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Use of multi-spectral imagery and LiDar data to quantify compositional and structural characteristics of vegetation in red-cockaded woodpecker (Picoides borealis) habitat in North Carolina

Joelle Marie Carney

USE OF MULTI-SPECTRAL IMAGERY AND LIDAR DATA TO QUANTIFY COMPOSITIONAL AND STRUCTURAL CHARACTERISTICS OF VEGETATION IN RED-COCKADED WOODPECKER (*PICOIDES BOREALIS*) HABITAT IN NORTH CAROLINA

By

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This study evaluated habitat parameters for the red-cockaded woodpecker (RCW; *Picoides borealis*) on three tracts in Hoke County, North Carolina. Multi-spectral imagery was used to classify shadow, non-vegetation, herbaceous, hardwoods, and loblolly and longleaf pine trees. Field data were collected for image classification training and validation. Overall classification accuracy for separating hardwood from pine trees, was 80.8%. When separating longleaf (*Pinus palustris* Mill.) and loblolly (*Pinus taeda* L.) pine from hardwoods the accuracy was 73.7%. Field-based height/diameter relationships were applied to LiDAR-identified trees to predict diameter classes. Due to differences in management regimes and site conditions, each tract had different majority pine diameter classes. Average height, diameter, basal area, and stem density per plot were reported from matched, unmatched, and total LiDAR trees to field

trees. Differences between the height, diameter, basal area, and stem density values occurred between the matched and unmatched LiDAR- and field-identified trees.

DEDICATION

I would like to dedicate this research to my parents, John and Susan Carney, and to my very close friends: Jen Mannas, Jennifer Jacobs, and Clint Smith.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION AND BACKGROUND

The Red-cockaded Woodpecker (*Picoides borealis*)

In 1970, the red-cockaded woodpecker (RCW; *Picoides borealis*) was listed as an endangered species by the U.S. Fish and Wildlife Service (USFWS) and received protection under the Endangered Species Act of 1973. This woodpecker ranges from Virginia to Texas and nests and forages in mature, open-grown pine forests with little understory vegetation. The RCW is the only species of woodpecker to excavate nest cavities within the trunks of living pine trees old enough to have developed sufficient heartwood (Zwicker and Walters 1999). Although it will utilize different southern pine species for nest cavities, it prefers mature longleaf pine (*Pinus palustris*). This habitat preference is undoubtedly a contributing factor in the RCW population decline in that longleaf pine has been greatly diminished in geographic extent throughout its former natural range. The decline in the longleaf pine ecosystem was largely due to overlogging and fire suppression during the turn of the 20th century (Conner et al. 2001; Frost 1993; Martin and Boyce 1993). Management practices conducive to maintenance of mature pine habitat have led to RCWs being present on several Department of Defense installations, national wildlife refuges, and state parks and forests throughout the southern United States. Generally, RCWs prefer open pine savannas and woodlands with large old pines for their nesting and roosting habitat and low densities of small pines, little to no hardwood or pine mid-story, very little to no overstory hardwoods, and abundant native bunchgrasses and forb groundcovers (USFWS 2003). Older large pines are preferred for excavating cavities because the heartwood keeps the cavity interior free of resin so as not to entrap the RCWs as they excavate and raise their young (USFWS 2003).

Floristic structure influences both nesting and foraging habitat quality for terrestrial birds, and plays an important part in habitat selection (Beier and Drennan 1997; Fuller and Henderson 1992). Several studies have noted the strong importance of mid-story and understory vegetation height and composition in characterizing RCW habitat quality. Variability of these habitat attributes directly affects RCW fitness and breeding success rates. Rudolph et al. (2002) reported that RCWs exhibited overall reduced foraging behavior on areas where hardwood vegetation was well developed. They found RCWs preferred to forage in stands with a low density of mid-story vegetation. Foraging occurred at greater heights above ground on tracts with greater mid-story heights and densities. Zwicker and Walters (1999) suggested that RCWs select foraging trees based on individual tree age or size (or both). RCW selection of overall habitat preference was based on tree species composition at the landscape and/or stand levels. Furthermore, Zwicker and Walters (1999) stated RCWs were found to have preferences for pines >23 cm diameter at breast height (DBH) and avoided pines <13 cm DBH. Komarek (1974) found RCWs would abandon cavity tree clusters when the height of the mid-story/understory approached nest cavity heights.

Descriptive information on forest vegetation has traditionally been collected by manual assessments of DBH, tree heights, stand structure, and vegetation composition.

Basic information required for describing forest structure is often expensive and time consuming to collect and requires periodic updates to remain valid (Xiao and McPherson 2004). Comprehensive measurements may be possible (although expensive) on individual stands, but are rarely feasible at the landscape level.

The use of remote sensing is an alternative to field measurements for forest (i.e., habitat) assessments over large land areas and can provide detailed information at reduced costs (Evans et al. 2006). The purpose of this study was to determine ways to utilize multi-spectral imagery and LiDAR (Light Detection and Ranging) data to evaluate a series of forest stand parameters associated with RCW habitat that cannot be feasibly assessed with traditional inventories across extensive landscapes. Pine stem density and basal area by size class are key biophysical parameters in assessing RCW nesting and foraging habitat (Tweddale and Allen 2005). Identification of requisite habitat, or areas that could be modified to generate such habitat, at the landscape level would provide wildlife management professionals options to potentially expand the range of this species. This would also provide pathways for interaction between isolated populations, thereby potentially strengthening the species gene pool.

Multi-spectral Imagery for Forest Assessments

Vegetation has unique spectral reflectance characteristics with strong absorption in red wavelengths and strong reflectance in near-infrared wavelengths, which allow separation of plants from other ground surface covers (Xiao et al. 2004). Research has shown basic forest type maps could be produced with film-based, color-infrared imagery sensitive to these spectral ranges (Evans et al. 1985; Hill et al. 1982; Onufer 1981). More detailed identification of individual tree species or species groups has also been demonstrated in analysis of digital multi-spectral imagery (Batten and Evans 1998; Casey 1999; Hughes et al. 1986; Knight et al. 2004). In addition, fusing spectral imagery with LiDAR data can take advantage of the strengths of both sensors for the purpose of improving estimates of forest stand characteristics (Leckie et al. 2003; McCombs et al. 2003). Utilizing multi-spectral and LiDAR data, processing methods, data storage, and computing power needed for data analysis are approaching the point where large area surveys over management units are possible (Leckie et al. 2003).

Forest Measurements with LiDAR

Typical small-footprint (<1 m) LiDAR systems have been described by Baltsavias 1999; Dubayah et al. 2000; and Lefsky et al. 2002. Modern LiDAR systems utilize highly accurate positioning systems generate x, y, z coordinate data from aerial platforms by laser at pulse rates of over 100 kHz. The laser ranging device measures the distance from the aircraft to the ground based on exact timing between each outgoing pulse and its received reflection. Pulses are directed to the ground in a side-to-side pattern across the flight path. Aircraft location and orientation are determined by use of a Differential Global Positioning System (DGPS) and an Inertial Measurement Unit (IMU). Data from these devices are used to determine the exact position of the LiDAR pulses on the Earth's surface (Evans et al. 2006). LiDAR sensors generally utilize laser wavelengths between 900-1064 nm which correspond with high vegetation reflectance (Lefsky et al. 2002). The spatial resolution (up to several points per m^2), measurement accuracy, and spectral response of these systems to vegetation have led to a significant body of research on the use of small-footprint LiDAR data for forest assessments (Brandtberg et al. 2003; Eggleston 2001; Evans et al. 2006; Lefsky et al 2002; McCombs et al. 2002; Popescu et al. 2003; Zimble et al. 2003). These sensors directly measure the three-dimensional distribution of plant canopies as well as subcanopy topography. They have the ability to provide accurate estimates of vegetation height, cover, and canopy structure (Lefsky et al. 2002). The location of trees and their heights derived from LiDAR intuitively have a number of possible uses in defining the structural character of a stand, and thus the habitat suitability for various wildlife species such as the RCW. This conceptual framework of spatial habitat assessment has been demonstrated over a landscape area in central Idaho by (Zimble et al. 2003).

