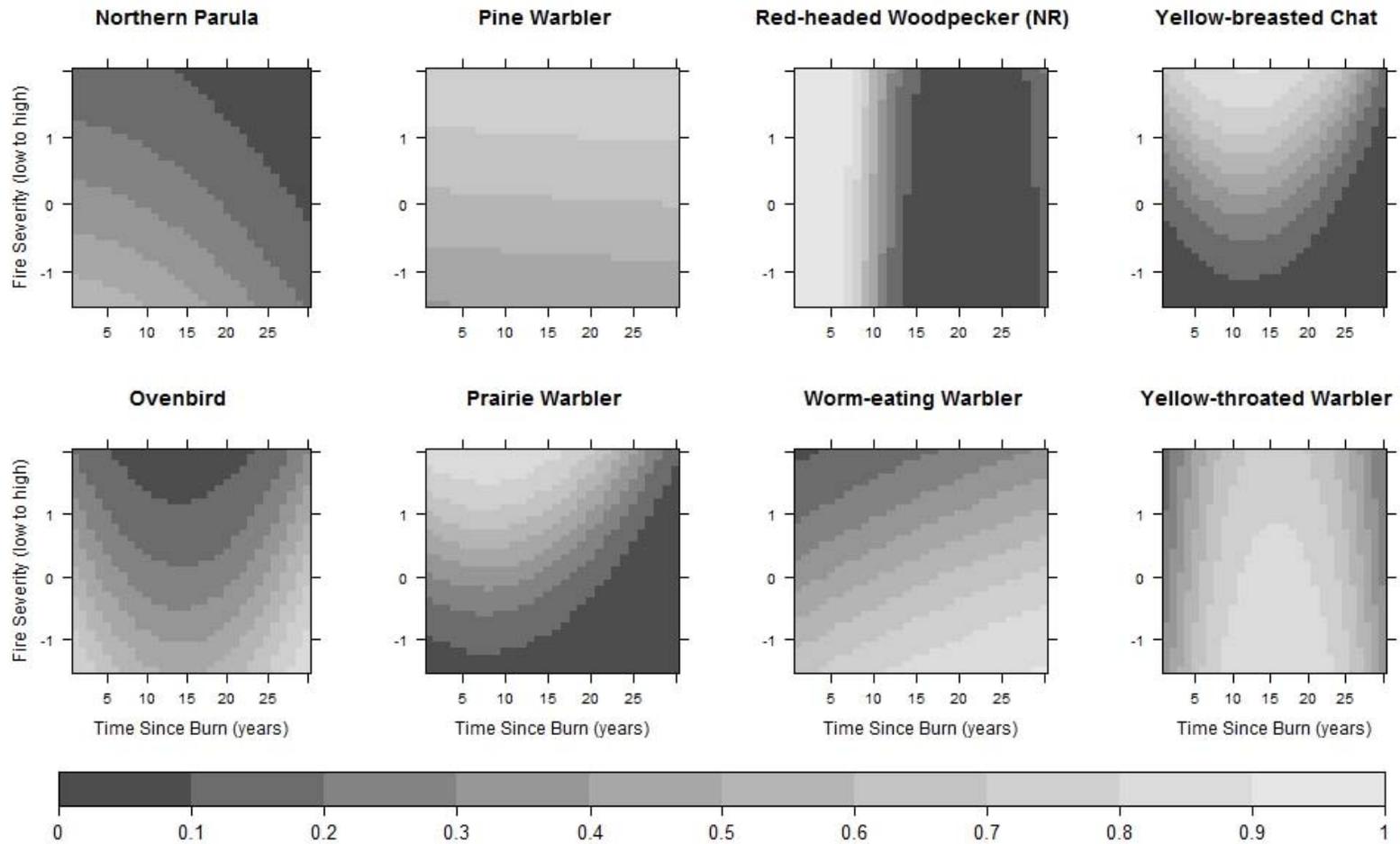


Figure 3.2. Parameter estimates and 2*SE for the effects of fire on species occurrence within Great Smoky Mountains National Park. Species with estimates entirely to the right of the dashed vertical line occurred more frequently in burned areas and those entirely to the left of the line occurred less frequently.

