ABSTRACT

ARCARO, ZACHARY EMERSON. Evaluating the Use of LIDAR Multiple Return Data to Characterize Forest Structure in Croatan National Forest. (Under the direction of Dr. Hugh A. Devine).

Vegetation structure is known to be a predictor of animal habitat suitability, but characterizing structure is generally limited to field plot sampling. The goal of this project was to evaluate the use of LIDAR (LIght Detection And Ranging) in characterizing forest structure in two forest communities of the Southeastern U.S., specifically pond pine \((Pinus serotina)\) and longleaf pine \((Pinus palustris)\) woodlands. The LIDAR data was used to create a surface of vegetation heights using a canopy height model (CHM). The CHM was used to locate treetops for tree density and height estimates, and to estimate the percent cover in five forest strata. The LIDAR derived estimations were compared to data collected in field plots within nine pond pine and eleven longleaf pine dominated stands on the Croatan National Forest. Two habitat assessment case studies were done to explore the potential for the LIDAR derived CHM data in that arena.

Local maxima (peaks) within areas assumed to represent single canopies were identified in order to locate treetops within the CHM. A generalized height to crown width equation developed for southern yellow pine trees was used as the basis for a variable sized search window used to find individual treetops. Once individual tree locations were modeled, tree density estimates (trees per hectare) were calculated and then compared to density estimates based on field data. Higher accuracies were achieved among the longleaf pine stands with six of the eleven (55%) plots having statistically insignificant differences between the estimates when compared using the Wilcoxon non-parametric test. Three of six (50%) pond
pine stands also had insignificant differences in estimated density with the field based
estimates being consistently higher than the LIDAR estimates. The height comparisons
between trees measured in the field and those identified from the LIDAR data revealed that
six of the eleven longleaf pine stands (55%) and five of eight pond pine stands (63%) had
insignificant differences in tree height.

Vertical structure for each of the plots was characterized using percent cover estimates in five
forest strata, including canopy (>19m), subcanopy 1 (14-19m), subcanopy 2 (9-14m), shrub
layer (4-9m) and herbaceous layer (<4m). A comparison of the structure characterization
based on field and LIDAR data was made using Wilcoxon tests. These tests revealed that the
LIDAR data characterized the strata within the pond pine plots well but largely failed within
the longleaf pine plots. It was also concluded from the results that within the pond pine plots
the characterization was generally more accurate in the upper strata.

The characterization of forest structure was designed to provide a demonstration of habitat
modeling applications using LIDAR data. Two indigenous bird species, the loggerhead
shrike (Lanius ludovicianus) and Swainson’s warbler (Limnothlypis swainsonii) were
selected as case studies. The literature suggests that these species strongly respond to
structural components of vegetation when selecting territory used for nesting and feeding.
Our goal was to explore how the data could be used to model structural features known to be
important to loggerhead shrike (isolated perches) and Swainson’s warbler (shrub thickets).
The goal of the case studies was not to directly test the habitat quality based on
characterizing the structure, but to provide a framework species modelers could use to
incorporate LIDAR derived structure variables into their models. Based on the results of the analysis and the products of the habitat characterizations, the use of LIDAR to predict forest structure for use with habitat modeling appears promising.
Evaluating the Use of LIDAR Multiple Return Data to Characterize Forest Structure in Croatan National Forest.

by
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DEDICATION

This work is dedicated to my grandmother, Audrey Jean Besant, whose wisdom, grace and giving spirit enhanced my life beyond measure.
BIOGRAPHY

I attended the Ohio State University, where I majored in civil engineering with a specialization in remote sensing. After being introduced to the world of aerial photography, satellite imaging and geographic information science, I knew I had found my professional calling. I was drawn in by the challenging nature of the work and the ability to look at the environment from unique perspectives using diverse and developing technologies. While at Ohio State University I enjoyed playing ultimate Frisbee, I earned a black belt in Tang Soo Do and I met my future wife, Sera.

A week after graduation Sera and I were married and then later that summer we left for two years in Namibia where we served as Peace Corps volunteers. After being trained in the local language and culture we were placed at a secondary school in the rural northern part of the country. I taught math, science and computer skills to eager students and learned to feel at ease in front of the classroom. We dearly enjoyed our time in Namibia and as the end of our service grew near we decided extend our journey abroad.

After two brief months back in the States we left home again, this time for China, where we taught English at private language school. Our students and Chinese coworkers became fast friends who helped us adapt to their fascinating culture.

While in China, I decided to return to my chosen field and applied to the graduate school at North Carolina State University. Although I was a bit nervous about being a student again, I was quickly put at ease by Dr. Hugh Devine and the welcoming crowd in the Center for Earth Observation as well as by my advisor Dr. Alexa McKerrow. The experiences I have been granted as a graduate student at NCSU will be cherished as I move on to the challenges ahead.
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1. Introduction

Since the 1970’s, airborne Light Detection and Ranging (LIDAR) has been successfully applied to research in a diversity of fields (Hyyppä et al. 2004). The earliest uses include bathymetric and hydrographic surveys for mapping submerged coastal areas (Wehr and Lohr 1999). Other uses include flood risk modeling, mapping of transportation and electrical transmission corridors, measurement of snow and ice covered areas and terrain modeling (Wehr and Lohr 1999, Lim et al. 2003). More recent applications of LIDAR have included locating and mapping buildings in urban environments (Lichti et al. 2002) and creating highly accurate hydrologic maps (Colson 2007).

LIDAR is also now emerging as an important technology for the characterization of vegetation structure in forestry and ecology. Traditional remote sensing techniques, while useful in characterizing forest composition and monitoring vegetation health, are not able to provide information about the vertical vegetation structure (Wang et al. 2004, Song and Woodcock 2003, Edwards et al. 2002). The ability to reliably and accurately map vertical structure over large areas could greatly benefit those modeling forest wildlife (Edwards et al. 2002). LIDAR technology has tremendous potential for assessing this important characteristic in vegetated areas (MacArthur 1964, Wynne 2004).
2. **Objectives**

The objective of this study was to evaluate the use of LIDAR data to characterize the vertical canopy structure of longleaf pine (*Pinus palustris*) and pond pine (*Pinus serotina*) forested stands within the Croatan National Forest (CNF). Specifically, we wanted to quantify useful stand-level and tree-level metrics, as well as to characterize both canopy and subcanopy vegetation structure. For individual trees, the goal was to find the locations and heights in order to quantify forest density (trees per hectare) and height distribution. The characterization of whole canopy vegetation was designed to be useful for wildlife habitat modeling and included creating maps of vegetation height and characterized forest structure as well as height distribution. In order to select structure variables that would be useful for habitat modeling, two indigenous bird species, the loggerhead shrike (*Lanius ludovicianus*) and Swainson’s warbler (*Limnothlypis swainsonii*) were selected as case studies.

3. **Background**

3.1. **LIDAR**

3.1.1 **Components**

LIDAR, also known airborne laser scanning, is a remote sensing technique that uses precise spatial location and the two way travel time of laser light pulses to produce a highly accurate representation of the targeted ground area (Means et al. 2000). The main components of a LIDAR system are the laser scanner, a GPS receiver, an inertial monitoring unit (IMU) and a control unit (Reutebuch et al. 2005). LIDAR is an “active” remote sensing technique,
meaning the laser scanner transmits the original signal and receives the reflected signal
(Wehr and Lohr 1999). The laser scanner is able to locate return points within the targeted
area by combining the angle of the reflection and the time elapsed between sending and
receiving the signal.

The information collected by the laser scanner is georeferenced with position and orientation
information from the GPS and IMU. The GPS system, with differential correction, provides
the spatial location of the platform while the IMU provides instantaneous information about
the orientation (pitch, yaw and roll) of the aircraft (Wehr and Lohr 1999). By combining
these data, a precise location can be determined for each laser return. The final component of
a LIDAR system is the control unit, which is necessary to set the parameters of and monitor
the system during operation.

The output from a LIDAR sensor is a “cloud” of irregularly spaced points, each of which is
referenced by three dimensional (XYZ) coordinates. The point density is determined by the
type of sensor, as well as the altitude of the aircraft. Common point spacing for LIDAR
systems ranges from less than one point every ten meters to multiple points per square meter
(Raber et al. 2007). LIDAR sensors typically use lasers with wavelengths between 800 nm
and 1000 nm (Wehr and Lohr 1999). This is in the near infrared part of the spectrum and
provides minimal absorbance by the ground and vegetation. Also, as this part of the optical
spectrum and exposure can damage eyesight, LIDAR is generally restricted to above 500 m
in altitude for safety reasons (Wulder and Franklin 2003, Wehr and Lohr 1999). LIDAR
**sensors are typically operated from aircraft, although both space and ground based systems have also been created (Parker et al. 2004, Vierling et al. 2008).**

### 3.1.2 Variations

According to Lefsky et al. (2002) “Key differences among LIDAR sensors are related to the laser’s wavelength, power, pulse duration and repetition rate, beam size and divergence angle, the specifics of the scanning mechanism (if any) and the information recorded for each reflected pulse.” This large set of variables has enabled LIDAR systems to be quite diverse; however, LIDAR systems for use in terrestrial applications can generally be divided into two main types: waveform and discrete return (Bradbury et al. 2005).

Waveform LIDAR records the amplitude of the return pulses in a continuous fashion (Harding et al. 2001). This type of LIDAR is often referred to as “large footprint” because the size of the laser beam as it reaches the ground (generally 5-70 m) is large compared to discreet return, which generally has a small footprint (less than 1 cm to tens of cm; Dubayah and Drake, 2000). Waveform LIDAR has been used successfully in determining many forest characteristics such as canopy height and structure (Goetz et al. 2007, Lefsky 1997, Harding et al. 2001). While it is particularly useful for concisely characterizing large vegetated areas, it cannot be used to characterize vegetation at the plot or tree level due to a lower spatial resolution. Discrete return LIDAR devices record only the heights of major peaks within the
return signal, with these peaks representing discrete objects (Lefsky et al. 2002). The number of peaks recorded per pulse can vary from system to system. Discrete return LIDAR is useful for both characterizing vegetation canopy characteristics as well as mapping the ground (Flood and Gutelis 1997). The extensive use of discrete return LIDAR by the surveying and photogrammetry communities has led to this technology being more widely available than waveform LIDAR (Lefsky et al. 2002). Data from a discrete return LIDAR sensor were used this thesis.

3.1.3 LIDAR in Forest Applications

LIDAR has a long history of applications related to forest measurement with the earliest research dating back to around 1980 (Wulder and Franklin 2003, Hyyppa et al. 2004). Examples of this early work include research done by Aldred and Bonner (1985) demonstrating the applicability of LIDAR for estimating forest metrics such as stand heights and crown cover density as well as the successful efforts of Maclean and Krabill (1986) to create predictive models of timber volume. These early studies were carried out without the aid of modern GPS technology and employed profiling LIDAR (Wulder and Franklin 2003). Profiling LIDAR systems lack a scanning mechanism and therefore scan a single trace across the study area as the aircraft is in flight. While this profiling method performed well, the scanning methods now used allow for more precise estimates to be made as wide areas of forest may be directly measured.