The most commonly cited forest measurement determined with LiDAR is tree height. St-Onge (1999), working in boreal forests in the Abitibi region of Quebec, Canada, compared tree heights measured from the ground with tree heights measured by small-footprint high-density LiDAR. This study demonstrated that laser measurements have accuracies comparable to that of ground measurements.

To determine individual tree heights using LiDAR, an analyst must first identify target trees within the LiDAR data. Recent studies have illustrated a variety of different approaches taken towards tree recognition and height determination (Brandtberg et al. 2003; Eggleston 2001; Persson et al. 2002; Popescu et al. 2004; Zimble 2002). The approach of identifying LiDAR canopy trees used in this project was based on the one described by McCombs et al. (2003). Their methodology identified groups of pixels (i.e., assumed tree crowns) in a LiDAR-derived first-return surface that were higher than neighboring pixels. The highest value within each group defined the tree peak and its height above a LiDAR-derived ground surface. Specifically the highest value within each group defined the tree peak and its height above a LiDAR-derived ground surface. Their method evaluated high- and low-density planting spacings in a 15 year old loblolly stands located in Mississippi State University's Starr Memorial Forest in east central Mississippi.

Objectives

The primary goal of this study was to utilize high-resolution multi-spectral imagery and LiDAR remote sensing technologies to aid in generating a landscape-scale habitat suitability model for RCWs. To help achieve this goal, the following questions were defined for this research:

1) Is it possible to generate a classified image layer from the multi-spectral imagery to differentiate pine [i.e., longleaf (*Pinus palustris*) and loblolly (*Pinus taeda*)] from hardwood canopy species composition within forest stands?

2) Could a geospatial layer produced from LiDAR data be used to determine the average size (i.e., diameter distribution) of pine dominated stands classified from the multi-spectral imagery?

CHAPTER II

METHODS

Site Description

The rectangular (E-W oriented) study area encompassed three separate forest tracts located on, or adjacent to, Fort Bragg (United States Army Installation Base) in Hoke County, North Carolina. The area was approximately 30 km^2 in size. Tracts included: Blue Farm, a private forest land managed partly for pine straw production; and McCain Tract, a state owned conservation area, and the southwest corner of Fort Bragg (Figure 3.1). The study area located on the Coastal Plain within the Sand Hill region of North Carolina is characterized by flat land to gently rolling hills and valleys. Predominant vegetation typically associated with this region includes grassland and early-succession habitats, pine woodland, and river bottoms. Elevation ranges from sea level near the coast to about 182.9 m in the Sand Hills of the Southern Inner Coastal Plain (Outcalt and Sheffield 1996; North Carolina Geographical Survey 2005). Mean annual temperature is about 16.2° C with annual precipitation averaging 118.6 cm (State Climate Office of North Carolina 2006).

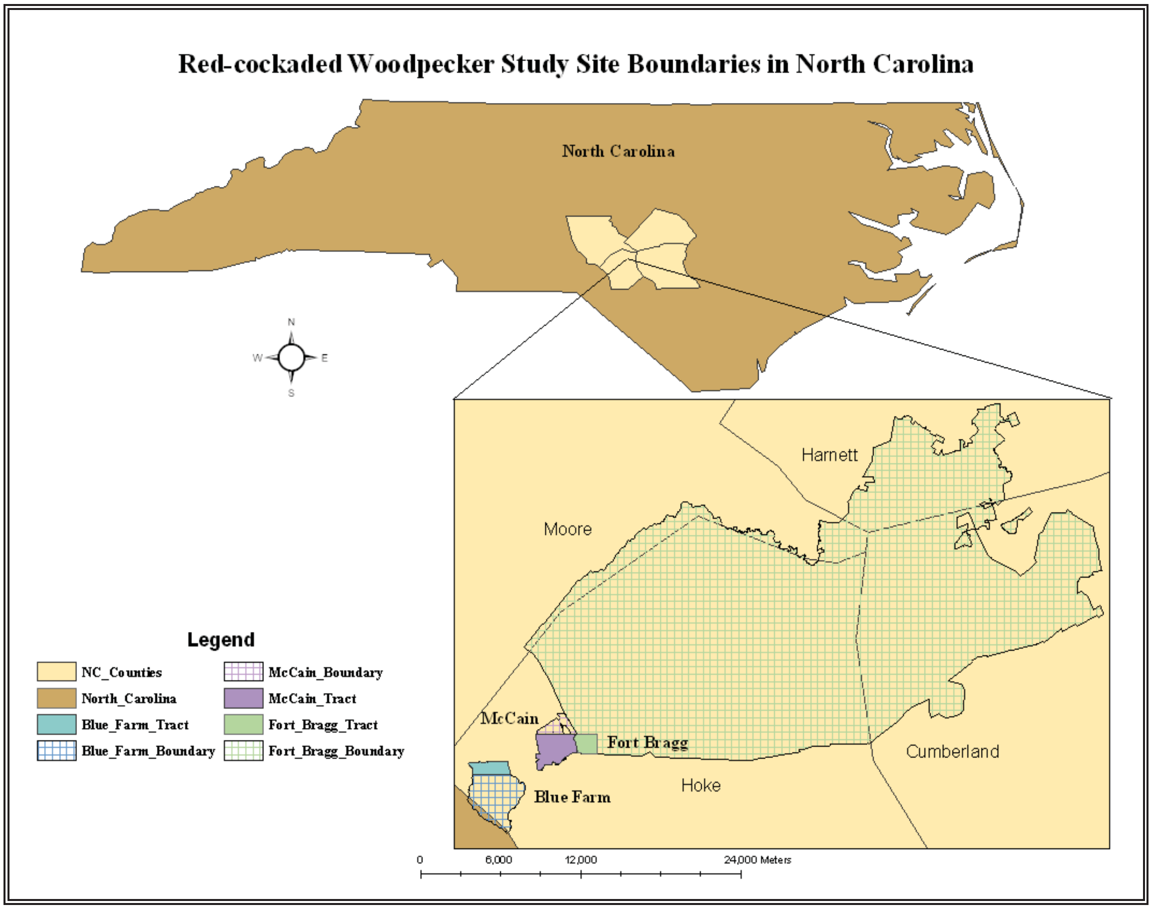

Figure 3.1 Blue Farm, McCain, and Fort Bragg Tracts and overall ownerships in the red-cockaded woodpecker (*Picoides borealis*; RCW) study area location in Hoke County, North Carolina.

Field Data

Field data were collected in November and December 2006 for all woody cover classes. A total of sixty-nine 0.04 ha circular plots were randomly placed across the three tracts; 22 plots on McCain, 23 plots on Ft. Bragg, and 24 plots on Blue Farm. Information recorded on overstory/mid-story trees (>0.9 m tall, >2.54 cm DBH) on each plot consisted of: total height (taken to nearest 0.1m), DBH (taken to nearest 0.3cm), location (i.e., distance and azimuth from plot center to determine tree location using GPS coordinates from each plot center), height to live crown (taken to nearest 0.1m), crown diameter (taken to nearest 0.1m), and species identification.

Remote Sensing Data

LiDAR Data

Airborne LiDAR data were provided by Land Air Mapping[1] at a nominal posting density of 4.0 points per m^2 and were recorded as first, only (meaning just 1 return was recorded), second, and third returns. Data were delivered in Universal Transverse Mercator (UTM; NAD83, GRS80) x, y, z coordinates. Data were originally provided in tiled format (i.e., regular grids of all data points) across the study area, which included all points in overlapping regions of flight lines. The data were re-processed by the vendor to remove points beyond the flight-line overlap boundaries. Thus, points from one flight line would not overlap points from adjacent flight lines.