Figure 3.3. Patterns of occurrence as influenced by both fire severity and time since burn. Average predictions for all models contributing to 75% of the cumulative AIC weight. The probability of occurrence is greater in lighter areas.







APPENDICES

Appendix A

Landsat images used to calculate difference Normalized Burn Ratio fire severity indices within burned areas.

| Site Name | Fire Start Date | Sampling Points ¹ | Landsat Scene: pre fire (date) | Landsat Scene: post fire (date) |
|-------------------------|-----------------|------------------------------|--------------------------------------|--------------------------------------|
| Arbutus-Stony_2007 | 4/10/2007 | 30 | LT5019035000615210 (6/1/2006) | LT5019035000713910 (5/19/2007) |
| Beard Cane Gap_2011 | 9/14/2011 | 11 | LT50190352011182EDC00 (7/1/2011) | LE70190352012177EDC00 (6/25/2012) |
| Beard Cane_2008 | 4/24/2008 | 6 | LT50190352007139GNC01 (5/19/2007) | LT50190352008206GNC01 (7/24/2008) |
| Blacksmith_1999 | 8/19/1999 | 15 | LT70190351999189EDC00 (7/8/1999) | LT50190352000184XXX02 (7/2/2000) |
| Buck Shank_2007 | 5/24/2007 | 17 | LT5019035000618450 (7/3/2006) | LT5019035000817450 (6/22/2008) |
| Bunker Lead_1993 | 9/11/1993 | 3 | LT50190352004163GNC02 (7/31/1993) | LT50190351995186AAA01 (7/5/1995) |
| Calderwood_2010 | 9/10/2010 | 10 | LT50190352009176GNC02 (6/25/2009) | LT50190352011182EDC00 (7/1/2011) |
| Cattail II_2007 | 8/5/2007 | 6 | LT5019035000618450 (7/3/2006) | LT5019035000817450 (6/22/2008) |
| Chilly Spring Knob_2006 | 4/5/2006 | 16 | LT5019035000516510 (6/14/2005) | LT5019035000618410 (7/3/2006) |
| Grave Gap_2004 | 4/9/2004 | 5 | LT50190352002253LGS01 (9/10/2002) | LT70190352004267EDC02 (9/23/2004) |
| Gregory Ridge_2007 | 4/20/2007 | 5 | LT5019035000616810 (6/17/2006) | LT5019035000713910 (5/19/2007) |
| Hatcher Mountain_2005 | 4/8/2005 | 5 | LT50190352004163GNC02 (6/11/2004) | LT50190352006184GNC01 (7/3/2006) |