Advances in technique and the introduction of new technologies, such GPS and sophisticated
computer software, have enabled the improvement and expansion of the use of LIDAR in forest mensuration in recent years (Næsset 1997, St-Ogne and Renaud 2001, Næsset 2002, Goodwin et al. 2006). The majority of this work has been oriented towards providing inventory information for forestry operations. Estimating forest canopy fuel parameters for fire behavior models has been another important application (Anderson et al. 2005). In addition to methods that are based on average canopy heights and are used for stand-wide estimations of forest parameters, much work has been put into identifying and measuring individual trees. Work carried out by Hyyppä and Hyyppä, (2001), and Persson et al. (2002), has shown that tree position and height, crown diameter and volume can be accurately estimated using small footprint LIDAR. The goal for this type of research has largely been to improve the accuracy and quality of inventory assessments. Efforts at individual tree delineation have been largely successful, although Koch et al. (2006) have noted that trees in mixed forests with both deciduous and evergreen trees tend to be more difficult to isolate.

### 3.1.4 LIDAR in Wildlife Applications

In recent years the exploration of LIDAR as a tool for characterizing vegetation structure for use in habitat modeling has been increasing and the consensus seems to be that it is a potent tool (Hill et al. 2003, Hinsley et al. 2002, Nelson et al. 2005, Goetz et al. 2007). Vierling et al. (2008) note that LIDAR can be employed both as a *predictive* tool used to help create distribution models based on what is known about species’ preferences or as an *exploratory* tool used to better understand the selection criteria used by species of known distributions.
As an example of the predictive power of LIDAR Vierling et al. (2008) point to research on the Delmarva fox squirrel (*Sciurus niger cinereus*; Nelson et al. 2005). In this study it was known that the squirrel was endemic to older forested stands with closed-canopies and open understories (Nelson et al. 2005). Using this knowledge they used LIDAR analysis to identify and locate potential habitat. The specific criteria they used included an average canopy height of over 20m, average canopy closure of at least 80%, as well as an assessment of forest contiguity and a lack of impervious surfaces or open water. Their LIDAR analysis identified 53 potential sites, thirty-two of which were visited and assessed; out of these thirty-two assessed sites, 78% were confirmed as suitable habitat according to an established habitat model (Dueser et al. 1988). The authors concluded that the use of LIDAR had been successful in identifying potential habitat and that similar methods could be used in the future to evaluate large areas.

Another example in which LIDAR has been used to identify potential habitat is research done by Leyva et al. (2002) for the black-capped vireo (*Vireo atricapilla*) on the grounds of Fort Hood Military Reservation. The authors noted that this small migrant bird prefers shrubland areas with dense, irregular thickets and identified three different habitat formations common in their study area. The three habitat formations were “donut” habitat formed by tanks maneuvering around trees, “linear” habitat found along roads and “classical” habitat with non-circular areas containing vegetation of the type and structure normally associated with the species.
The LIDAR analysis carried out by the researchers involved separating the LIDAR returns into height classes and identified potential habitat based on criteria derived from observations made within the study area. Field evaluations, including measuring vegetation within different strata and recording black-capped vireo presence, were then carried out on the potential habitat sites. Classification accuracies of 58% for the donut habitat, 8% for the linear habitat and 44% for the classical habitat were reported. These accuracy assessments were based on the vegetation measurements made in the field. The authors identified several sources of error, most of which they concluded could be resolved with refined selection criteria, such as the inclusion of a fourth pre-defined habitat type.

Efforts to use LIDAR as an exploratory tool include work done by Hinsley et al. (2002, 2006). In these studies evidence was found that the survival rate of two species of tit (Parus sp.) was related to the height of the vegetation surrounding the nestboxes. For blue tits (P. caeruleus) there was a positive relationship between mean chick mass and taller vegetation, while for great tits (P. major) this relationship was negative.

3.1.5 Comparison with other Remote Sensing Technology

Within the field of remote sensing LIDAR has taken its place alongside many other technologies including satellite and radar imagery and aerial photography. The unique qualities of LIDAR derived data, most notably the ability to create highly accurate three dimensional representations over wide areas, have made it a welcome addition to the toolbox of remote sensing scientists. LIDAR has many advantages over other techniques and in
some cases has substantially supplanted their use (Baltsavias 1999). The more common situation, however, is that LIDAR is used in addition to, or in concert with, more established methods.

Compared with passive optical sensors (POS) used for aerial photography and satellite imagery, LIDAR has the advantage of being able to penetrate the forest canopy (Weishampel et al. 2000). This permits LIDAR to provide a richer picture of forest structure and allows it to be especially useful for forestry and wildlife applications (Hyyppä et al. 2000, Lefsky et al. 2001). Goetz et al. (2007) found that LIDAR metrics were consistently better predictors of habitat than traditionally remotely sensed variables such as canopy cover. LIDAR, however, cannot provide the spectral response of POS imagery; therefore, although LIDAR technology may replace other remote sensing technologies for some purposes, the relationship on the whole is complementary (Baltsavias 1999). For example, work done by Hill and Thompson (2005) has explored the use of integrating LIDAR and spectral data for estimating forest parameters. In that study, data from a hyper-spectral optical sensor, useful for determining dominant species, was combined with canopy height models (CHM) derived from LIDAR. The authors were able to create “an ecologically meaningful thematic map” using unsupervised classification with the integrated information (Hill and Thompson 2005). This type of fusion has a lot of potential; indeed, the full integration of POS and LIDAR sensors is seen as a revolutionary possibility (Ackermann 1999).

Radio Detection and Ranging (RADAR) sensors are another remote sensing system that can
penetrate the forest canopy and therefore be used to characterize forest structure.

Interferometric Synthetic Aperture Radar (InSAR) technology in particular has been studied for use with vegetation and, unlike LIDAR or POS, it has the ability to penetrate cloud cover (Wulder and Franklin 2003, Imhoff et al. 1997). InSAR has however proven in many studies to be less accurate for vegetation characterization purposes when compared to LIDAR (Norheim et al. 2002, Hyde et al. 2006, Goetz et al. 2007). Despite the lower accuracy, Ackermann (1999) notes that digital terrain map (DTM) creation by InSAR at some scale and accuracy ranges is more appropriate based on cost considerations. Also, in locations with continuous cloud cover or in time sensitive situations such as forest fires with high smoke levels, InSAR might be the only choice. Investigations of LIDAR and InSAR fusion have been made as well. Slatton et al. (2001) concluded that estimation of vegetation height was improved with the combined data. However, more recent research done by Nelson et al. (2007) indicates that for the creation of forest volume estimates, adding InSAR data to LIDAR data does little to improve the results.

3.2 Case Studies

Two bird species were chosen as case studies for this project: the loggerhead shrike (Lanius ludovicianus) and Swainson’s warbler (Limnothlypis swainsonii). This was done in order to demonstrate the potential use of LIDAR derived data for characterizing vegetation structure known to be important in predicting wildlife habitat. These species are native to North
Carolina’s coastal plain and have been chosen because important components of their habitat requirements are related to the vertical forest structure. The Croatan National Forest represents an important habitat area for these species, especially as development in the Eastern portion of the state encroaches on other suitable areas.

3.2.1 Loggerhead Shrike

The loggerhead shrike (LOSH) is a small bird about the size of a robin that hunts insects and small animals like a hawk (Telfer 1993). In addition to the raptor-like hunting style, the species is notable for its unique habit of impaling prey on thorns before eating (Yosef 1996). LOSH have been declining in number in recent years; although researchers do not have conclusive evidence, habitat loss and fragmentation are considered the likely culprits (Herker 2004). This bird prefers open grassy landscapes with well spaced trees and shrubs. Isolated trees and shrubs with dense foliage are preferred for nesting while taller, more open (but still isolated) vegetation will be used as a perch from which to hunt and maintain territory (Pruitt 2000, Wiggins 2005). The longleaf pine (Pinus palustris) savanna community provides suitable habitat for the loggerhead shrike in the Southeast United States (Hall et al. 1997). Based on these habitat preferences it was proposed that the following variables should be assessed using analysis of LIDAR derived data: instances of trees and clumps of shrubs that are isolated from other such tall vegetation.

3.2.2 Swainson’s Warbler

Swainson’s warbler (SWWA) is a small foraging bird found in many forest types including
the pocosin and pond pine communities (Mayer 2006, Hamel et al. 1982). Many studies (Meanley 1971, Bushman and Therres 1988, Graves 2002) have been conducted to assess the habitat requirements of this shy and elusive species. Their findings indicate that the most important factor for SWWA is the presence of dense understory vegetation, often consisting of giant cane, tangles of vines, shrubs and/or trees. The species has shown little dependence on any one particular type of vegetation and has therefore been found in a remarkable variety of forest types including bottomland hardwoods, loblolly plantations and thickets of rhododendron and mountain laurel in the Appalachian Mountains (Brooks and Legg 1942, Graves 2002, Bassat-Touchell and Stouffer 2006). Typical habitat often includes complete canopy cover although several sources indicate that canopy closure is not required as long as a thick shrub layer shades the ground (Hamel et al. 1982, Bassat-Touchell and Stouffer 2006). Given this set of habitat characteristics, the aim was to use the LIDAR data to identify instances of areas covered with dense thickets.

4. Study Area

4.1 Location

The study area, the Croatan National Forest (CNF), is located in North Carolina’s coastal plain (Figure 1). The 64,785 hectare (159,886 acre) site is bounded by the Neuse River on the east, the White Oak River on the west, the Trent River on the north, and is separated from Bogue Sound on the south by State Road 24. The site was chosen because it is home to the loggerhead shrike and Swainson’s warbler as well as its accessibility for field data collection, its distinctive forest types and the availability of LIDAR data coverage. The study area is
characterized by flat terrain, which is typical of the topography found in the coastal plain.

4.2 Croatan National Forest History

The CNF was created in 1936 by Theodore Roosevelt as part of a New Deal program to shift land from agricultural use to timber production (Jacobs 2002). The forest has been successfully managed for wood products up to the present date, with significant areas used for loblolly pine (*Pinus taeda*) production in 30-35 year rotations (Phillips 1997). Although the forest continues to produce timber, the most recent Land and Resource Management Plan (LRMP) for the CNR places a great deal of emphasis on ecological restoration and preservation, as well as on recreation and non-timber forest products.

4.3 Forest Communities within the Croatan National Forest

In addition to the loblolly pine stands, the CNF is also home to stands dominated by longleaf pine and pond pine. Longleaf pine communities, including the mesic and wet pine flatwoods and pine savanna are found throughout the CNF. These communities are characterized by open canopies. Depending on soil type, drainage and fire regime the understory may range from almost entirely wiregrass (*Aristida stricta*) or at another extreme, dense shrubs and hardwood saplings (Schafale and Weakly 1990).