LiDAR data from each tract were used to generate canopy and ground elevation raster models at a resolution of 0.5 m. Canopy models were created using the first and only returns by use of linear interpolation methods (grid derived from a Triangular Irregular Network [TIN]) using Imagine (ERDAS, 2001)[1]. Ground models were generated using a surface of first returns and a surface of last returns then processed using LiDAR Analyst 3.05.02 module of ArcGIS 9.0 (ESRI, 2005). These elevation models were later used to determine locations of trees and their associated heights for evaluation of stand structure.

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[1] Mention of company or product names is made for information purposes only and does not constitute offical endorsement by Mississippi State University or its employees.

Multi-spectral Imagery

Airborne multi-spectral imagery provided by GeoData Airborne Mapping and Measurement[2] was acquired with CCD (charged coupled device) cameras in the summer (July) 2005 at 0.25 m resolution in four spectral channels: blue (450 nm), green (550 nm), red (650 nm), and Near Infrared (850 nm). Individual frames were ortho-rectified to a ground digital elevation model (DEM) by the provider then pieced together in a mosaic for each of the three study tracts. Upon subsequent processing of the multi-spectral imagery, positive matching of tree crowns visible in the imagery to specific ground- or LiDAR-derived tree locations was not adequate using this rectification process. The mosaics were re-registered to a canopy-based, LiDAR-derived DEM of the study area by utilizing a 3rd order polynomial model. This model, based on several hundred manually selected control points, improved registration between the imagery and LiDAR surface (Figure 3.2) yet still fell short of registration accuracy needed for individual tree analysis based on simultaneous use of both data sets. This shortcoming, however, was not crucial to the project's outcome.

[2] Mention of company or product names is made for information purposes only and does not constitute offical endorsement by Mississippi State University or its employees.

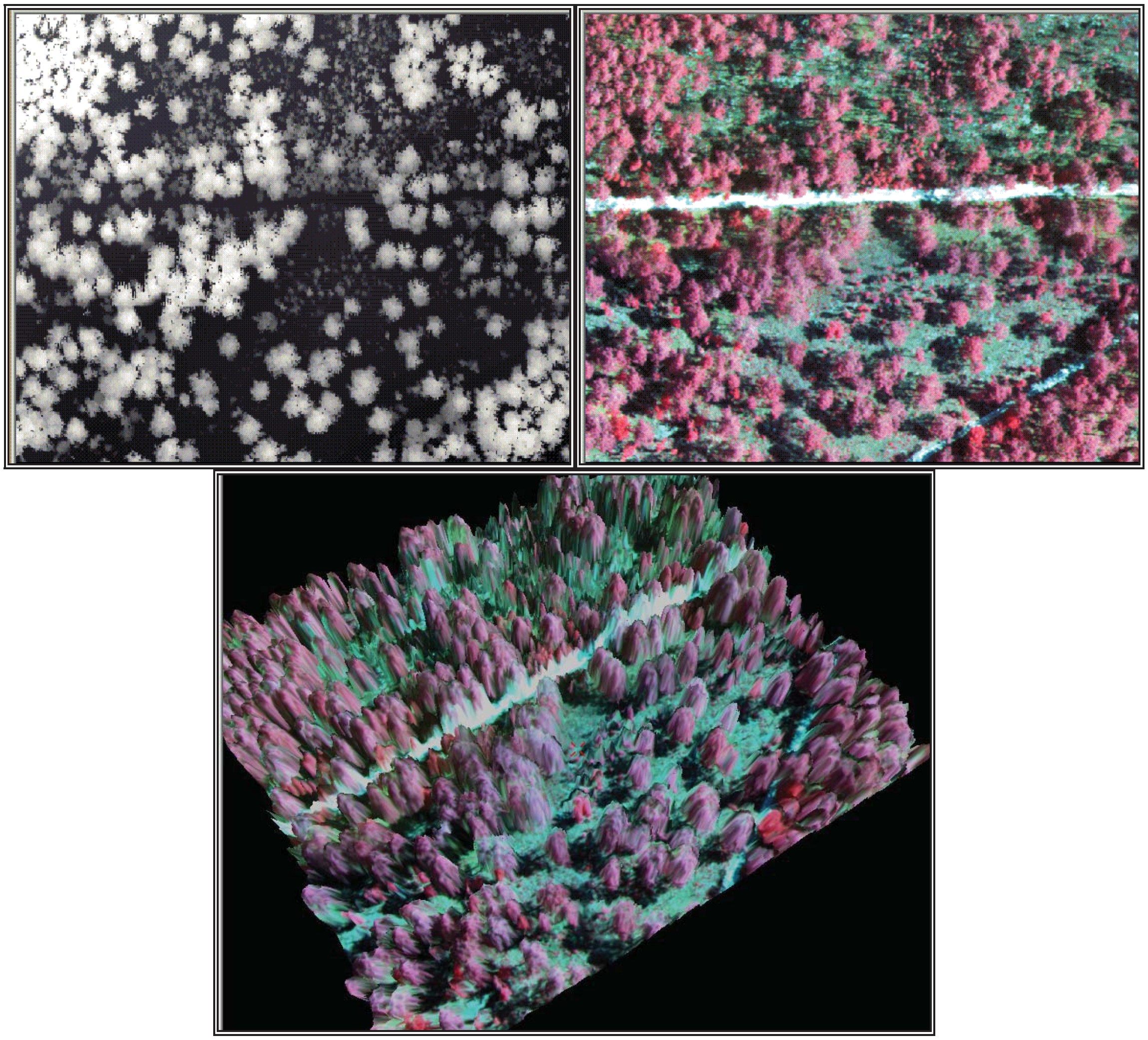

Figure 3.2 First return LiDAR canopy surface (upper left), color-infrared multi-spectral imagery (upper right) and 3-D depiction of the two combined (bottom) for a small section of the McCain Tract in Hoke County, North Carolina.

Object-oriented Classification of Multi-spectral Imagery

Ground inspections of the three tracts provided guidance as to classification techniques that would be successful in species identification of individual trees or groups of trees. In general, most longleaf pines occurred as either open-grown individuals or in small groups. Loblolly pine tended to occur near bottomlands and depressions – wet tracts that could be readily distinguished from other targets. Broadleaf hardwoods occurred either in clumps in canopy gaps between pines or in contiguous stands at lower slope positions and along drainages. Given the tendency of these targets of interest to occur as groups rather than individuals, classification based on objects (group) rather than pixel-based techniques was deemed appropriate.

The object oriented classification method used in this research was essentially that described by Repaka et al. (2004) in which relationships of several categories of object characteristics are used and each may be assigned weighting factors. Classification of imagery was performed with eCognition™ version 4.0 software (Definiens 2004). Procedures involved four basic steps: object generation through image segmentation, development of a classification hierarchy and membership function definitions, classification of image objects, and validation.

Field data were used to validate areas of hardwoods from pine (i.e., loblolly and longleaf) cover types. After areas exhibiting differing vegetation types were recorded with a GPS unit, the spectral reflectance values were examined to determine appropriate cut-off values for each membership function.

Image Segmentation

Image segmentation was instrumental in the isolation of groups of pixels with similar attributes that represented majority of the overstory tree crowns, making it possible to develop membership functions based on individual trees or groups of trees rather than the classic pixel-based training techniques utilized in other classification protocols. The segmentation process in eCognition™ utilized three distinct parameters for object creation: scale, color/shape, and smoothness/compactness. Scale dictates the relative final size of image objects, the larger the scale parameter the larger objects appear to become. Color and shape were complementary parameters that controlled the grouping of pixels (Oruc et al. 2004). Color was a weighting factor that dictated to what extent the spectral value influenced object pixel aggregation. Shape has a value in inverse proportion to color; a high color weight will have a low shape weight. Shape value was also modified by two components, compactness and smoothness, that influenced the contiguity of image objects by changing shape textures. Scale, color, and shape parameters were manually manipulated to generate image objects that covered individual tree crowns or groups of trees visible in the imagery (Figure 3.3). For the original pixel size of 0.25 m, the following segmentation parameters generated the best (i.e., visually compared to original imagery) representation of tree cover: scale = 12, color = 0.9, and shape = 0.1 (with shape being qualified by values of compactness = 0.5 and smoothness = 0.5). Spectral bands used in segmentation were blue (450 nm), green (550 nm), red (650 nm), and NIR (850 nm). All four bands were treated equally given a weight value of 1.0 when considered for contribution.