Appendix A Continued

| Site Name | Fire Start Date | Sampling Points ¹ | Landsat Scene: pre fire (date) | Landsat Scene: post fire (date) |
|----------------------|------------------------|-------------------------------------|---------------------------------------|--|
| Hickory_1986 | 4/3/1986 | 13 | LT50190351984140XXX01 (5/19/1984) | LT50190351986257XXX03 (9/14/1986) |
| Laurel Falls II_2009 | 4/27/2009 | 7 | LT50190352004163LGS01 (6/11/2004) | LT50190352010243EDC00 (8/31/2010) |
| Lynn Hollow_1999 | 6/9/1999 | 3 | LT50190351999149XXX01 (5/29/1999) | LT50190352000184XXX02 (7/2/2000) |
| Lynn Hollow_2014 | 3/21/2014 | 8 | LE70190352013227EDC00 (8/15/2013) | LC80190352014126LGN00 (5/6/2014) |
| Mitchell Branch_2008 | 7/3/2008 | 3 | LT50190352007139GNC01 (5/19/2007) | LT50190352008206GNC01 (7/24/2008) |
| Morton Bluff_1987 | 12/8/1987 | 4 | LT50190351987180XXX02 (6/29/1987) | LT50190351988167XXX04 (6/15/1988) |
| Ogle Hollow_2008 | 4/25/2008 | 4 | LT50190352008206GNC01 (5/19/2007) | LT50190352007139GNC01 (7/24/2008) |
| Pine Knot_1988 | 3/24/1988 | 3 | LT50190351987180XXX03 (6/29/1987) | LT50190351989137XXX03 (5/17/1989) |
| Rich_1987 | 11/14/1987 | 7 | LT50190351987180XXX02 (6/29/1987) | LT50190351988167XXX04 (6/15/1988) |
| Round Top_1987 | 11/15/1987 | 4 | LT50190351987180XXX02 (6/29/1987) | LT50190351989137XXX03 (5/17/1989) |
| Sharp_2001 | 11/12/2001 | 8 | LT50190352001154XXX02 (6/3/2001) | LT50190352003160LGS01 (6/9/2003) |
| Shop_1988 | 3/23/1988 | 10 | LT50190351987180XXX02 (6/29/1987) | LT50190351989137XXX03 (5/17/1989) |
| Slaty_1987 | 8/24/1987 | 3 | LT50190351987180XXX02 (6/29/1987) | LT50190351988167XXX04 (6/15/1988) |
| Tabcat II_2003 | 4/3/2003 | 6 | LT5019035000115410 (6/3/2001) | LT5019035000316010 (6/9/2003) |

Appendix A Continued

| Site Name | Fire Start Date | Sampling Points ¹ | Landsat Scene: pre fire (date) | Landsat Scene: post fire (date) |
|--------------------|------------------------|-------------------------------------|---------------------------------------|--|
| Tunnel_2001 | 3/26/2001 | 11 | LT50190352000136XXX00 (5/15/2000) | LT50190352001154XXX02 (6/3/2001) |
| Wear Cove Gap_2009 | 4/20/2009 | 5 | LT50190352008206GNC01 (7/24/2008) | LE70190352009152EDC00 (6/01/2009) |

¹Sampling points within overlapping fires are included in the most recent fire total only.

Appendix B

Field-derived fire severity index

Fire Severity Index

Is Fire the source of the disturbance?

- **Fire: Scorch:** Charring, absence/reduced duff layer, soil discoloration.
- **Pine Beetle:** Dead trees will be pines. Often occurs in isolated patches. Hardwoods will often regenerate in these areas. Leaf and Duff layers not reduced.
- **Blowdown:** Can occur in isolated patches or large tracts (tornado). Hardwoods will often regenerate in these areas. Leaf and Duff layers not reduced. Trees of all species may be snapped or blown over/uprooted.

Fire severity within a 50 meter radius should be based on agreement of two or more of the criteria below.

Consider Each Category (they may suggest different severity)

| | Unburned | Low | Mod-Low | Mod-Hi | High |
|-----------------------------------|----------|------|---------|---------|--------|
| Percent Overstory Mortality | 0 | 0-10 | 10-30 | 30-60 | >60 |
| Percent Understory Mortality(BB*) | 0 | 5-25 | 25-50 | 50-75 | 75-100 |
| Duff-depth | >6 | >6 | 4-6cm | 2-4cm | <2cm |
| Char-Height (Hardwoods only) | 0 | <0.3 | 0.3-1.0 | 1.0-3.0 | >3.0 |

| Class | Severity | Description |
|-------|---------------|---|
| 0 | Unburned | No evidence of fire. |
| 1 | Low Severity | Fewer than 10% of understory trees killed. Charring below 0.3m in height on hardwoods. Duff and coarse woody debris intact. |
| 2 | Moderate-Low | Less than 30% of overstory trees killed. Some understory tree mortality. Charring 0.3-1m on hardwoods. Duff and coarse woody debris charred, but not deeply altered. |
| 3 | Moderate-High | 30-60% of overstory trees killed along with 50-75% of understory trees. Char height consistently reaches greater than 1.0m on hardwoods. Depending on time-since-burned, duff and coarse woody debris are deeply charred or otherwise reduced. Pine regeneration is common may be overstory gaps. |
| 4 | High Severity | More than 60% of overstory trees killed along with most or all understory trees. Evidence of stand replacement fire. Depending on time-since burned, duff and coarse woody debris may be largely consumed. Numerous or large patches of exposed soil. Extensive pine regeneration. |