4.3.1 Longleaf Pine

In pre-European settlement times longleaf pine was the dominant forest species in vast areas of the Southeastern United States. The species was exploited extensively in the 19th century
for lumber and naval stores (Jose et al. 2006, Earley 2004). Even if not put into agricultural production, areas from which the longleaf pine was removed rarely regenerated to their original composition (Jose et al. 2006), due in large part to an increase in fire suppression. In addition, loblolly pine which had been relegated to bottomlands, was able to out compete the slower growing, fire-adapted longleaf (Preston and Braham 2002). In recent years, however, longleaf pine and the various forest communities associated with it have been increasingly recognized as worthy of preservation (Jose et al. 2006). Indeed, ecologists have documented some of the Earth’s highest species richness per square meter in longleaf communities (Peet and Allard 1993). Mature longleaf stands, which characteristically have a very open canopy, are also home to the red cockaded woodpecker (*Picoides borealis*; Jose et al. 2006, Earley 2004). This species is federally listed as Endangered and lives in strongly territorial family groups, with unmated males helping to fledge young (Ehrlich et al. 1988). Major efforts have been made within the CNF to protect the woodpecker; to a large extent this has meant expanding and protecting longleaf pine stands (Jacobs 2002).

### 4.3.2 Pond Pine

Pond pine ecosystems are found within the CNF as well. Pond pine communities often occupy what are known as pocosins, which are areas with deep peat soils and extremely poor drainage (Schafale and Weakly 1990). Over long periods of time dead plant matter will build up in a pocosin causing the center to have a higher elevation than the surrounding area; indeed, the term pocosin is derived from an Algonquin term meaning “swamp on a hill” (Kologiski 1977). The central areas with the deepest peat are home to the low pocosin
community. This community is characterized by dense shrubs under 1.5 meters tall and a sparse canopy often composed of pond pine, fetterbush (*Lyonia lucida*), titi (*Cyrilla racemiflora*) and loblolly-bay (*Gordonia lasianthus*; Schafale and Weakly 1990). As the peat depth decreases this community grades to high pocosin and then pond pine woodlands. High pocosin areas are characterized by dense shrubs up to three meters tall and are usually dominated by pond pine, fetterbush, titi and inkberry (*Ilex glabra*; Schafale and Weakly 1990). The pond pine woodlands community occupies the outer reaches of the pocosin areas. It is characterized by a very dense shrub layer often over five meters tall and a canopy composed of pond pine. The extensive pocosin areas within the CNF have been largely immune to conversion to loblolly plantation due to poor soils and the extensive efforts that would be needed facilitate improved drainage (Braham personal communication 2007).

5. Data

5.1 LIDAR Data

The multiple return LIDAR data used in this research was acquired between February and April 2003. It is publicly available and was downloaded from the USGS Center for LIDAR Information and Knowledge (CLICK) website (US Geological Survey 2008a). The data was delivered in (XYZ) ASCII text format and has an average point spacing of 4.6 m. The horizontal datum is NAD83 (1995) North Carolina State Plane feet and the vertical datum is NAVD88 US Survey Feet.
A digital elevation model (DEM) derived from the “bare earth” LIDAR data and compiled by Tom Colson of North Carolina State University was used in this research (Floodplain Mapping Program 2004). The resolution is 20 feet, the horizontal datum is NAD83 (1995) North Carolina State Plane feet and the vertical datum is NAVD88 US Survey Feet.

The LIDAR data were acquired through a joint program between the State of North Carolina and the Federal Emergency Management Agency (FEMA) to update the floodplain delineation within the state (NC Floodmaps 2008). The project was completed in three phases at a total cost of around $72 million. The first phase covered the eastern section of the state including the Croatan National Forest. A byproduct of the data collection is the “multiple returns” data from which the bare earth points are isolated and used for mapping.

5.2 Stand Data

An Environmental Systems Research Institute, Inc (ESRI) shapefile of the forest stand data was acquired from personnel at the Croatan National Forest main office (O. Jones personal communication 2007). In the dataset the forest is divided into 2510 stands, of which 498 have been classified by the foresters as longleaf pine stands and 368 as pocosin pine stands within the database. Each stand has many data fields associated with it that were important for this study, including stand age, trees per acre, forest type and site fertility.
5.3 Reference Data

Panchromatic digital orthophoto quarter quads (DOQQs) with two-foot resolution were used as a visual reference for vegetation characteristics. These data were downloaded from the North Carolina State clearinghouse for geospatial information in GeoTIFF format (NC OneMap 2008). The spatial reference is NAD 83 State Plane North Carolina FIPS 3200 Feet; the imagery was acquired in fall 2003.
5.4 Field Data

5.4.1 Collection Methods and Rational

Field data were collected in August 2007 from within the Croatan National Forest in order to assess the accuracy of the LIDAR analysis (Figure 2). The data consists of measurements taken at twenty locations within longleaf pine and pocosin pine stands. Eleven locations were longleaf pine dominant and nine were pond pine dominant. At each point an attempt was made to sample four sub-points, although this was not possible at three of the locations due to time constraints, so a total of 76 sub-plots were measured. The methods used for field plot sampling were based on the procedures set forth by the Breeding Biology Research and Monitoring Database (BBIRD; US Geological Survey 2008b). The BBIRD protocol was chosen over other established methods, such as the one devised for the U.S. National Forest Inventory and Analysis (FIA), because of its utility for wildlife applications.

A stratified random design with a goal of ten plots per forest type was used to select sample points. The sites were limited to be between 40 m and 100 m of the nearest road within longleaf and pond pine stands. The 40 m minimum distance was enforced in an effort to minimize any edge effects while the 100 meter threshold was used to minimize the time spent traversing through the often extremely dense vegetation. Thirty potential sites were initially chosen on the assumption that some of the sites would fall in locations that would
prove to be inappropriate for measurement (e.g. recently cleared or burned). Once the potential field plot locations were created randomly using ArcGIS 9.2 (ESRI 2008), they were loaded into the GPS receiver, which was used to navigate to the points while in the field. Although attempts were made to capture all thirty, a number of sites were eliminated due to inaccessibility (closed or overgrown roads, etc.). Ultimately eleven longleaf sites and nine pond pine sites were sampled.

Once a point was located in the field, a plot was established, with each site consisting of four sub-plots. The sub-plots were arranged in triangular fashion, with three sub-plots forming corners and the fourth one in the middle (Figure 3). As per the BBIRD protocol, the three outer sub-plots were 30 meters away from the central sub-site and located at 120 degrees from each other. At the center of each sub-plot the GPS receiver was used to record the location. The rationale for having four samples (the sub-plots) for each site is that collecting data in this manner allows for a better understanding of the variability within individual stands.

Each sub-plot consisted of a 5 meter radius within an 11.3 meter radius sub-plot. At the center of the 11.3 m sub-plot several measurements were made. Eight strata of the forest were assessed for cover class and four were assessed for height. The eight strata include the canopy layer, two subcanopy layers, shrub and herbaceous layers as well as leafy litter, woody debris and bare ground. Cover class based on the Carolina Vegetation Survey (CVS) protocol was determined for all eight strata (Lee et al. 2006). The CVS protocol was used in
this case in order to more fully characterize the structure as it has ten divisions compared to the six used by BBIRD. The vegetation strata were categorized as canopy (>19m), subcanopy 1 (14-19m), subcanopy 2 (9-14m), shrub layer (4-9m) and herbaceous layer (<4m). These heights were based on an initial assessment of the characteristics of the study area and were maintained throughout the study. Convex densiometer readings were also taken at each sub-plot in order to assess total forest cover.

Within the 11.3 meter sub-plot, measurements were made for every tree with a diameter at breast height (DBH) of at least 8cm. The location of each tree was recorded relative to the center of the sub-plot using a compass for bearing and a hypsometer for distance. In addition to location, each tree was measured for height and DBH as well as assessed for canopy characteristics. The height was measured using the hypsometer and the DBH with a steel tape. The canopy characteristics of each tree within five previously mentioned vegetation layers were also indicated with presence/absence. The presence and location of standing dead trees, or snags, was also recorded.

Within the 5 meter radius sub-plot, shrubs and saplings over 50 cm tall were counted and recorded by species and class size. Vegetation without a single central stem fell into the small size class if the stem diameter at 10cm above the ground was below 2.5 cm and the large size class if the diameter was 2.5 cm or above. If a single central stem was present, and the vegetation was below 1.4 m tall and had a DBH under 2.5 cm, it fell into the small class size while vegetation with a single central stem with a DBH from 2.5 cm to 8cm was counted.
in the large size class. These criteria are taken from the BBIRD protocol. If it was estimated that there were more than 400 stems within the 5m sub-plot the count of the vegetation in the small class size was limited to a 1m radius. This reduction of sub-plot size occurred in 89 percent of the plots (68 of 76 plots) due to the very dense vegetation of the CNF. An example of the field data collection sheet used is included in Appendix A.

6. Methodology

6.1 Preprocessing

Before proceeding with the analysis it was necessary to first prepare the LIDAR data. Important considerations at this stage involved choosing a method of interpolation, selecting an appropriate raster cell size and creating the canopy height model (CHM). The interpolation process converted the LIDAR data from a point cloud of X, Y and Z values into a smooth raster surface, which could have been created using a range of cell sizes. The CHM is a raster where each cell value represents the height of the vegetation above the ground and is the input for all subsequent analyses. These processes are described in detail below and are summarized in Figure 4.

6.1.1 Interpolation

The interpolation chosen was carried out using the Topo to Raster tool within ESRI ArcGIS. This tool applies the ANUDEM engine which was originally developed for hydrologically correct DEM creation (Hutchinson 1988, 1989). According to Wahba (1990), ANUDEM
employs a modification of the spline technique called a discretised thin plate spline. Because the LIDAR data included all returns (returns from the ground and all levels of vegetation) it was necessary to employ an interpolation method able to accommodate abrupt changes in elevation while maintaining global surface continuity and honoring known data points (Mitasova personal communication 2008). As Topo to Raster met these requirements it was determined to be more appropriate for use in this project than other methods of interpolation such as inverse distance weighting (IDW), kriging and creating a triangulated irregular network (TIN). The Topo to Raster tool has several user-defined parameters including a Roughness penalty and a Discretisation error factor which control the extent to which the surface is smoothed (ESRI 2008). In order to choose the best combination, many test rasters were created using various permutations based on a range of roughness and discretisation factors. The combination ultimately used was the one judged to best approximate the forest vegetation when compared to the 2m orthophoto. Specifically, we visually evaluated the ability of the interpolation to maintain realistic peaks around individual trees without either over or under generalizing from the known LIDAR points.