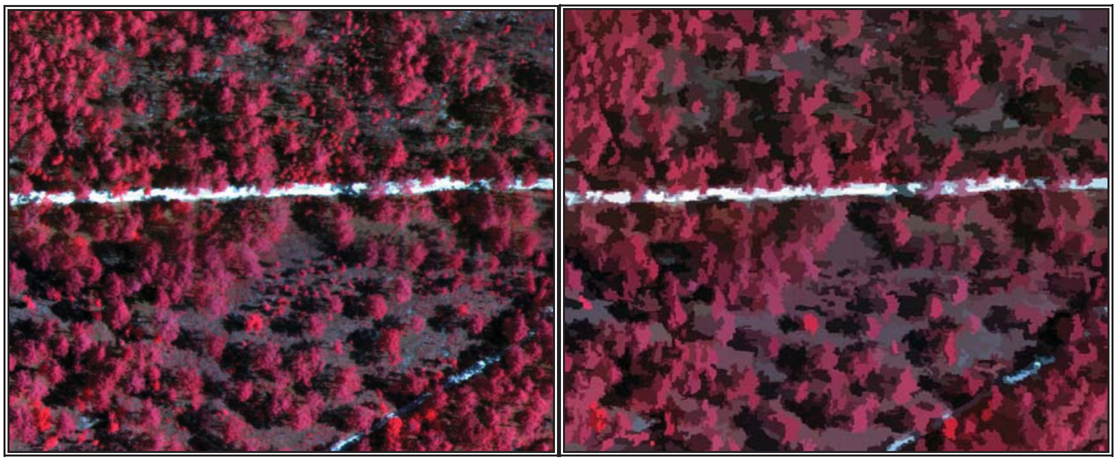

Figure 3.3 Subset of original color-infrared multi-spectral imagery of portion of McCain Tract located in Hoke County, North Carolina (left) and image segmentation of the canopy tree crowns (right).

Characteristics of resulting image objects were used to classify species groups (i.e., pine: longleaf vs. loblolly, hardwood, other vegetation), non-vegetation, and shadow classes. Object-based statistical descriptors were generated from pixels that comprised the object. This included the mean value in each reflectance band, the standard deviation of each band, relative brightness compared to overall image brightness, and ratio of mean reflectance value compared to image mean in each band. One derived object value, normalized difference vegetation index (NDVI; infrared-red/(infrared+red), was generated for use in vegetation discrimination and classification. NDVI values, were viewed interactively to develop the classification schema for both hierarchy of the classification and the classification decision logic used to identify classes of interest.

Classification Hierarchy and Membership Functions

Unlike typical pixel-based classification schemes, an object based approach was used. The software utilized was eCognition™ to generate a more intuitive set of classification rules that in some instances take on a form similar to the mental processes used in aerial photography interpretation. To meet the project's objective, objects were first differentiated into shadow and non-shadow. Cover classes shadow, non-vegetation, and herbaceous were broken out based on the logic diagram given in Figure 3.4.

Membership functions used for classification take the form of class probability based on values or ranges determined from assessment of object values compared to known targets. For example, the shadow class was defined as all objects with a brightness value < 65 (Figure 3.5). Note that some functions do not have a hard cut-off value. The fuzzy decision probability was determined by both class function and its interaction with other class membership functions. Class assignment for a given object was based on class membership function that returns the highest class probability value (range 0.0-1.0).

The hierarchical classification scheme (Figure 3.4) that used membership functions (See Figures 3.5, 3.6) was a combination of logical ordering of image elements based on spectral and photo-interpretive properties. Shadow and non-shadow were differentiated by use of mean brightness for each image object. This object value was the relative brightness (i.e., magnitude of reflectance) of all input channels taken together. The function used for shadow distinction had a cut-off value of 65; object brightness values above this number were considered non-shadow.

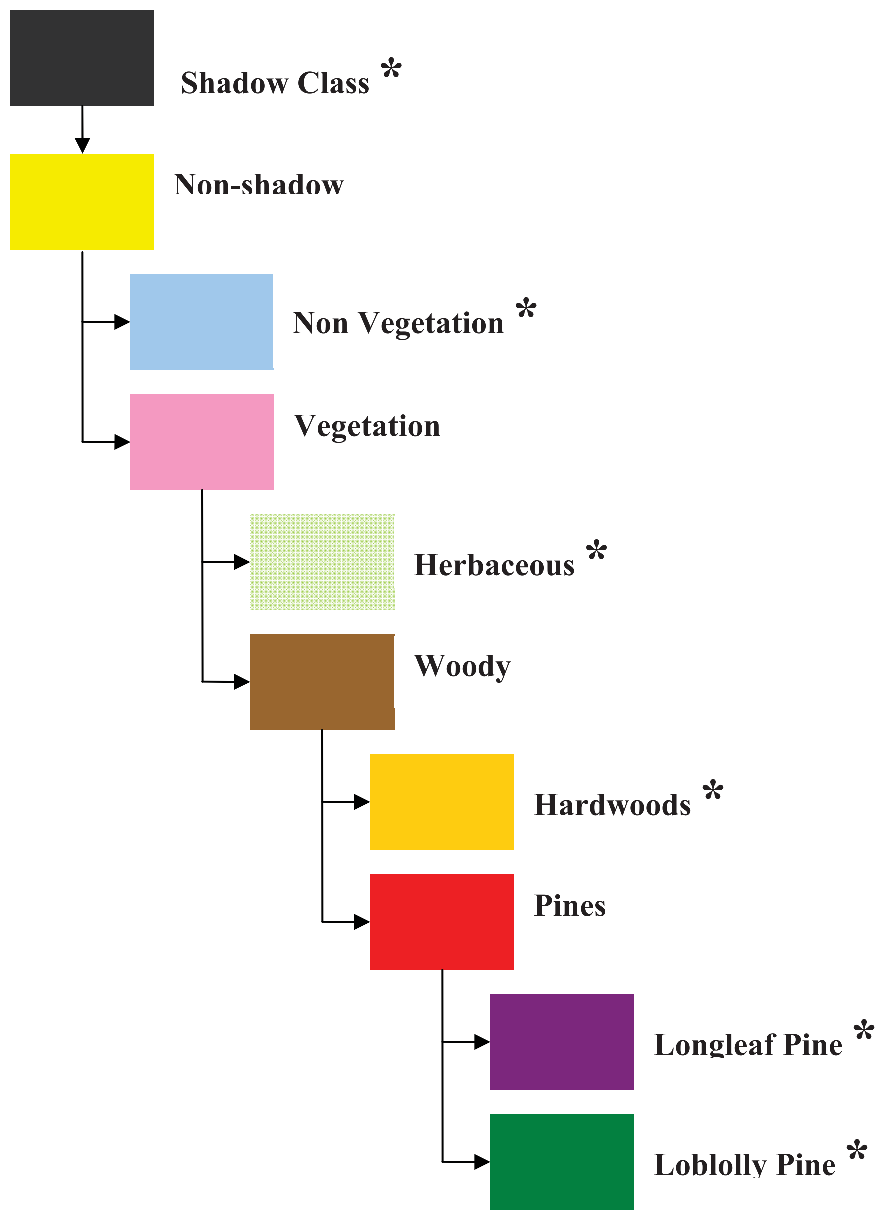

Figure 3.4 Classification hierarchy for red-cockaded woodpecker (*Picoides borealis*) canopy assessment in Hoke County, North Carolina. Classification of features in color-infrared multi-spectral imagery was based on object properties.

*Final classes for which accuracy was reported.