Notes:

- Char will wash away with time.
- Due to differences in vegetation severity and substrate severity within a fire, overstory mortality within a given severity class may be higher than indicated above, while duff and coarse woody debris are not deeply affected. For example, an intense head fire may kill 75% of the overstory, but may not remove a tremendous amount of duff. The result would be stand replacement, but the regeneration would be hardwoods instead of yellow pine and herbs.
- Multiple fire scars and few dead trees indicate fire severity of 2 or 3. Hardwoods will scar more easily than pines.
- For burns greater than 15 years old, age structure and species composition can give clues to severity of past burns though interpretations will vary widely. Even aged Virginia pine stands with charring on logs and stumps represent historic high severity fire.
- Maples and Black-gum are the most susceptible to fire.

*BB – Cover classes using Braun-Blanquet (1928).

Appendix C

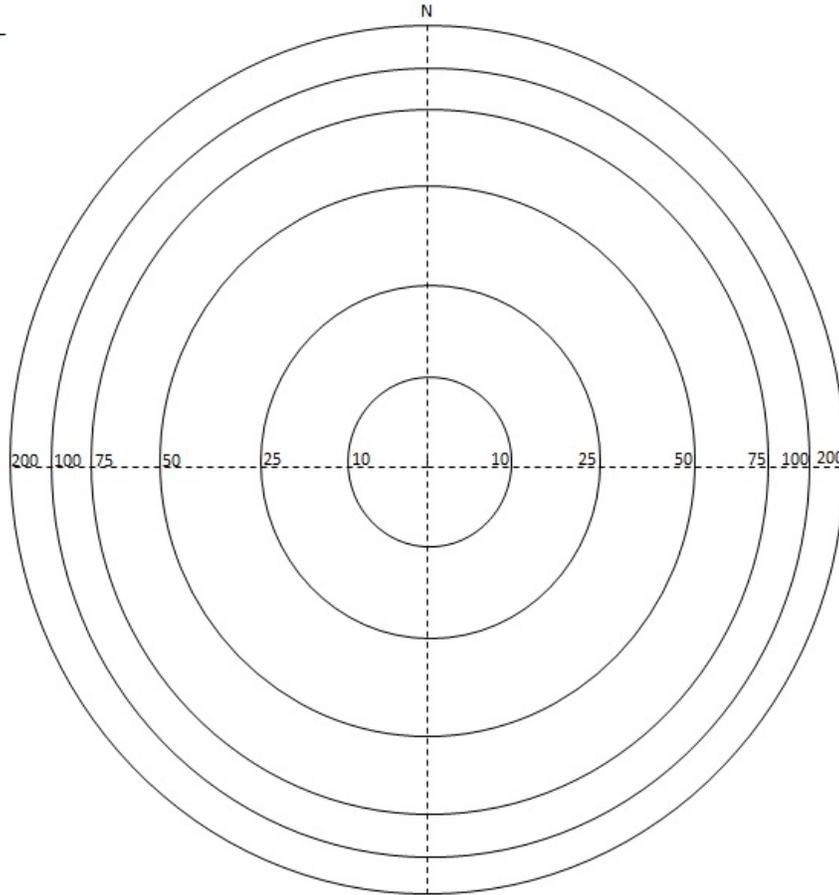
Point count datasheet used for mapping individual bird locations during each visit to a survey point.