6.1.2 Cell Size

A cell size of one square meter was used to derive the interpolated surface. This resolution was chosen because it is highly interpretable in the context of a woodland system, it is not computationally burdensome and it was compatible with the goals of the study. Also, it can be found in wide use among similar lines of research within the literature. For example, one meter resolution was used in research done by Patenaude et al. (2004) successfully
demonstrating the use of LIDAR to quantify forest above ground carbon content as well as in work done by Hinsley et al. (2002) to quantify woodland structure and habitat quality using LIDAR. In both of these cases the LIDAR data with point spacing similar to the data used in this project was used in a forested environment.
6.1.3 DEM and CHM

The final step for preprocessing the LIDAR data was the creation of the CHM. The cells in the interpolated raster, which contained elevation values for the vegetation, were converted into height values by subtracting the bare ground elevation values from the DEM. For example, a cell in the CHM with a height value of 12 m might have been derived from an interpolated vegetation elevation of 20 m and a DEM bare ground value of 8 m. This method is a variant of the procedure widely used for creating canopy height models from LIDAR data (Genç et al. 2003, Anderson 2003, Lefsky 2002). For some cells the interpolated elevation was less than the bare ground elevation; this resulted in negative height values. These negative values were attributed to accuracy errors in the LIDAR data as well as the interpolation procedures. Across the 76 subplots, the negative values ranged from -0.0001 m to -6.8 m with an average value of -0.76 m. All negative values were treated as low vegetation.

6.2 Identifying Trees

The ability to identify trees from remotely sensed data is important from both a commercial as well as an ecological standpoint (Chen et al. 2007). It allows for better accuracy with regard to vegetation assessment and thereby improves any models that are based on this information (Wynne 2004, Kini and Popescu 2004). Trees were located in this study using a variable size window local maximum (LM) function. This technique has been developed by
Sorin Popescu (Popescu 2002, Popescu et al. 2002, Popescu and Wynne 2004) and has been used in a wide variety of applications in forested environments (Lim et al. 2003, Barilotti et al. 2007). “The LM technique used with LIDAR data operates on the assumption that the highest laser elevation value among laser hits of the same tree crown is the apex” (Popescu et al. 2002). Specifically, the local maximum filter looks at the neighborhood around each pixel and assigns each pixel, one by one, a value equal to that of the highest valued pixel within the neighborhood.

The LM filter is commonly used with a static window size (e.g. 5x5 or 7x7 matrix), which is not ideal in forest applications because if the window is too big, the small trees are overlooked and if it is too small, the same tree might counted more than once. Thus, in situations where trees with small and large canopies are mixed together, employing a variable sized window function may provide better results (Popescu et al. 2002).

In order to proceed with the analysis it was necessary to determine what window sizes and shapes would be most appropriate. Equation 1 was used to relate total tree height (H) and crown width (CW) for pine trees:

\[
CW = 3.75105 - 0.17919(H) + 0.01241(H)^2 \quad \text{Equation 1.}
\]

This equation is based fieldwork carried out by Popescu and Wynne (2004) within pine stands in the Piedmont region of Virginia. The dominant pine species within their study site
were loblolly pine, Virginia pine (*Pinus virginiana*) and shortleaf pine (*Pinus echinata*). These southern pine species were considered sufficiently similar to the longleaf and pond pines to allow for the use of the same tree height/crown width relationship. In addition, when dealing with pine stands, Popescu and Wynne (2004) found that using circular windows to identify individual crowns was more appropriate than filtering with square windows. Using equation (1) it was determined that the window sizes listed in Figure 5b should be employed to accommodate for the range of tree heights within the study area.

The variable window size local maximum function was performed using the modeler within ERDAS Imagine 9.0 (Figure 5a). In the first stage of the process the CHM was passed through five neighborhood functions of varying size (Figure 5b) producing five new LM rasters. These five LM rasters, along with the CHM, were then used as input for a conditional statement. The conditional statement function read the value of each pixel in the CHM and assigned the value of one of the five LM raster files, depending on the value of the pixel in the CHM. The CHM and the product of the conditional statement were then fed into another function which compared the two, cell by cell. If the output from the conditional statement was the same as the CHM, then that cell qualified as a tree top and was given its height value, if not, that meant the cell did not represent a treetop and was given a value of zero. The resulting raster gave the location and height of the treetops within the study area. Refer to Appendix B for full details on this process. A minimum height requirement of three meters was enforced to eliminate the possibility of high points within areas of low vegetation being isolated as trees.
6.3 Case Studies - Wildlife Modeling and Structure Characterization

In addition to modeling density and height of individual trees, another objective of this project was a forest canopy characterization including the vertical distribution of the canopy. If the CHM successfully characterizes the forest vertical structure then it would be a useful product to aid in the creation of wildlife habitat models. Three example applications have been prepared in order to demonstrate how the CHM might be utilized. Two involve characterizing specific habitat features known to be important to birds and the third is a generalized vegetation canopy characterization.

6.3.1 Loggerhead Shrike

The loggerhead shrike (LOSH) prefers grassy savannas with isolated perches from which to hunt. The height of the preferred LOSH perch varies between studies. Yosef (1996) suggests < 5.5 m while Lefranc (1997) provides a range from 2-10 m depending on the habitat structure characteristics. The presence of grasses, bare ground or low herbaceous cover surrounding the perch is very important (Pruitt 2000). Also, a study by Chavez-Ramirez et al. (1994) found that LOSH restricted their use of foraging substrate to within 10 m of elevated perches. The typical nesting sites for this species are closely related to the preferred hunting perches (Lee 2001). A study by Gawlick and Bildstein (1990) found that the area within 10 m of a nest was generally short vegetation (under one meter). In the case
of nesting habitat, the selection of sites in isolated patches of vegetation is thought to be related to avoiding predators more so than spotting prey (DeGeus 1990).

Given these habitat requirements for the LOSH the goal was to use the CHM to characterize forest canopy dispersion. Specifically, this meant setting a threshold for the minimum height of a foraging perch/nesting substrate, as well as for the maximum height of the herbaceous layer (Figure 6). Based on the literature (Yosef and Grubb 1993, Morrison 1980), these heights were set at 2 m and 1 m respectively. A threshold for “isolation” was also set; the literature indicates that 10 m of very low vegetation around a perch is optimal (Gawlick and Bildstein 1990). See Appendix B for full details of the scripts used to implement this model. In order to maximize the usefulness of this analysis, the focus was not on finding a few perfect sites but rather producing a continuous field of suitability. This allows for the end-user to have the flexibility to set thresholds suitable for their particular needs.

6.3.2 Swainson’s Warbler

LIDAR data was also used to characterize some forest structure variables known to influence habitat quality for Swainson’s warbler (SWWA). This bird prefers dense, shady areas in which to forage and nest. Researchers in one study concluded that thickets with stem with around 30,000 to 50,000 stems/ha provide the cover necessary for high-quality Swainson's warbler habitat (Graves 2002). Although the numbers of stems per hectare vary among studies, the conclusion that dense thickets are one of the most important elements of SWWA habitat is well recognized (Meyers and Wright 2003, Eddleman et al. 1980). These thickets
have been shown to be valuable as habitat when they occupy areas as large as 400 ha to small areas (approximately 0.25 ha) formed by localized disturbances such as downed trees (Graves 2002).

Given these habitat requirements for SWWA the goal was to use the CHM derived from LIDAR data to identify forest density, with emphasis on finding understory thickets. Although identifying and counting 30,000-50,000 stems/ha using LIDAR technology currently is not feasible, it should be possible to identify areas where dense, shrub height vegetation exists. This was done by specifying a height range for thickets and by assuming that in areas that are indeed thickets very few of the LIDAR returns will be from the ground or very low vegetation. The height of occupied vegetation varies in the literature. Thompson (2005) notes that the average height of cane in her study area was 2.22 m, Thomas et al. (1996) found the minimum height to be 3.6 m and Graves (2002) indicated that the thicket and shrub layer may be up to 5 m tall. While some researchers demonstrate that SWWA can breed successfully in areas with no overstory, Eddleman et al. (1980), observed no SWWA in forests with tree heights less than 7.6 m.

The method used to identify potential SWWA habitat involved first identifying areas with an overabundance of low vegetation as unsuitable. The height of the shrub layer vegetation was then characterized for the remaining cells in the CHM (Figure 7). The criteria used to evaluate the individual cells were based on the height values of all cells within a five meter radius. In order to remove areas without the necessary amount of shade, cells were
designated as unsuitable if over 50% of the surrounding cells were less than 2 m in height. The remaining cells were given a value based on the average height of the surrounding shrub layer vegetation. Height values of vegetation over 7.6 m were not included when calculating this average in an effort to limit the characterization to the shrub layer of the forest. The goal of this process was to identify potential SWWA habitat within pond pine forest communities. Full details regarding the scripting used to implement this model are included in Appendix B.

6.3.3 Generalized Vegetation Canopy Characterization

In this case study, a canopy characterization of the vertical structure of the vegetation was done based on the CHM. Instead of a specific height value for each cell, a raster in which the cell values contain a summary of the vertical structure of the surrounding vegetation is produced. In contrast to the potential LOSH and SWWA habitat models, this application was intended to be more widely applicable and was not created for a specific wildlife species. To create the generalized vegetation canopy characterization, the CHM cells were first reclassified into three different height classes (low, medium and high) based on thresholds (Figure 8). The thresholds were determined at the beginning of the field data collection based on field observations. The height thresholds used to characterize the forest strata include the canopy (>19 m), subcanopy (9-19 m) and the combined shrub and herbaceous layers (<9 m). A neighborhood filter was used to determine the percent of cells in each height class within five meters. A final conditional function was used to classify each cell into a generalized structure category (tall canopy, open understory) based on predetermined proportions of vegetation heights in the neighborhood (Table 1). For example, using this
algorithm a grassy field would result in a patch in the grid marking each cell as “low” while a structurally diverse forest with a roughly equal amount of cells in each bin would be categorized as “mixed.”

7. Results and Discussion

7.1 Locating Individual Trees

7.1.1 Tree Density

The counts of individual trees identified from the LIDAR and field data were converted into trees per hectare (TPha) estimates and then compared to the field estimates using the Wilcoxon test (also known as the Mann-Whitney test; Zar 1999). The conversion to TPha was necessary in order to adjust for the slight difference in area between the true circle used for the field-based count and the pixilated circle in the LIDAR-based count. Results were compiled separately for each plot, as well as across stands for the pond pine (Table 2) and longleaf stands (Table 3). The Wilcoxon test was used to determine whether the density estimates for the plots based on the LIDAR-based count were different from the estimates based on the field-based count. The test is non-parametric and does not assume a normal distribution in the data; this was important as the distributions within the plots could not uniformly and unambiguously be said to have normal distributions. An alpha value of 0.05 was used for this test and throughout the analyses. Three of the pond pine plots did not have the minimum number of data points for this test and no results were reported. Within the
analysis of the individual plots three of the six (50%) remaining pond pine plots and six of
the eleven (55%) longleaf pine plots were not significantly different. In order to test for
differences in estimates between the field-based and LIDAR-based estimates by forest type,
the mean TPha values from among the nine pond pine plots and eleven longleaf pine plots
were used. For the pond pine plots the difference was significant ($P = 0.042$) while the
difference was not significant for the longleaf pine plots ($P = 0.168$).