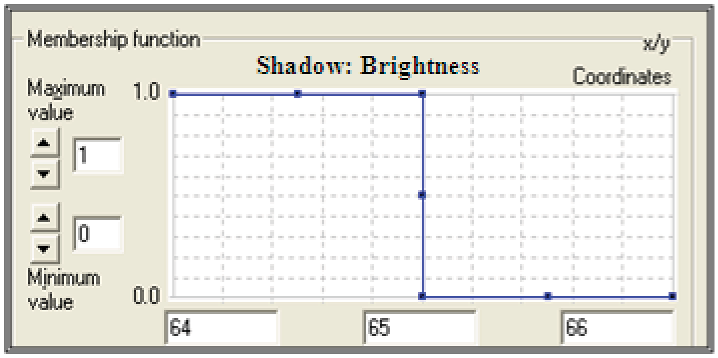

Figure 3.5 Example of shadow membership function derived from image objects in multi-spectral data processed through eCognition™ segmentation routine. This function is based on the relative object brightness value. Membership probability for the shadow class peaks at 1.0 (100 % probability of class membership) at values of 64 or lower with a 0.5 probability at 65.

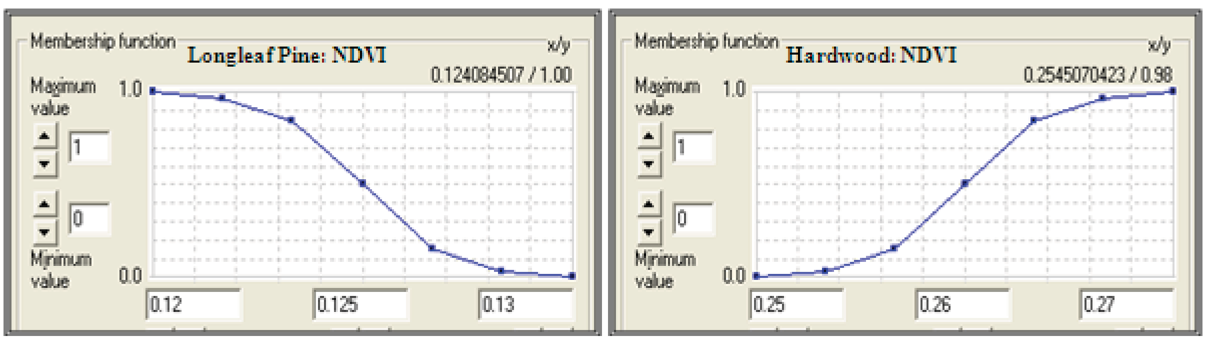

Figure 3.6 Membership functions based on Normalized Difference Vegetation Index (NDVI) for longleaf pine (*Pinus palustris* Mill.), and hardwoods. Membership probability peaks (1.0; 100 % probability) for longleaf pine at 0.12 and hardwoods at 0.27. Fuzzy membership probability overlaps at values generally centered at 0.26 for hardwoods, and 0.125 for longleaf pine for 0.5 probability associated with the two classes.

The non-shadow class was further subdivided by use of a membership function based on NDVI to separate non-vegetation and vegetation. Green vegetation had high reflectance in the near-infrared and low reflectance in the visible red wavelength of light, thus making it highly distinguishable from non-vegetation by use of the NDVI function.

The vegetation class was further subdivided into herbaceous and woody classes. The woody class was then subdivided into hardwood and pine classes. Finally, the pine class was subdivided into loblolly and longleaf pine classes.

Image Classification Accuracy Assessment

Classification was performed based on membership functions defined for the classes indicated in Figure 3.4 then tested for accuracy by use of *a priori* or known individual tree locations in the plot data and non-tree classes designated throughout the study area since. Non-woody categories of shadow, herbaceous, and non-vegetation were identified from prior knowledge of these areas. Seventy-five samples or verification sites taken with GPS were taken from each woody category (i.e., hardwood, and pine). All non-woody categories (i.e., shadow, non-vegetation, herbaceous) were interpreted from the CIR imagery and verified through prior knowledge and from the ground referenced data. These feature classes are dynamic in nature and often change (i.e., shadow on an image changes depending on the time of day the image was taken). Congalton and Green (1999) suggested at least a minimum of 50 samples should be collected for vegetation or land cover category for use in an error matrix. Chipman et al (2004) suggested the number of samples per category might be adjusted based on the relative importance of that category for a particular application such as assessing woody vegetation for RCW habitat. One hundred and nine sample verification sites per woody category (i.e., longleaf, loblolly, hardwood) were derived from GPS points taken in the field. Due to geospatial registration issues, individual trees in the classification did not always precisely match trees in field plot shapefiles. This was due to both inaccuracy of image rectification and inherent inaccuracy in GPS plot locations, and associated imprecision in determining azimuth and distance from those positions to individual trees. However, due to spatial pattern similarity between field plot trees and those in the classification, positive visual matches for validation could be made for most canopy tree field samples. Classification accuracy was calculated from samples based on commonly reported methods of error matrix calculations (Congalton et al. 1999).

The matrix used in this study compared, on a category-by-category basis, the relationship between known reference data (e.g., ground truth or field samples) to the corresponding results of an object-based supervised classification. The matrix determined how well the classification categorized the representative subset of the objects used in the training process of the supervised classification. The matrix listed the known cover types used for training (i.e., columns) versus objects actually classified into each cover type category by the classifier (i.e., rows) (Chipman et al. 2004). Commission errors were assessed by non-diagonal rows whereas omission errors were assessed by non-diagonal columns. Overall accuracy was found by dividing the total number of correctly classified objects by the total number of reference objects. In addition, individual accuracies (i.e., producer's and user's accuracies) for each category were calculated by dividing the number of correctly classified objects for the particular category by either the total number of objects from the corresponding column (i.e., producer's accuracy) or row (i.e., user's accuracy) (Chipman et al. 2004). A Kappa statistic is then used to measure the difference between the actual agreement between reference data and an automated classifier and the chance agreement between the reference data and a random classifier (Chipman et al. 2004).

Height-diameter Relationship Analysis

Total height of all plot trees was determined to the nearest 0.1 m while stem diameter was measured to the nearest 0.3 cm (0.1 inch). Individual tree data (pines only) from the field plots were analyzed to determine the relationship between stem diameter and tree heights. This regression function used the inverse value of tree heights which provided a prediction function that more closely tracked the continuum of height values associated with pine tree heights obtained on LiDAR-identified trees. The regression function was applied to LiDAR-identified trees to predict stem diameter for each LiDAR tree based on LiDAR estimated height.

LiDAR-based Tree Identification and Measurements

Canopy trees were identified and mapped within the three study tracts by use of LiDAR elevation models and modified procedures adopted from those described by McCombs et al. (2003). Spectral data were not incorporated into the tree identification function as described by McCombs et al. (2003) due to problems of inadequate registration between the imagery and LiDAR canopy surfaces. Their tree finding model was slightly modified to better identify canopy pine trees from an open natural stand instead of a loblolly plantation. Their version of the tree finding model subtracted the canopy and non-vegetation surfaces from one another then integerized the values before matching the maximum value per clump (a group of pixels with higher values than their neighbors that likely represent a tree location) to the original surface value to output tree peak values.

The tree finding model consisted of two spatial process models that identify and estimate height measurements of probable tree locations in the main canopy of forest stands. A smoothing filter was used across the canopy elevation model to eliminate "holes" in the canopy surface caused by LiDAR points that penetrated the main canopy thereby generating low points in the resulting surface model. Clumps of pixels were identified that could be trees based on user inputs of three radial search filters to identify small, medium, and large crown radii. These values were determined from field observations at representative tracts. Those values created aggregated groups of pixels (i.e., clumps) where the pixels in the identified clumps were higher than a set percentage of neighboring pixels based on the radial search criteria and probable height of live crown determined from a relative stem density function. Clumps were subjected to a sieving operation to eliminate small groups of pixels that did not likely represent real trees.

Output clumps were passed to the second algorithm which extracted the location and height value of the highest pixel in each clump as a tree location. A distance function was used to delete trees adjacent to, but shorter than, nearby neighbors (i.e., probable false trees identified) based on tree height. Short trees were allowed to be closer together than tall trees.