Point-Count Data Sheet

Tag Number _____ Type _____ Observer _____ Date _____
 Cloud Cover _____ Wind _____ Temperature _____

CtStartTime _____

| | |
|------|-------|
| 5 | _____ |
| 10 | _____ |
| 15 | _____ |
| 20 | _____ |
| 25 | _____ |
| 30 | _____ |
| 35 | _____ |
| 40 | _____ |
| 45 | _____ |
| 50 | _____ |
| 55 | _____ |
| 60 | _____ |
| 65 | _____ |
| 70 | _____ |
| 75 | _____ |
| 80 | _____ |
| 85 | _____ |
| 90 | _____ |
| 95 | _____ |
| 100 | _____ |
| >100 | _____ |



Notes:

*Point counts should be done between sunrise and 10:00 am during the morning chorus.

* Surveys should not be done in rain or when wind exceeds 15 miles per hour (Beaufort Land Scale 4+).

Appendix D

Avian species detected within Great Smoky Mountains National Park during point count surveys along with their scientific name and four letter bird codes used by the American Ornithologist Union 54th supplement.

| Common Name | Species | Species Code |
|------------------------------|----------------------------------|---------------------|
| Acadian Flycatcher | <i>Empidonax vireescens</i> | ACFL |
| American Crow | <i>Corvus brachyrhynchos</i> | AMCR |
| American Goldfinch | <i>Carduelis tristis</i> | AMGO |
| American Redstart | <i>Setophaga ruticilla</i> | AMRE |
| Barn Swallow | <i>Hirundo rustica</i> | BARS |
| Barred Owl | <i>Strix varia</i> | BADO |
| Belted Kingfisher | <i>Megaceryle alcyon</i> | BEKI |
| Black-and-white Warbler | <i>Mniotilta varia</i> | BAWW |
| Black-billed Cuckoo | <i>Coccyzus erythrophthalmus</i> | BBCU |
| Black-throated Blue Warbler | <i>Setophaga caerulescens</i> | BTBW |
| Black-throated Green Warbler | <i>Setophaga virens</i> | BTNW |
| Blue-gray Gnatcatcher | <i>Poliophtila caerulea</i> | BGGN |
| Blue-headed Vireo | <i>Vireo solitarius</i> | BHVI |
| Blue Jay | <i>Cyanocitta cristata</i> | BLJA |
| Broad-winged Hawk | <i>Buteo platypterus</i> | BWHA |
| Brown-headed Cowbird | <i>Molothrus ater</i> | BHCO |
| Brown Creeper | <i>Certhia americana</i> | BRCR |
| Brown Thrasher | <i>Toxostoma rufum</i> | BRTH |
| Canada Goose | <i>Branta canadensis</i> | CANG |
| Carolina Chickadee | <i>Poecile carolinensis</i> | CACH |
| Carolina Wren | <i>Thryothorus ludovicianus</i> | CARW |
| Cedar Waxwing | <i>Bombycilla cedrorum</i> | CEDW |
| Chimney Swift | <i>Chaetura pelagica</i> | CHSW |
| Chipping Sparrow | <i>Spizella passerina</i> | CHSP |
| Common Grackle | <i>Quiscalus quiscula</i> | COGR |
| Common Raven | <i>Corvus corax</i> | CORA |
| Cooper's Hawk | <i>Accipiter cooperii</i> | COHA |
| Downy Woodpecker | <i>Picoides pubescens</i> | DOWO |
| Eastern Bluebird | <i>Sialia sialis</i> | EABL |
| Eastern Meadowlark | <i>Sturnella magna</i> | EAME |
| Eastern Phoebe | <i>Sayornis phoebe</i> | EAPH |
| Eastern Towhee | <i>Pipilo erythrophthalmus</i> | EATO |
| Eastern Wood-pewee | <i>Contopus virens</i> | EAWP |
| Field Sparrow | <i>Spizella pusilla</i> | FISP |
| Gray Catbird | <i>Dumetella carolinensis</i> | GRCA |