Examples of the results from locating individual trees for a pond pine and longleaf pine site
can be seen in Figures 9 and 10 respectively. Figures 9a and 10a show the trees identified
from the LIDAR-based data along with the CHM. The locations of the trees match areas
with tall vegetation. Figures 9c and 10c show the trees identified from the field-based data
along with a reference image. The number of trees identified in the field is greater than the
number found in the LIDAR-based count. Due to small georeferencing errors, the DOQQ
images, the LIDAR-based data and the field GPS locations may not match perfectly. These
figures also contain graphs comparing tree heights from LIDAR- and field-based data
(Figures 9b and 10b), which will be discussed in the next section.

The results of the tree density comparison indicate that the method used to isolate trees based
on the LIDAR data was marginally effective in both stand types. Density in the longleaf pine
plots tended to be more successfully characterized than the pond pine plots. In general, the
LIDAR derived density estimates tended to be lower than the field based count. All three of
the pond pine plots with significant differences had higher field-based counts while the same
was true for three of the four longleaf pine plots (see Tables 2 and 3). Potential sources for
this evident bias are explored in detail in the following sections.

It is hypothesized that the difference between the LIDAR and field based tree counts may
stem from an undercount on the part of the LIDAR-based analysis. Smaller trees or trees
growing in close proximity to a larger tree could easily be missed by the tree isolation
algorithm, while few trees would be expected to be missed in the field-based count.
Although the variable sized window LM function is designed to allow for various tree sizes,
it may be unlikely to isolate individual trees if their canopies are physically combined. This
phenomenon is demonstrated in Figure 11, where it can be seen that there are several
instances of trees located in close proximity to one another. This is supported by the fact that
the LM function worked better in the longleaf pine plots, where the vegetation had a
tendency to be less dense compared to the areas dominated by pond pine.

In order to correct for this type of error, it may be necessary to adjust the variable size
window local maximum function used to identify trees. Specifically, while the relationship
between tree height and canopy width used in the algorithm was based on southern pine
species similar to longleaf and pond pine, it may not be optimized for the type of forests
found in the CNF. For example, the relationship was based on the assumption of the
presence of pure pine stands and this was often not the case within the study plots. Nine of
the twenty plots contained only pine trees while seven were composed of over 20% non-pine
species (Table 4). Furthermore, it may be useful to employ different tree isolation algorithms
for the longleaf and pond pine stands. Employing tree height to canopy width relationships specific to the two species (pond pine and longleaf pine) may increase the accuracy.

Seasonal discrepancies in the dates of data acquisition represent another possible source of error in the tree count estimates. The LIDAR data were acquired from February to April while the field data were collected in August. While most of the dominant species within the CNF are evergreen, including the pine trees and various bay trees, any deciduous vegetation within the study area most likely was in the leaf-off condition when the LIDAR was acquired. This would have a tendency to reduce the number of trees counted within the LIDAR-based estimates in areas with a significant number of deciduous trees. An example of this might be found in plot 22, where 18 of the 59 trees counted in the field were mature turkey oak (*Quercus laevis*). There was a significant difference in the LIDAR and field based counts for this plot and the season of LIDAR data acquisition possibly contributed to the discrepancy.

Another source of possible error is the inclusion of snags in the field based count. The trees recorded as snags in the various plots ranged from 0 to 11% of the total number of trees with a mean value across all twenty plots being 3.9% (Table 4). Although snags are included in the BBIRD protocol because of their importance for wildlife, the decision to include them in the count was based more on the idea that they would have impacted the LIDAR data at the time it was acquired. Thus all snags were assumed to have been a part of the canopy for the purposes of this project. While many snags surely did impact the LIDAR others probably did
The inclusion of snags in the field tree count might thus have introduced a source of error, with a bias towards increasing the number of trees recorded.

An additional source of error is related to the resolution of the LIDAR data. The LIDAR data has a point density of approximately 0.06 points per square meter. This low point density was adequate for creating floodplain maps but may not be as suitable for tree isolation. With a relatively limited number of points per square meter some trees may have been missed and the true nature of the vegetation within the study area may not have been fully captured. It is hypothesized that by capturing the vegetation with more fidelity, a higher LIDAR point density would have enabled the LM function to more accurately isolate trees. The low density of points is thought to have reduced the number of trees identified in the LIDAR data.

Another factor that would have affected the tree density estimate is the interpolation of the LIDAR data points used to create the CHM. Although the method chosen was selected as the best representation, it may not have captured the true nature of the vegetation. If the interpolation function either over- or under-smoothed the CHM surface then tree count could have been affected. An overly smooth interpolation would tend to reduce the tree count by removing the variation in height values that the LM function relied upon to identify trees. For example, the height values between two nearby points representing two trees with similar height may be interpolated in such a way as to allow for only one tree to be identified. As the interpolation process is integral to the analysis, this source of error is unavoidable to a
certain extent. However, it may be possible to choose a different interpolation method or level that would allow for a more accurate tree count.

7.1.2 Tree Heights

The height of the trees identified by the LIDAR-based analysis for each plot was compared to the height of trees found in the field. The Wilcoxon test was again used as it allowed for the presence of unequal sample sizes and variance, and was used to test whether the height of trees found in the field was significantly different from the height of the trees estimated using LIDAR data (Table 5). One of the pond pine plots had only one tree identified from the LIDAR data and had to be removed from the tree height comparison. Five of the eight remaining pond pine plots (63%) and six of the eleven longleaf pine plots (55%) had statistically insignificant differences. When the test was performed for the two forest types in general, no significant difference existed in the tree height estimates for either the pond pine (n = 8, P = 0.563) or the longleaf sites (n = 11, P = 1.00).

In order to allow for the growth of the trees during the interval of time between the LIDAR data acquisition and the field data collection a correction factor was applied to the LIDAR-based height values. The correction factor was calculated for each stand based on dominant species, as well as site index and stand age as reported within the data files acquired from the CNF main office (Table 6). The growth rates were derived from work done by Schumacher and Coile (1960) and are based on natural stands of pond and longleaf pine. These adjusted heights were used for all graphs and statistical calculations involving tree heights.
Although the statistical test indicated significant differences between the means in eight of the twenty plots, in many cases this difference may not be ecologically meaningful. Six of the eight pond pine plots (75%) and nine of the eleven longleaf pine plots (82%) had means that were within 3 meters (Table 5). For wildlife modeling, differences such as these may not be of practical significance.

The results from both the individual plots and the collective assessments indicate that the tree height estimation based on the LIDAR data was useful for characterizing the heights of the trees in the field. Heights within the longleaf pine plots were more accurately characterized than those in pond pine plots. Furthermore, even after the height correction factor was applied, the analysis of the results reveals a bias towards higher height values in the field-based data. All four of the pond pine plots with significant differences had higher means in the field data. The same was true for five of the seven longleaf pine plots. Although an attempt was made to correct for the growth of the trees over the nearly five year interval, the correction factor applied only approximates the actual amount of growth that occurred and this remains a potential source of error.

Another possible source of error may be traced to the discrepancy between the numbers of trees found in the field versus the number identified in the LIDAR data for some of the plots. In cases where the LIDAR count identified fewer trees, the trees that would be identified would tend to be the mature, tall trees with larger footprints in the LIDAR data. Thus, if not all the trees are identified and then only the tallest trees are included in the average there
would be a bias which would tend to increase the average height in the LIDAR data. A good example of this phenomenon might be plot 12, which had a significant difference in the mean heights between the LIDAR and field data. Forty-three trees were identified in the LIDAR data while ninety-five were found in the field. Records made in the field note an abundance of smaller trees that would be less likely to be identified from the LIDAR data (Figure 12).

Furthermore, the LIDAR-based height values may be underestimated due to the tendency of the laser to hit the tree below the apex. This would tend to bias the height comparison and the effect would be exacerbated by the leaf-off conditions present when the LIDAR data was acquired. In plots with a significant amount of deciduous vegetation the estimates of height could be low in the LIDAR-based height assessment. With a significant component of turkey oaks and other deciduous trees, plot 12 is a good example of this phenomenon. The mean tree height in the field based data is 12.9 m, which is 3.8 m lower than the LIDAR data based mean; the Wilcoxon test revealed that the difference between the two data sources is significant, with a P-value of less than 0.0001 (Table 5). The comparison for this site was recalculated after omitting the deciduous trees in order to test what effect their presence might have had. The new mean for the field trees rose to 14.0 m and although the difference between the LIDAR and field-based estimates remained significant (P = 0.024). This finding supports the idea that the leaf-off conditions might have exacerbated the tendency of LIDAR technology to underestimate vegetation height values.
7.2 Vegetation Characterization by Strata

In addition to the assessing the number and heights of trees, we compared the total vegetation structure based on the CHM derived from the LIDAR. Specifically, the field measurements of the cover class within various strata were compared to the percent cover by height values estimated from the CHM. In order to facilitate this comparison the cover class estimates made in the field using the CVS system were converted into percentages based on the median value of the range (Table 7). For example, the CVS cover class “6” corresponds to 10-25% cover (median value 17.5%). Therefore, if a stratum from the field was assigned a cover class of “6” then this was translated into 17.5% cover. The CHM values derived from LIDAR data were also divided by height and the percentage of each stratum was calculated. For each plot the percentage values from the sub-plots were compared using the Wilcoxon test (Table 8). In the table it can be seen that the cover estimates for subcanopy 1 stratum for the longleaf pine plots matched the field estimates for 54.5% of the plots. In other words, six of the eleven longleaf plots had no significant difference. The results of this analysis may also be viewed in Figures 13 and 14, where the percent cover by strata for the LIDAR- and field-based data is given for the pond and longleaf pine plots, respectively.

The assessment of the vegetation characterization by strata revealed that the LIDAR- and field-based data yielded mixed results. To a large extent, the assessment within the pond pine stands was successful, especially within the three highest strata. Within the longleaf pine stands, however, the results were generally poor. The sources of error likely to be present in this analysis are similar to the ones associated with the tree count and tree height.
The major exception is that because this analysis used the CHM directly, the tree isolation algorithm has been removed as a source of error. The interpolation process is thought to have affected the results and may play a part in the low success rate within the longleaf pine stands. An additional issue is the underestimation of the height values due to the lower resolution of the LIDAR. Also, the seasonal discrepancy in the dates of data acquisition would again introduce bias in plots with significant deciduous vegetation.

The interpolation of the LIDAR return points to create the CHM, specifically the sharp transition (decay) in height values around tall trees, is thought to have effected the vegetation characterization. For example, if the heights between two nearby return points are interpolated and if one point is on the edge of a tree canopy and the other is from the ground near the tree, then there will be intermediate height values between the two points due the interpolation forcing a smooth curve between the points. Even if there is no vegetation between these points in the field, the intermediate values would be interpreted in the CHM as midstory vegetation. It is hypothesized that this would have affected the characterization of herbaceous, shrub and subcanopy 2 strata by increasing the percent cover in the LIDAR data. Similarly, if the canopy of a tall tree is represented by only one or two LIDAR X,Y and Z points, the sharp decay of the interpolated surface around these few points is unlikely to mimic the natural shape of the canopy foliage. The percent cover in the upper strata could therefore be underestimated. Both of these effects would be more pronounced in the longleaf pine stands due to the interspersion of low vegetation between the canopies of tall trees. The decreased effectiveness of the characterization in the lower strata across all plots and the
lower overall effectiveness of the characterization within the longleaf pine plots, especially in the canopy strata, may be attributable in part to this phenomenon.