Summary tables were compiled outputting the number and percentages for matched field to LiDAR-derived trees, omission and commission values per tract location and for combined tracts to assess how well the tree finding model performed at separating canopy trees from non-canopy trees. The upper quartile, or 25% canopy trees were separated from the rest of the canopy trees to evaluate the model's performance at finding the dominant and codominant canopy trees. This was done strictly on the basis of evaluating the performance of the tree finding model's ability to correctly identify upper canopy trees.

Diameter-height Mapping

The classification developed from the multi-spectral data was used to label all LiDAR-identified trees as to tree type (i.e., longleaf pine, loblolly pine, or hardwood). The DBH/height relationship equation developed from field data was applied to all LiDAR-identified pine trees to attribute those tree locations with a predicted DBH. This height-diameter output was used as the basis for determining dominant stand type by diameter size class in the RCW habitat evaluation process. The last step to identifying size classes geospatially was to examine the relative size of LiDAR-identified pines on a unit area basis to compare tree sizes grouped by the U.S. Fish and Wildlife Service Recovery Guidelines: (1) < 24.5 cm (< 10"), Basal Area (BA)= <2.3 m^2/ha, and < 50 stems/ha; (2) ≥24.5 to ≤35 cm (≥10 – ≤14"), BA 0 – 9.2 m^2/ha; (3) > 35 cm (> 14"), BA= >4.6 m^2/ha, and >45 stems/ha; and pine type (i.e., loblolly or longleaf) (USFWS 2003). These three pine size classes formed the basis for determining areas of currently suitable RCW habitat or areas that, through proper management, could be made suitable for use by RCWs.

Pine Height, DBH, Basal Area, and Stem Density Output

All field and LiDAR-derived samples were summarized on a per plot basis by tract location and combined across all three tracts, including measured attributes: diameter at breast height (DBH), total height, and stem density. Linear regression analysis was preformed between the LiDAR- and field-derived measurements per plot and per tree for DBH, total height, and stem density to evaluate how well the LiDAR-derived estimates compared to the field-based measurements, and whether field and LiDAR values were significantly different.

CHAPTER III

RESULTS

Image Classification Accuracy Assessment

The resulting classification (Figure 3.7) provided a detailed spatial representation of the vegetative components on the study tracts.

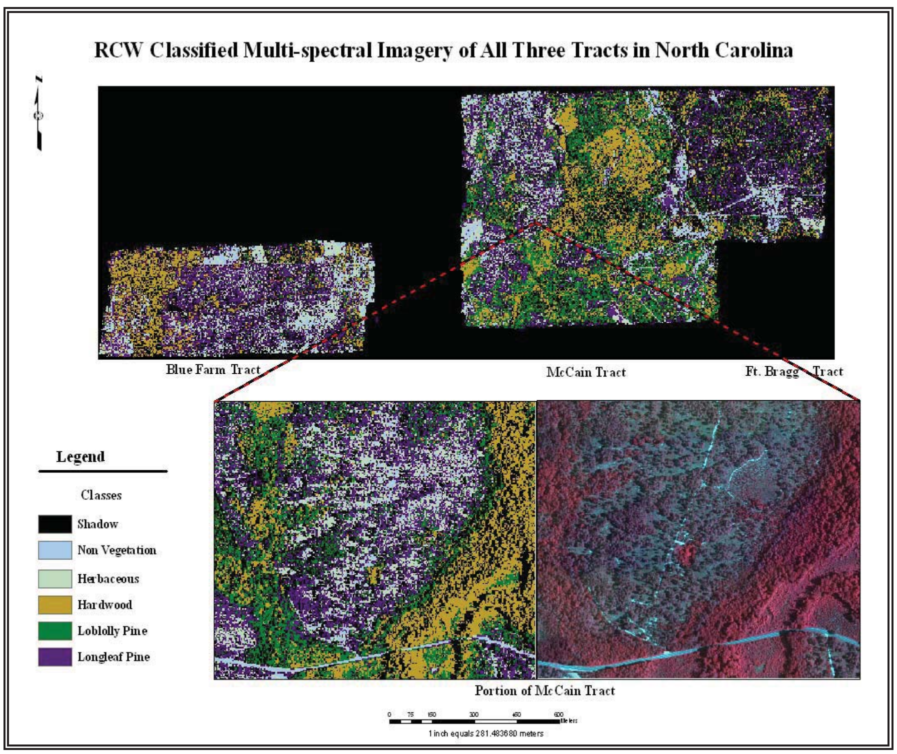

Figure 3.7 Classified imagery of all three (Blue Farm, McCain, Ft. Bragg) ownership tracts and enlarged portion of part of the McCain Tract illustrating detail in the object-based classified output product (lower left) as compared to the original color-infrared imagery (lower right).

Overall accuracy of the multispectral image classification of all classes including separating the pine cover type into loblolly and longleaf pine was 73.7% (Table 3.1). The overall Kappa statistic was 0.7 while individual cover type Kappa values ranged from 0.5 for the loblolly pine cover type to 0.9 for the longleaf pine cover type when the classification separated the pine cover type into loblolly and longleaf (Table 3.2). The overall classification accuracy when loblolly and longleaf were combined into one pine cover type was 80.8% (Table 3.3), and the overall Kappa statistic increased to 0.7 (Table 3.4).

For accuracies given in Table 3.2; producer's accuracy for longleaf pine was 90.8% with a user's accuracy of 58.9%. Producer's accuracy for loblolly pine was 61.5% with a user's accuracy of 69.1%. Hardwoods had a producer's accuracy of 57.8% and a user's accuracy of 80.8%. When the pine species were combined into a pine class (Table 3.4), producer's accuracy was 94.0% and user's accuracy 77.4%. For shadow, producer's accuracy was 93.3% with a user's accuracy of 81.4%. Producer's accuracy for non-vegetation was 80.0% and user's accuracy was 95.2%. The herbaceous class had a producer's accuracy of 64.0% with a user's accuracy of 80.0%. Individual Kappas (Tables 3.2, 3.4) were: longleaf = 0.9, loblolly = 0.5, hardwoods = 0.5, pines = 0.9, shadow = 0.9, non-vegetation = 0.8, and herbaceous = 0.6.

Table 3.1 Classification error matrix for all classes including the separation of the pine class into loblolly and longleaf pine *(Pinus taeda* L. and *Pinus palustris* Mill.) cover types for the 2005 images of the three study areas (McCain, Ft. Bragg, Blue Farm) in North Carolina.

		Reference						
		Longleaf Pine	**Loblolly Pine**	**Hardwoods**	**Shadow**	**Non Vegetation**	**Herbaceous**	**Totals**
Classified	**Longleaf Pine**	99	31	24	2	0	12	168
	Loblolly Pine	8	67	22	0	0	0	97
	Hardwoods	2	11	63	2	0	0	78
	Shadow	0	0	0	70	4	12	86
	Non-Vegetation	0	0	0	0	60	3	63
	Herbaceous	0	0	0	1	11	48	60
	Totals	109	109	109	75	75	75	552
	n	552	**Overall Accuracy:**			**73.7%**		

Table 3.2 Classification accuracy and Kappa statistics derived from the classification error matrix of the separated pine classes into loblolly and longleaf pine (*Pinus taeda* L. and *Pinus palustris* Mill.) and other cover types for the 2005 images of the three study areas (McCain, Ft. Bragg, Blue Farm) in North Carolina.

	Reference Total	Class Total	Correct	Producer's Accuracy	User's Accuracy	Kappa
Longleaf Pine	109	168	99	90.8%	58.9%	0.9
Loblolly Pine	109	97	67	61.5%	69.1%	0.5
Hardwoods	109	78	63	57.8%	80.8%	0.5
Shadow	75	86	70	93.3%	81.4%	0.9
Non-Vegetation	75	63	60	80.0%	95.2%	0.8
Herbaceous	75	60	48	64.0%	80.0%	0.6
		Overall Kappa:	**0.68**			

Table 3.3 Classification error matrix for the pine class (loblolly *Pinus taeda* L. and longleaf *Pinus palustris* Mill. combined) and other cover types for the 2005 images of the three study areas in North Carolina.