Appendix D Continued

| Common Name | Species | Species Code |
|-------------------------------|-----------------------------------|---------------------|
| Great Blue Heron | <i>Ardea herodias</i> | GBHE |
| Great Crested Flycatcher | <i>Myiarchus crinitus</i> | GCFL |
| Hairy Woodpecker | <i>Picoides villosus</i> | HAWO |
| Hermit Thrush | <i>Catharus guttatus</i> | HETH |
| Hooded Warbler | <i>Wilsonia citrina</i> | HOWA |
| Indigo Bunting | <i>Passerina cyanea</i> | INBU |
| Kentucky Warbler | <i>Geothlypis formosa</i> | KEWA |
| Louisiana Waterthrush | <i>Parkesia motacilla</i> | LOWA |
| Mourning Dove | <i>Zenaida macroura</i> | MODO |
| Northern Bobwhite | <i>Colinus virginianus</i> | NOBO |
| Northern Cardinal | <i>Cardinalis cardinalis</i> | NOCA |
| Northern Flicker | <i>Colaptes auratus</i> | NOFL |
| Northern Parula | <i>Parula americana</i> | NOPA |
| Osprey | <i>Pandion haliaetus</i> | OSPR |
| Ovenbird | <i>Seiurus aurocapilla</i> | OVEN |
| Pileated Woodpecker | <i>Dryocopus pileatus</i> | PIWO |
| Pine Siskin | <i>Carduelis pinus</i> | PISI |
| Pine Warbler | <i>Setophaga pinus</i> | PIWA |
| Prairie Warbler | <i>Setophaga discolor</i> | PRAW |
| Red-bellied Woodpecker | <i>Melanerpes carolinus</i> | RBWO |
| Red-breasted Nuthatch | <i>Sitta canadensis</i> | RBNU |
| Red-eyed Vireo | <i>Vireo olivaceus</i> | REVI |
| Red-headed Woodpecker | <i>Melanerpes erythrocephalus</i> | RHOW |
| Red-shouldered Hawk | <i>Buteo lineatus</i> | RSHA |
| Red-tailed Hawk | <i>Buteo jamaicensis</i> | RTHA |
| Red Crossbill | <i>Loxia curvirostra</i> | RECR |
| Rose-breasted Grosbeak | <i>Pheucticus ludovicianus</i> | RBGR |
| Northern Rough-winged Swallow | <i>Stelgidopteryx serripennis</i> | NRWS |
| Ruby-throated Hummingbird | <i>Archilochus colubris</i> | RTHU |
| Ruffed Grouse | <i>Bonasa umbellus</i> | RUGR |
| Scarlet Tanager | <i>Piranga olivacea</i> | SCTA |
| Swainson's Thrush | <i>Catharus ustulatus</i> | SWTH |
| Swainson's Warbler | <i>Limnothlypis swainsonii</i> | SWWA |
| Tufted Titmouse | <i>Parus bicolor</i> | TUTI |
| Turkey Vulture | <i>Cathartes aura</i> | TUVU |
| Veery | <i>Catharus fuscescens</i> | VEER |
| White-breasted Nuthatch | <i>Sitta carolinensis</i> | WBNU |

Appendix D Continued

| Common Name | Species | Species Code |
|-------------------------|-------------------------------|---------------------|
| White-eyed Vireo | <i>Vireo griseus</i> | WEVI |
| Wild Turkey | <i>Meleagris gallopavo</i> | WITU |
| Wood Thrush | <i>Hylocichla mustelina</i> | WOTH |
| Worm-eating Warbler | <i>Helmitheros vermivorus</i> | WEWA |
| Yellow-billed Cuckoo | <i>Coccyzus americanus</i> | YBCU |
| Yellow-breasted Chat | <i>Icteria virens</i> | YBCH |
| Yellow-rumped Warbler | <i>Setophaga coronata</i> | YRWA |
| Yellow-throated Vireo | <i>Vireo flavifrons</i> | YTVI |
| Yellow-throated Warbler | <i>Setophaga dominica</i> | YTWA |

Appendix E

Species occurrence predictions and 95% confidence intervals for points sampled within Great Smoky Mountains National Park. Model averaged predictions for models that incorporate the influence of fire severity and time since burn. Averaged models include those that contribute to 75% of the cumulative AIC weight (Chapter 3).