The fact that the LIDAR data were acquired in 2003 and the field data were collected in 2007 represents a potentially significant source of error for this analysis. A primary reason for this is the growth of the vegetation within the study area. While mature trees might be expected to gain some height over a five year interval, the shrubs and young trees of the lower strata could have greater changes in height. This is consistent with the results in the pond pine plots, where estimates of the percent cover from the field data were consistently higher than the LIDAR-based estimates in the herbaceous layer (Figure 13). Furthermore, the growth of vegetation would tend to bias the results towards a greater percent cover in the field data.

Prescribed burns within the CNF represent another potential source of error related to the time difference in the data acquisition dates. Fires designed to mimic the natural fire regime for the area and may be set as frequently as every two or three years within longleaf pine stands. These fires often burn with very low intensity and damage or kill only low lying vegetation. Evidence of fire, such as scorched earth and blackened bark was observed in the field at many of the sites. Although it was not possible to determine with certainty when or if fires had occurred within the last five years, it is hypothesized that they would have had an effect on the analysis. The level of error introduced by fire would be dependent on the timing of the burns relative to the LIDAR and field data acquisition. Fire that occurred in the interval between the acquisition dates would tend to bias the results by lowering the percent
cover in the lower strata of the field data. In areas where fires were set prior to the LIDAR data acquisition and then not set again within the five year interval would tend to bias the percent cover in the lower strata by increasing the height. The lower rate of successfully matching the LIDAR and field data within the lower strata, especially within the longleaf pine sites, is consistent with the hypothesis that prescribed burning affected the data.

7.3 Structure Classification – Case Studies

The goal for the case studies was to demonstrate additional possible uses for the LIDAR data beyond tree isolation and canopy strata characterization. The applications are each based on the CHM and are not associated with the tree isolation algorithm. Further accuracy assessment was not carried out for these applications. It is assumed that the errors associated with the CHM and relevant to the canopy strata assessment would be applicable to all subsequent analyses, including the example applications.

7.3.1 LOSH characterization

The goal for this case study was the identification of potential loggerhead shrike habitat within the longleaf pine stands of the CNF. This habitat assessment is based only on vegetation structure and forest type criteria. It is important to understand that other criteria necessary for the presence of LOSH might not also be present at the sites modeled. An example of the LOSH habitat characterization can be seen in Figure 15. The figure shows the area containing plot 13 and represents an output typical for the LOSH habitat characterization. The wooded region visible in Figure 15e contains areas of potential habitat
of variable suitability highly interspersed with unsuitable areas. The field visible in the northwest corner is area that was completely eliminated as potential habitat due to a lack of perches. The photograph of plot 13a (Figure 15d) shows the open nature of the longleaf pine understory as well as the presence of dead trees that might serve as hunting perches for LOSH. In order to make use of data such as this, it may be desirable to determine how much area within a stand must be suitable before the stand represents viable habitat. For example, some areas within the plot shown have high suitability, but the stand overall might not have enough suitable habitat to support LOSH.

Characterizing potential LOSH habitat involved identifying areas with isolated perches surrounded by low vegetation suitable for foraging. The accuracy of this potential habitat model would be highly dependent on the ability of the CHM to reliably characterize the vegetation, especially in the lower strata. As discussed above, there were many factors that may have affected the accuracy of the CHM and the subsequent modeling of perches necessary for LOSH. These perches are quite important for the species’ success in an area, yet they need not be physically substantial. To this end, the interpolation process and the low LIDAR point density may have contributed to an underestimation in the number of perches by either causing them to be missed altogether or smoothed beyond recognition. Additionally, criteria within the model used to characterize habitat limited potential foraging areas to cells with a height value between 1 and 2 m. Such narrow bounds for ecologically important height distinctions would tend to increase uncertainty in the habitat models given the decreased rate of success in characterizing the lower strata.
7.3.2  **SWWA Characterization**

The goal for this characterization was to identify potential Swainson’s warbler habitat within the pond pine stands of the CNF. This characterization is similar to the LOSH in that the habitat assessment used only criteria based on vegetation structure and the forest type. It should therefore be regarded as potential habitat characterization only, as other criteria necessary for the presence of SWWA might not also be present. An example of the SWWA habitat characterization can be seen in Figure 16. The figure shows the area containing plot 28 and represents a typical output for the SWWA habitat characterization. About one half of the area shown was modeled as potential habitat, with the denser stand on the right side of the road containing a higher proportion of suitable habitat. The photograph taken at plot 28a (Figure 16d) shows the dense vegetation often encountered in the field plots that would be considered favorable habitat for SWWA.

Modeling potential SWWA habitat involved identifying areas with dense vegetation in the lower strata creating shaded habitat suitable for nesting and foraging. Again, the accuracy of this potential habitat model would be highly dependent on the ability of the CHM to reliably characterize the vegetation, especially in the lower strata. Although the SWWA potential habitat model benefits from the fact that the lower strata were more successfully characterized in the pond pine plots compared to the longleaf plots, the many error sources discussed above would also apply here. The overall effect of the errors is unknown; however, the overestimation in the LIDAR data of the percent cover in the herbaceous strata would tend to decrease the extent of the potential habitat.
7.3.3 Generalized Vegetation Canopy Characterization

The goal of this process was to provide a general characterization of the forest vegetation. An example of the output may be seen in figure 17. The figure shows the area containing plot 21, which was in a longleaf pine stand. The majority of the stand was characterized as “high” or “mixed” with some gaps in the canopy and the area beyond the edges of the stand categorized as “low” vegetation. This type of information could be useful as an initial assessment of the vegetation structure of an area or be used for a generic structure characterization before more specific models could be created for a wildlife species.

Furthermore, when compared to the CHM the simplified characterizations produced may be more interpretable, especially when summarized. If one was interested in the midstory, for example, if it may be more useful to know that 25 percent of an area contains predominantly “mid” vegetation rather than knowing that 40 percent of the height values are between 9 and 19 meters. The difference is that with the CHM it would be less clear if the midstory level height values were interspersed across the stand or if there was a distinct patch of midstory level trees.

This characterization summarizes the information contained in the CHM; therefore the accuracy of the CHM would be the determining factor in how well the vegetation was characterized. The interpolation process, and particularly errors due to the decay in height values, may have most heavily influenced this characterization. Specifically, the bias towards creating midstory height values in the CHM where perhaps there is no midstory vegetation would have inflated the number of cells categorized as “Mid,” “Mid/High” and
possibly “Mixed.” This would have been at the cost of other categories such as “High” and especially “Low/High” as it would be more difficult for areas to qualify for these if the midstory values were overestimated. Again, similar to what was discussed above with regard to the strata characterization analysis, this would have affected the more open canopies of the longleaf pine stands to a greater extent than in the pond pine stands.

The values used for this analysis were based on existing literature and the local conditions in the study area, however, this approach was meant to be useful in a range of applications. Therefore it should be recognized that the three variables (the height bins, the window size and the percent allocated into various bins) each have a range of possible values; different combinations might have advantages for modeling different wildlife species. Future applications of this work would ideally allow researchers to select their own values for the variables based on their knowledge of the study site and wildlife species under consideration.

8. Conclusion

This project attempted to characterize the vegetation structure for longleaf and pond pine forests within the CNF using LIDAR derived data; although the characterization was successful to a large extent, there is potential for improvement. As part of the analysis, an attempt was made to identify trees within the study area using an algorithm based on finding the local maximum within variable size windows. Tree density and tree height estimates derived from this algorithm were compared to estimates based on field observations. The stand-wise analysis revealed that, while the characterization of the tree density within the
pond pine stands was less than optimal \((P = 0.042)\), the methods used were able to successfully characterize the density of the longleaf pine stands \((P = 0.168)\) as well as the height estimations for both the pond pine \((P = 0.563)\) and longleaf pine \((P = 1.00)\). These results, as well as those based on individual stands, indicate that the density estimation was more successful in the longleaf pine plots than in the pond pine plots; although in both cases the field based estimates were often significantly higher. The assessment of the tree height comparison yielded better results, with the difference between the average values being less than three meters in all but four of the twenty plots. In addition to identifying trees, a characterization of the whole vegetation canopy was made as well; this was based on percent cover within five forest strata. The assessment revealed that the LIDAR data characterized the strata within the pond pine plots well but largely failed within the longleaf pine plots. Furthermore, within the pond pine plots the characterization was generally more accurate in the upper strata.

In order to improve the results of the forest vegetation structure characterization, several strategies may be helpful. For the tree density and tree height analyses, changing the tree isolation algorithm may improve the results. More specifically, the relationship between tree height and crown width could be tailored to better characterize the forest types found in the CNF, possibly by designing separate algorithms for the longleaf and pond pine dominant stands. Changing the interpolation technique used to create the CHM was also seen as a possibly useful step to improve both the tree isolation and vegetation strata analyses. Furthermore, the seasonal and temporal differences in the data acquisition dates introduced
significant uncertainty into the results. Although more recent data was not available for use with this project, reducing the time difference between the LIDAR data and field data collection would mitigate these issues.

This project used case studies of potential habitat for loggerhead shrike and Swainson’s warbler, as well as the generalized vegetation canopy characterization to demonstrate the potential usefulness of vertical forest structure information derived from LIDAR data. These applications represent the great potential that LIDAR technology has for improving habitat models for many wildlife species. Although the methods explored in this paper were used for species native to the CNF, they were intended to be widely adaptable. They may be modified to better estimate the habitat of the case study species within the study area or be adapted for other species in other areas. The work done for this project may be increasingly important in the future as LIDAR technology becomes more widespread and the need for more accurate habitat models continues to grow.
REFERENCES CITED


Table 1: Threshold system for generalized vegetation canopy characterization.

<table>
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<tr>
<th>Category Name</th>
<th>Value In Output</th>
<th>General Description</th>
<th>Low Vegetation &lt; 9m</th>
<th>Midstory Vegetation 9 - 19m</th>
<th>High Vegetation &gt;19m</th>
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<td>Mostly Low Vegetation</td>
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<td></td>
</tr>
<tr>
<td>Low/Mid</td>
<td>2</td>
<td>Low and Midstory Vegetation Combined</td>
<td>&gt;40%</td>
<td>&gt;20%</td>
<td></td>
</tr>
<tr>
<td>Low/High</td>
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<td>Low and High Vegetation Combined</td>
<td>&gt;40%</td>
<td></td>
<td>&gt;20%</td>
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<td>&gt;40%</td>
<td>&gt;20%</td>
</tr>
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<tr>
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<td>variable</td>
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Table 2: Tree density assessment results for pond pine plots.