		Reference					
		Pines	**Hardwoods**	**Shadow**	**Non Vegetation**	**Herbaceous**	**Totals**
Classified	**Pines**	205	46	2	0	12	265
	Hardwoods	13	63	2	0	0	78
	Shadow	0	0	70	4	12	86
	Non-Vegetation	0	0	0	60	3	63
	Herbaceous	0	0	1	11	48	60
	Totals	218	109	75	75	75	552
	n	552		**Overall Accuracy:**		**80.8%**	

Table 3.4 Classification accuracy and Kappa statistics derived from the classification error matrix of the combined pine class (loblolly *Pinus taeda* L. and longleaf *Pinus palustris* Mill. combined) and other cover types for the 2005 images of the three study areas in North Carolina.

	Reference Total	**Class Total**	**Correct**	**Producer's Accuracy**	**User's Accuracy**	**Kappa**
Pines	218	265	205	94.0%	77.4%	0.9
Hardwoods	109	78	63	57.8%	80.8%	0.5
Shadow	75	86	70	93.3%	81.4%	0.9
Non-Vegetation	75	63	60	80.0%	95.2%	0.8
Herbaceous	75	60	48	64.0%	80.0%	0.6
					Overall Kappa	**0.74**

Pine Tree Height to Diameter Relationship

The regression equation for predicting DBH from total height was as follows:

$$\ln(\text{DBH}) = -0.640235 + 1.0165769 * \ln(\text{total height}) \quad \text{(Equation 3.1)}$$

This field-based equation was used to predict DBH for LiDAR-identified tree heights. The relationship had an associated R^2 of 0.73 with an RMSE of 0.26.

Tree Finding Model Output

A validation check was performed on the tree finding model output. Omission (i.e., field trees not identified in LiDAR data), commission (i.e., trees falsely identified in LiDAR data) and correctly matched trees were reported for the entire canopy and for the tallest 25% canopy trees.

Figure 3.9 illustrates that canopy trees were identified in the LiDAR data and some smaller trees in canopy gaps and open areas were also detected. Omission errors were calculated for reporting how well the LiDAR data matched to the field data. Table 3.5 is a combination of results obtained on all tracts for the entire canopy and pines were matched at 52.3 % with the hardwoods matching at 12.8 %. Loblolly pines were matched at 44.7 % with longleaf pines matched at 54.5 %. For all tracts combined, the total number of LiDAR-identified trees was 722 and total number of field data trees was 1,243.

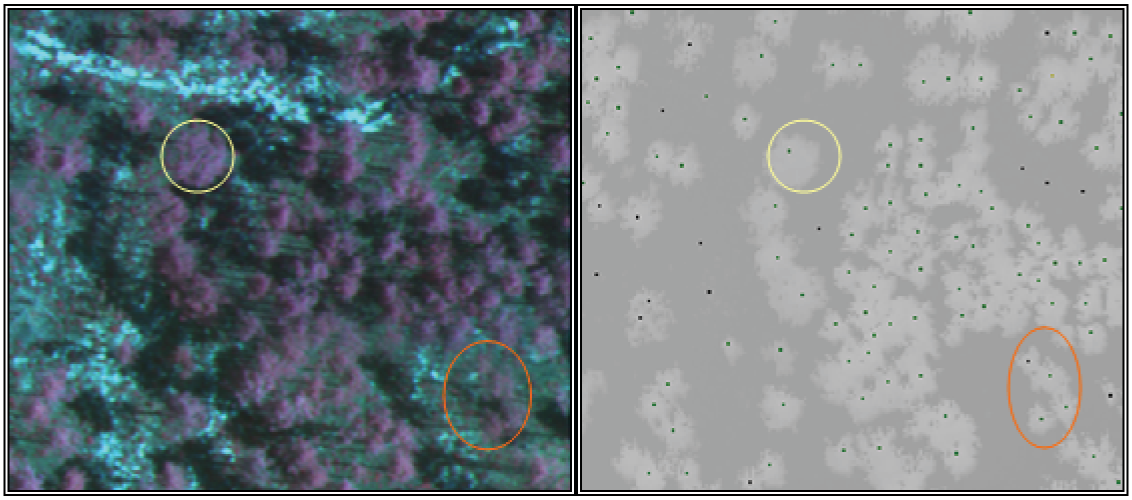

Figure 3.8 Multi-spectral imagery of a small portion of the McCain Tract rendered as color-infrared image (left), and results of tree finding algorithm (green spots on canopy model; right) for a small portion of the McCain Tract within the Red-cockaded woodpecker (*Picoides borealis*) study area in 2006.

Table 3.5 Commission and omission errors in matching field-identified to LiDAR-predicted samples of hardwood and pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) canopy trees for the entire forest canopy on the McCain, Ft. Bragg, and Blue Farm Tracts in Hoke County, North Carolina in 2007.

All Three Tracts						
	Field-Identified Samples				**LiDAR-Predicted Samples**	
	Hardwood	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	62	397	76	321	**Matched**	459
Omission	422	362	94	268	**Commission**	263
Total	484	759	170	589	**Total**	722
% Matched	**12.8**	**52.3**	**44.7**	**54.5**	**% Matched**	63.6
% Omission	**87.2**	**47.7**	**55.3**	**45.5**	**% Commission**	36.4

Note: Model refers to Tree Finding Model developed by McCombs et al 2003.

On the McCain Tract (Table 3.6), pines were found at 60.2 % and hardwoods at 9.8 % accuracy. Loblolly pines were matched at 59.3 % with longleaf pine matched at 60.2 %. Pines on Fort Bragg were found with 35.7 % and hardwoods at 15.2 % accuracy

(Table 3.7). Loblolly pines were matched at 28.0 % with longleaf pine matched at 38.6 %. On the Blue Farm Tract (Table 3.8), pines were found with 63.9 % accuracy and hardwoods with 12.4 % accuracy. Loblolly pines were matched at 44.4 % with longleaf pine matched at 64.7 %.

Table 3.6 Commission and omission errors in matching field-identified to LiDAR-predicted samples of hardwood and pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) canopy trees for the entire forest canopy on the McCain Tract in Hoke County, North Carolina in 2007.

McCain Tract						
	Field-Identified Samples				**LiDAR-Predicted Samples**	
	Hardwood	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	13	160	51	109	**Matched**	173
Omission	120	106	35	71	**Commission**	85
Total	133	266	86	181	**Total**	259
% Matched	**9.8**	**60.2**	**59.3**	**60.2**	**% Matched**	**66.8**
% Omission	**90.2**	**39.8**	**40.7**	**39.2**	**% Commission**	**32.8**

Note: Model refers to Tree Finding Model developed by McCombs et al 2003.

Table 3.7 Commission and omission errors in matching field-identified to LiDAR-predicted samples of hardwood and pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) canopy trees for the entire forest canopy on the Ft. Bragg Tract in Hoke County, North Carolina in 2007.

Ft. Bragg Tract						
	Field-Identified Samples				**LiDAR-Predicted Samples**	
	Hardwood	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	30	99	21	78	**Matched**	129
Omission	168	178	54	124	**Commission**	120
Total	198	277	75	202	**Total**	249
% Matched	**15.2**	**35.7**	**28.0**	**38.6**	**% Matched**	**51.8**
% Omission	**84.8**	**64.3**	**72.0**	**61.4**	**% Commission**	**48.2**

Note: Model refers to Tree Finding Model developed by McCombs et al 2003.

Table 3.8 Commission and omission errors in matching field-identified to LiDAR-predicted samples of hardwood and pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) canopy trees for the entire forest canopy on the Blue Farm Tract in Hoke County, North Carolina in 2007.