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<tr>
<th>plot ID</th>
<th>LIDAR Tree Count</th>
<th>Trees per Hectare</th>
<th>Field Tree Count</th>
<th>Trees per Hectare</th>
<th>Greater TPHa?</th>
<th>Result at α = 0.05</th>
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<td>249</td>
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All Pond Pine Plots Wilcoxon Test P-Value 0.0420 reject H0
Table 3: Tree density assessment results for longleaf pine plots.

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<thead>
<tr>
<th>Plot ID</th>
<th>LIDAR Tree Count</th>
<th>Trees per Hectare</th>
<th>Field Tree Count</th>
<th>Trees per Hectare</th>
<th>Greater TPha?</th>
<th>Result at α = 0.05</th>
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All Longleaf Pine Plots Wilcoxon Test P-Value 0.1677 Fail to Reject H0
Table 4: Field tree count by species.

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<td>Total live, non-<em>Pinus</em></td>
<td>0</td>
<td>0</td>
<td>48</td>
<td>0</td>
<td>9</td>
<td>0</td>
<td>36</td>
<td>1</td>
<td>25</td>
<td>16</td>
</tr>
<tr>
<td>% live, non-<em>Pinus</em></td>
<td>0</td>
<td>0</td>
<td>50.53</td>
<td>0</td>
<td>30</td>
<td>0</td>
<td>28.36</td>
<td>4.167</td>
<td>42.37</td>
<td>27.12</td>
</tr>
</tbody>
</table>
Table 5: Tree height assessment results.

### Tree Height Assessment

#### Pond Pine Plots

<table>
<thead>
<tr>
<th>Plot ID</th>
<th>mean height</th>
<th>Difference Greater mean</th>
<th>Number of trees</th>
<th>Wilcoxon Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LIDAR</td>
<td>Field</td>
<td>LIDAR</td>
<td>Field</td>
</tr>
<tr>
<td>1</td>
<td>11.7</td>
<td>11.6</td>
<td>0.2</td>
<td>22</td>
</tr>
<tr>
<td>6</td>
<td>5.9</td>
<td>6.3</td>
<td>-0.4</td>
<td>10</td>
</tr>
<tr>
<td>8</td>
<td>6.9</td>
<td>6.2</td>
<td>-1.3</td>
<td>26</td>
</tr>
<tr>
<td>14</td>
<td>18.5</td>
<td>18.6</td>
<td>-1.1</td>
<td>31</td>
</tr>
<tr>
<td>17</td>
<td>17.3</td>
<td>17.5</td>
<td>0.4</td>
<td>57</td>
</tr>
<tr>
<td>27</td>
<td>5.3</td>
<td>10.6</td>
<td>-4.2</td>
<td>10</td>
</tr>
<tr>
<td>28</td>
<td>12.4</td>
<td>17.9</td>
<td>-5.5</td>
<td>10</td>
</tr>
<tr>
<td>29</td>
<td>5.3</td>
<td>7.2</td>
<td>-1.8</td>
<td>18</td>
</tr>
</tbody>
</table>

Wilcoxon test for means of all pond pine plots **0.563** Fail to Reject

#### Longleaf Pine Plots

<table>
<thead>
<tr>
<th>Plot ID</th>
<th>mean height</th>
<th>Difference Greater mean</th>
<th>Number of trees</th>
<th>Wilcoxon Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LIDAR</td>
<td>Field</td>
<td>LIDAR</td>
<td>Field</td>
</tr>
<tr>
<td>2</td>
<td>11.6</td>
<td>12.2</td>
<td>-0.6</td>
<td>Field</td>
</tr>
<tr>
<td>5</td>
<td>19.1</td>
<td>20.5</td>
<td>-1.5</td>
<td>Field</td>
</tr>
<tr>
<td>7</td>
<td>14.8</td>
<td>14.9</td>
<td>-0.1</td>
<td>Field</td>
</tr>
<tr>
<td>12</td>
<td>16.7</td>
<td>12.9</td>
<td>3.8</td>
<td>LIDAR</td>
</tr>
<tr>
<td>13</td>
<td>17.9</td>
<td>19.8</td>
<td>-2.0</td>
<td>Field</td>
</tr>
<tr>
<td>15</td>
<td>22.5</td>
<td>19.6</td>
<td>2.9</td>
<td>LIDAR</td>
</tr>
<tr>
<td>19</td>
<td>17.2</td>
<td>17.8</td>
<td>-0.6</td>
<td>Field</td>
</tr>
<tr>
<td>20</td>
<td>12.5</td>
<td>14.8</td>
<td>-2.2</td>
<td>Field</td>
</tr>
<tr>
<td>21</td>
<td>22.3</td>
<td>24.3</td>
<td>-2.0</td>
<td>Field</td>
</tr>
<tr>
<td>22</td>
<td>21.1</td>
<td>17.5</td>
<td>3.6</td>
<td>LIDAR</td>
</tr>
<tr>
<td>23</td>
<td>16.3</td>
<td>16.7</td>
<td>-0.6</td>
<td>Field</td>
</tr>
</tbody>
</table>

Wilcoxon test for means of all longleaf pine plots **1.000** Fail to Reject
Table 6: Correction factor used to adjust for growth between data acquisition dates. The growth rates are based on the findings of Schumacher and Coile (1960).

<table>
<thead>
<tr>
<th>Plot ID</th>
<th>Year Established</th>
<th>Age in 2003</th>
<th>Site Index</th>
<th>5yr growth (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pond Pine Plots</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1924</td>
<td>79</td>
<td>50</td>
<td>0.15</td>
</tr>
<tr>
<td>6</td>
<td>1920</td>
<td>83</td>
<td>50</td>
<td>0.30</td>
</tr>
<tr>
<td>8</td>
<td>1920</td>
<td>83</td>
<td>50</td>
<td>0.15</td>
</tr>
<tr>
<td>14</td>
<td>1920</td>
<td>83</td>
<td>50</td>
<td>0.15</td>
</tr>
<tr>
<td>17</td>
<td>1920</td>
<td>83</td>
<td>70</td>
<td>0.30</td>
</tr>
<tr>
<td>27</td>
<td>1925</td>
<td>78</td>
<td>50</td>
<td>0.15</td>
</tr>
<tr>
<td>26</td>
<td>1904</td>
<td>99</td>
<td>60</td>
<td>0.30</td>
</tr>
<tr>
<td>29</td>
<td>1920</td>
<td>83</td>
<td>50</td>
<td>0.15</td>
</tr>
</tbody>
</table>

| Longleaf Pine Plots |
|---------------------|------------------|-------------|------------|---------------|
| 2                   | 1930             | 73          | 50         | 0.30          |
| 5                   | 1920             | 75          | 70         | 0.30          |
| 7                   | 1933             | 70          | 50         | 0.30          |
| 12                  | 1936             | 67          | 70         | 0.30          |
| 13                  | 1935             | 68          | 80         | 0.30          |
| 15                  | 1925             | 78          | 70         | 0.30          |
| 19                  | 1925             | 78          | 70         | 0.30          |
| 20                  | 1930             | 73          | 80         | 0.30          |
| 21                  | 1930             | 73          | 80         | 0.30          |
| 22                  | 1930             | 73          | 80         | 0.30          |
| 23                  | 1930             | 73          | 70         | 0.30          |
Table 7: Cover class conversion values.

<table>
<thead>
<tr>
<th>CVS Cover Class</th>
<th>Percent Cover Range</th>
<th>Percent Value Used For Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>trace</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0-1%</td>
<td>0.5</td>
</tr>
<tr>
<td>3</td>
<td>1-2%</td>
<td>1.5</td>
</tr>
<tr>
<td>4</td>
<td>2-5%</td>
<td>3.5</td>
</tr>
<tr>
<td>5</td>
<td>5-10%</td>
<td>7.5</td>
</tr>
<tr>
<td>6</td>
<td>10-25%</td>
<td>17.5</td>
</tr>
<tr>
<td>7</td>
<td>25-50%</td>
<td>37.5</td>
</tr>
<tr>
<td>8</td>
<td>50-75%</td>
<td>62.5</td>
</tr>
<tr>
<td>9</td>
<td>75-95%</td>
<td>85</td>
</tr>
<tr>
<td>10</td>
<td>95-100%</td>
<td>97.5</td>
</tr>
</tbody>
</table>
Table 8: Summary of the canopy strata analysis results. The percent cover in each stratum for the eleven longleaf plots and the nine pond pine plots were compared using the Wilcoxon test.

<table>
<thead>
<tr>
<th>Canopy Strata Analysis Summary - Wilcoxon Test Results</th>
<th>Fail to Reject $H_0$</th>
<th>Reject $H_0$</th>
<th>% matching</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Longleaf</strong></td>
<td>2</td>
<td>9</td>
<td>18.2</td>
</tr>
<tr>
<td>canopy layer</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>subcanopy 1</td>
<td>6</td>
<td>5</td>
<td>54.5</td>
</tr>
<tr>
<td>subcanopy 2</td>
<td>4</td>
<td>7</td>
<td>36.4</td>
</tr>
<tr>
<td>shrub layer</td>
<td>5</td>
<td>6</td>
<td>45.5</td>
</tr>
<tr>
<td>herbaceous</td>
<td>4</td>
<td>7</td>
<td>36.4</td>
</tr>
<tr>
<td><strong>Pond</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>canopy layer</td>
<td>5</td>
<td>1</td>
<td>83.3</td>
</tr>
<tr>
<td>subcanopy 1</td>
<td>6</td>
<td>0</td>
<td>100.0</td>
</tr>
<tr>
<td>subcanopy 2</td>
<td>5</td>
<td>1</td>
<td>83.3</td>
</tr>
<tr>
<td>shrub layer</td>
<td>2</td>
<td>4</td>
<td>33.3</td>
</tr>
<tr>
<td>herbaceous</td>
<td>4</td>
<td>2</td>
<td>66.7</td>
</tr>
</tbody>
</table>
Figure 1: Map of the Croatan National Forest and surrounding area.
Figure 2: Map outlining the location of longleaf pine and pond pine stands within the Croatan National Forest. The locations of sample plots are also indicated.
Figure 3: Example plot layout diagram. This was adapted from the BBIRD protocol (US Geological Survey 2008b).
Figure 4: Overview of preprocessing procedure.
Figure 5a: The tree isolation algorithm used to identify trees using a variable sized window local maximum function.

<table>
<thead>
<tr>
<th>Cell/Meter Diameter</th>
<th>3</th>
<th>3</th>
<th>5</th>
<th>5</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;Circular Radius&quot;</td>
<td>1</td>
<td>1.5</td>
<td>2</td>
<td>2.5</td>
<td>3</td>
</tr>
<tr>
<td>Appropriate Tree Heights</td>
<td>&lt;13.1m</td>
<td>13.1-18m</td>
<td>18-21.3m</td>
<td>21.3-24.1m</td>
<td>&gt;24.1m</td>
</tr>
</tbody>
</table>

Figure 5b: Window sizes used for tree isolation by the local maximum function.

Figure 5: Tree isolation parameters.
Figure 6: Process used to characterize potential loggerhead shrike habitat.
Figure 7: Process used to characterize potential Swainson’s warbler habitat.
Figure 8: Process used to create the generalized vegetation canopy characterization.
Figure 9 a-d: Example of tree isolation within a pond pine stand. The figure shows sample plot 14.
Figure 10 a-d: Example of tree isolation within a longleaf pine stand. The figure shows sample plot 7.
Figure 11: Trees identified in the field with calculated canopy widths indicated. Note that many trees are in close proximity to one another and that their canopies overlap. It is hypothesized that the tree isolation algorithm is less able to accurately distinguish trees in this type of situation.
Figure 12: Photograph of plot 12. Smaller trees may be less likely to be identified in the LIDAR-based analysis.
Figure 13: Percent cover by strata in pond pine plots. The error bars show standard deviation.
Figure 14: Percent cover by strata in longleaf pine plots. The error bars show standard deviation.
Figure 15a-e: Example results from LOSH habitat characterization. The figure shows sample plot 13
Figure 16a-e: Example results from SWWA habitat characterization. The figure shows sample plot 28.
Figure 17a-e: Example results from generalized vegetation canopy characterization. The figure shows sample plot 21.
Appendix A. Data sheets used for field data collection

These are the front and back of a data sheet used for field data collection.
<table>
<thead>
<tr>
<th>Species</th>
<th>Bearing</th>
<th>Distance</th>
<th>Height</th>
<th>DBH</th>
<th>Strata</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>SC1</td>
<td>SC2</td>
<td>S</td>
<td>H</td>
<td></td>
</tr>
</tbody>
</table>
Appendix B. Scripts from ERDAS Imagine

The model builder within ERDAS Imagine was used to create and run the processes used to isolate trees and characterize the habitat for the three example applications. The scripts were exported and included in the appendix in order to demonstrate the specific methods employed in the analysis.

Tree Isolation Script Exported from Imagine

```plaintext
COMMENT "Generated from graphical model: c:/temp/plots/models/trees2.gmd";
#
# set cell size for the model
# SET CELLSIZE MIN;
#
# set window for the model
# SET WINDOW UNION;
#
# set area of interest for the model
# SET AOI NONE;
#
# declarations
#
Float RASTER CHM FILE OLD NEAREST NEIGHBOR AOI NONE "c:/temp/plots/plots200m/CHM.img";
Float RASTER n22_Trees FILE NEW USEALL ATHEMATIC FLOAT SINGLE "c:/temp/plots/trees/Trees.img";
FLOAT MATRIX n4_Custom_Float;
FLOAT MATRIX n9_Custom_Float;
FLOAT MATRIX n10_Custom_Float;
FLOAT MATRIX n11_Custom_Float;
FLOAT MATRIX n12_Custom_Float;
#
# load matrix n4_Custom_Float
#
n4_Custom_Float = MATRIX(9, 9:
  0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 1, 0, 0, 0, 0,
  0, 0, 0, 1, 1, 1, 0, 0, 0,
  0, 0, 0, 0, 1, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0);
#
# load matrix n9_Custom_Float
#```
n9_Custom_Float = MATRIX(8, 8:
   0, 0, 0, 0, 0, 0, 0, 0,
   0, 0, 0, 0, 0, 0, 0, 0,
   0, 0, 1, 1, 1, 0, 0, 0,
   0, 0, 1, 1, 1, 0, 0, 0,
   0, 0, 1, 1, 1, 0, 0, 0,
   0, 0, 0, 0, 0, 0, 0, 0,
   0, 0, 0, 0, 0, 0, 0, 0);
#
# load matrix n10_Custom_Float
#
# n10_Custom_Float = MATRIX(8, 8:
   0, 0, 0, 0, 0, 0, 0, 0,
   0, 0, 0, 1, 0, 0, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0,
   0, 0, 0, 0, 0, 0, 0, 0,
   0, 0, 0, 0, 0, 0, 0, 0);
#
# load matrix n11_Custom_Float
#
# n11_Custom_Float = MATRIX(8, 8:
   0, 0, 0, 0, 0, 0, 0, 0,
   0, 0, 1, 1, 1, 0, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0,
   0, 0, 0, 0, 0, 0, 0, 0);
#
# load matrix n12_Custom_Float
#
# n12_Custom_Float = MATRIX(8, 8:
   0, 0, 0, 1, 0, 0, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0,
   1, 1, 1, 1, 1, 1, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0,
   0, 1, 1, 1, 1, 1, 0, 0);
#
# function definitions
#
#define n16_memory Float(FOCAL MAX ( CHM , $n12_Custom_Float) )
#define n15_memory Float(FOCAL MAX ( CHM , $n11_Custom_Float ) )
#define n14_memory Float(FOCAL MAX ( CHM , $n10_Custom_Float ) )
#define n13_memory Float(FOCAL MAX ( CHM , $n9_Custom_Float ) )
#define n12_memory Float(FOCAL MAX ( CHM , $n4_Custom_Float ) )
#define n18_memory Float(CONDITIONAL {\
Swainson’s Warbler Habitat Model Script Exported from Imagine

COMMENT "Generated from graphical model: c:/temp/plots/models/swwa4.gmd";

# set cell size for the model
#
SET CELLSIZE MIN;
#
# set window for the model
#
SET WINDOW UNION;
#
# set area of interest for the model
#
SET AOI NONE;
#
# declarations
#
Float RASTER n1_CHM FILE OLD NEAREST NEIGHBOR AOI NONE
"c:/temp/plots/plots200m/CHM.img";
Float RASTER n14_swwa29 FILE NEW USEALL ATHEMATIC FLOAT SINGLE
"c:/temp/plots/swwa/swwa29.img";
FLOAT MATRIX n6_Custom_Float;
#
# load matrix n6_Custom_Float
#
n6_Custom_Float = MATRIX(11, 11:
  0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0,
  0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0);
#
# normalize matrix n6_Custom_Float
#
if (global sum ($n6_CustomFloat) NE 0)
   {n6_CustomFloat = $n6_CustomFloat / global sum}

(n6_CustomFloat);}
#
# function definitions
#
#define n8_memory Integer(CONDITIONAL { \
   ($n1_CHM < 2) 1,\n   ($n1_CHM >=2) 0\n   }\n   )
#define n10_memory Float(FOCAL SUM ( $n8_memory, $n6_Custom_Float) )
#define n12_memory Float((($n10_memory) / 81) * 100\n   )
#define n3_memory Integer(EITHER 7600 IF ( $n1_CHM >= 7.6 ) OR ($n1_CHM *\n   1000) OTHERWISE \n   )
#define n5_memory Float(FOCAL MEAN ( $n3_memory, $n6_Custom_Float,\n   IGNORE_VALUE 7600 ) \n   )

n14_swwa29 = EITHER $n5_memory/1000 IF ( $n12_memory < 50) OR 0 OTHERWISE ;
QUIT;

Loggerhead Shrike Habitat Model Script Exported from Imagine

COMMENT "Generated from graphical model: c:/temp/plots/models/losh2.gmd";
#
# set cell size for the model
# SET CELLSIZE MIN;
#
# set window for the model
# SET WINDOW UNION;
#
# set area of interest for the model
# SET AOI NONE;
# declarations

Integer RASTER n6_temp;
Integer RASTER n12_plot29 FILE NEW USEALL ATHEMATIC 8 BIT UNSIGNED INTEGER "c:/temp/plots/losh_isolation/plot29.img";
Float RASTER CHM FILE OLD NEAREST NEIGHBOR AOI NONE "c:/temp/plots/plots200m/CHM.img";
FLOAT MATRIX n8_Custom_Float;

# load matrix n8_Custom_Float

n8_Custom_Float = MATRIX(22, 22:
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
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0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0);#

# normalize matrix n8_Custom_Float

if (global sum ($n8_Custom_Float) NE 0)
  {n8_Custom_Float = $n8_Custom_Float / global sum ($n8_Custom_Float);}#

# function definitions

n6_temp = CONDITIONAL {
($CHM < 1) 0,
($CHM >= 1 AND $CHM < 2) 1,
($CHM >= 2 AND $CHM <= 10) 150,
($CHM > 10) 0
}

#define n10_memory Float(FOCAL SUM ( $n6_temp , $n8_Custom_Float , IGNORE_VALUE 150 ) )

n12_plot29 = EITHER $n10_memory IF ( $n6_temp == 150 ) OR 0 OTHERWISE ; QUIT;

Generalized Vegetation Canopy Characterization Model Exported from Imagine

COMMENT "Generated from graphical model:
c:/temp/may11/plots/models/character2.gmd";
# Step 1
# Step 2
# Step 3
# Step 4
# Step 5
#
# set cell size for the model
# SET CELLSIZE MIN;
#
# set window for the model
# SET WINDOW UNION;
#
# set area of interest for the model
# SET AOI NONE;
#
# declarations
#
Float RASTER n1_plot29 FILE OLD NEAREST NEIGHBOR AOI NONE "c:/temp/plots/plots200m/CHM.img";
Integer RASTER n22_plot29 FILE NEW USEALL ATHEMATIC 8 BIT UNSIGNED INTEGER "c:/temp/plots/character3/plot29.img";
FLOAT MATRIX n9_Custom_Float;
#
# load matrix n9_Custom_Float
#
n9_Custom_Float = MATRIX(12, 12:
  0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
  1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
  0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0,
  0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
  0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0);
#
# normalize matrix n9_Custom_Float
#
if (global sum ($n9_Custom_Float) NE 0)
  {n9_Custom_Float = $n9_Custom_Float / global sum ($n9_Custom_Float);}
# function definitions
#
#define n7_memory Float(CONDITIONAL {
  (CHM <= 19) 0,
  (CHM > 19) 1
})
#define n14_memory Float(FOCAL SUM ( $n7_memory , $n9_Custom_Float ) )
#define n20_memory Float(((n14_memory) / 81) * 100)
#define n5_memory Float(CONDITIONAL {
  (CHM <= 9) 0,
  (CHM > 9 AND CHM <= 19) 1,
  (CHM > 19) 0
})
#define n13_memory Float(FOCAL SUM ( $n5_memory , $n9_Custom_Float ) )
#define n19_memory Float(((n13_memory) / 81) * 100)
#define n3_memory Float(CONDITIONAL {
  (CHM < 9) 1
})
#define n10_memory Float(FOCAL SUM ( $n3_memory , $n9_Custom_Float ) )
#define n18_memory Float(((n10_memory) / 81) * 100)
n22_plot29 = CONDITIONAL {
  (n18_memory >=90) 1,
  (n18_memory >=40 AND n19_memory >=40) 2,
  (n18_memory >=40 AND n20_memory >=20) 3,
  (n19_memory >=65) 4,
  (n19_memory >=40 AND n20_memory >=20) 5,
  (n20_memory >=50) 6,
  (n18_memory >=0 AND n19_memory>=0 AND n20_memory>=0) 7
}
QUIT;