	Blue Tract					
	Field-Identified Samples				LiDAR-Predicted Samples	
	Hardwood	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	19	138	4	134	**Matched**	157
Omission	134	78	5	73	**Commission**	58
Total	153	216	9	207	**Total**	215
% Matched	**12.4**	**63.9**	**44.4**	**64.7**	**% Matched**	**73.0**
% Omission	**87.6**	**36.1**	**55.6**	**35.3**	**% Commission**	**27.0**

Note: Model refers to Tree Finding Model developed by McCombs et al 2003.

The number of unmatched LiDAR-derived trees the tree finding model found that were not recorded in the field data (commission) are given as a percentage for each Tract. For all tracts combined, the commission error was 36.4% (Table 3.5); 32.8% (Table 3.6) at McCain, 48.2% (Table 3.7) at Fort Bragg, and 27.0% (Table 3.8) at Blue Farm.

The upper 25 % of the canopy was assessed to evaluate if the model was able to find the larger trees as expected. Pines matched (field- to LiDAR-derived samples) at 72.0% accuracy and hardwoods at 42.9 % accuracy, with loblolly pines matched at 75.0 % and longleaf pines matched at 71.0 % overall (Table 3.9). On the McCain Tract, (Table 3.10) pines were matched at 84.9 % with hardwoods at 66.7 % and loblolly pines matched at 88.9 % and longleaf pines matched at 81.5 %. On the Fort Bragg Tract (Table 3.11) pines were matched at 54.6 % and hardwoods at 57.7 % with loblolly pines matched at 57.1 % and longleaf pines matched at 53.8 %. On the Blue Farm (Table 3.12), pines were matched at 80.2 % and hardwoods matched at 21.4 % with the loblolly pines matched at 57.1 % and longleaf pines matched at 82.0 %. Commission errors were reported as well for the upper 25% canopy. In all three tracts, percent commission for both hardwoods and pines was 33.5% (Table 3.9), McCain at 26.8% (Table 3.10), Fort Bragg at 47.1% (Table 3.11), and Blue Farm at 22.3% (Table 3.12).

Table 3.9 Commission and omission errors in matching field-identified to LiDAR-predicted samples of hardwood and pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) canopy trees for the upper 25% forest canopy on the McCain, Ft. Bragg, and Blue Farm Tracts in Hoke County, North Carolina in 2007.

All Three Tracts						
	Field-Identified Samples				LiDAR-Predicted Samples	
	Hardwoods	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	27	231	60	171	**Matched**	258
Omission	36	90	20	70	**Commission**	130
Total	63	321	80	241	**Total**	388
% Matched	**42.9**	**72.0**	**75.0**	**71.0**	**% Matched**	**66.5**
% Omission	**57.1**	**28.0**	**25.0**	**29.1**	**% Commission**	**33.5**

Note: Model refers to Tree Finding Model developed by McCombs et al 2003.

Table 3.10 Commission and omission errors in matching field-identified to LiDAR-predicted samples of hardwood and pine species (loblolly pine Pinus taeda L. and longleaf pine Pinus palustris Mill.) canopy trees for the upper 25% forest canopy on the McCain Tract in Hoke County, North Carolina in 2007.

McCain Tract						
	Field-Identified Samples				LiDAR-Predicted Samples	
	Hardwoods	**Pine**	**Loblolly**	**Longleaf**		**Model**
Matched	6	84	40	44	**Matched**	90
Omission	3	15	5	10	**Commission**	33
Total	9	99	45	54	**Total**	123
% Matched	**66.7**	**84.9**	**88.9**	**81.5**	**% Matched**	**73.2**
% Omission	**33.3**	**15.2**	**11.1**	**18.5**	**% Commission**	**26.8**

Note: Model refers to Tree Finding Model developed by McCombs et al 2003.

Table 3.11 Commission and omission errors in matching field-identified to LiDAR-predicted samples of hardwood and pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) canopy trees for the upper 25% forest canopy on the Ft. Bragg Tract in Hoke County, North Carolina in 2007.

Ft. Bragg Tract						
	Field-Identified Samples				LiDAR-Predicted Samples	
	Hardwoods	Pine	Loblolly	Longleaf		Model
Matched	15	66	16	50	**Matched**	81
Omission	11	55	12	43	**Commission**	72
Total	26	121	28	93	**Total**	153
% Matched	**57.7**	**54.6**	**57.1**	**53.8**	**% Matched**	**52.9**
% Omission	**42.3**	**45.5**	**42.9**	**46.2**	**% Commission**	**47.1**

Note: Model refers to Tree Finding Model developed by McCombs et al 2003.

Table 3.12 Commission and omission errors in matching field-identified to LiDAR-predicted samples of hardwood and pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) canopy trees for the upper 25% forest canopy on the Blue Farm Tract in Hoke County, North Carolina in 2007.

Blue Tract						
	Field-Identified Samples				LiDAR-Predicted Samples	
	Hardwoods	Pine	Loblolly	Longleaf		Model
Matched	6	81	4	77	**Matched**	87
Omission	22	20	3	17	**Commission**	25
Total	28	101	7	94	**Total**	112
% Matched	**21.4**	**80.2**	**57.1**	**82.0**	**% Matched**	**77.7**
% Omission	**78.6**	**19.8**	**42.9**	**18.1**	**% Commission**	**22.3**

Note: Model refers to Tree Finding Model developed by McCombs et al 2003.

Pine Size Class Determination

For each tract, field-to-LiDAR correctly matched canopy pine trees were grouped into pre-assigned diameter size classes based on the RCW Recovery Guidelines. Due to matched trees not having the same diameter values, many of the LiDAR predicted diameters fell into separate classes than the field diameters. Figure 3.9 illustrates the results of combining the classified multi-spectral imagery with the output from the tree finding model.

For all three tracts combined (Table 3.13), 29.7% field trees and 31.2% LiDAR trees fell into the < 24.5 cm DBH class, 36.3% field trees and 52.1% LiDAR trees fell in the 24.5 – 35 cm class, and 34.0% field trees and 16.6% LiDAR trees in the > = 35 cm class. For the McCain Tract, 22.5% field trees and 16.9% LiDAR trees fell into the < 24.5 cm DBH class, 35% field trees and 47.5% LiDAR trees fell in the 24.5 – 35 cm class, and 42.5% field trees and 35.6% LiDAR trees in the > = 35 cm class. For Fort Bragg, 56.6% field trees and 67.7% LiDAR trees fell in the < 24.5 cm class, 20.2% field trees and 31.3% LiDAR trees in the 24.5 – 35 cm class, and 23.2% field trees and 1.0% matched LiDAR tree in the > 35 cm class. For this tract in general, LiDAR overestimated the number of trees compared to the field data in the < 24.5 cm and 24.5 – 35 cm diameter classes. Blue Farm had 18.8% field trees and 21.7% LiDAR trees in the < 24.5 cm class, 49.3% field trees and 72.5% LiDAR trees in the 24.5 – 35 cm class, and 31.9% field trees and 5.8% LiDAR trees in the >= 35 cm class. In general for this tract, the LiDAR model overestimated number of trees compared to the field data in the < 24.5 cm and 24.5 – 35 cm classes and underestimated in the > =35 cm class.

Table 3.13 Comparison for the percent matched pine trees (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) for the field and LiDAR/multi-spectral tree samples per diameter size class for the entire forest canopy for the combined tracts (McCain, Blue Farm, and Fort Bragg Tracts) in Hoke County, North Carolina in 2007.

Percent Matched Pine Trees per Diameter Size Class			
	< 24.5cm	**24.5-35cm**	**>=35cm**
All Three Tracts - 69 Plots			
Field	29.7	36.3	34.0
LiDAR	31.2	52.1	16.6
McCain Tract - 22 Plots			
Field	22.5	35.0	42.5
LiDAR	16.9	47.5	35.6
Fort Bragg Tract - 23 Plots			
Field	56.6	20.2	23.2
LiDAR	67.7	31.3	1.0
Blue Farm Tract - 24 Plots			
Field	18.8	49.3	31.9
LiDAR	21.7	72.5	5.8

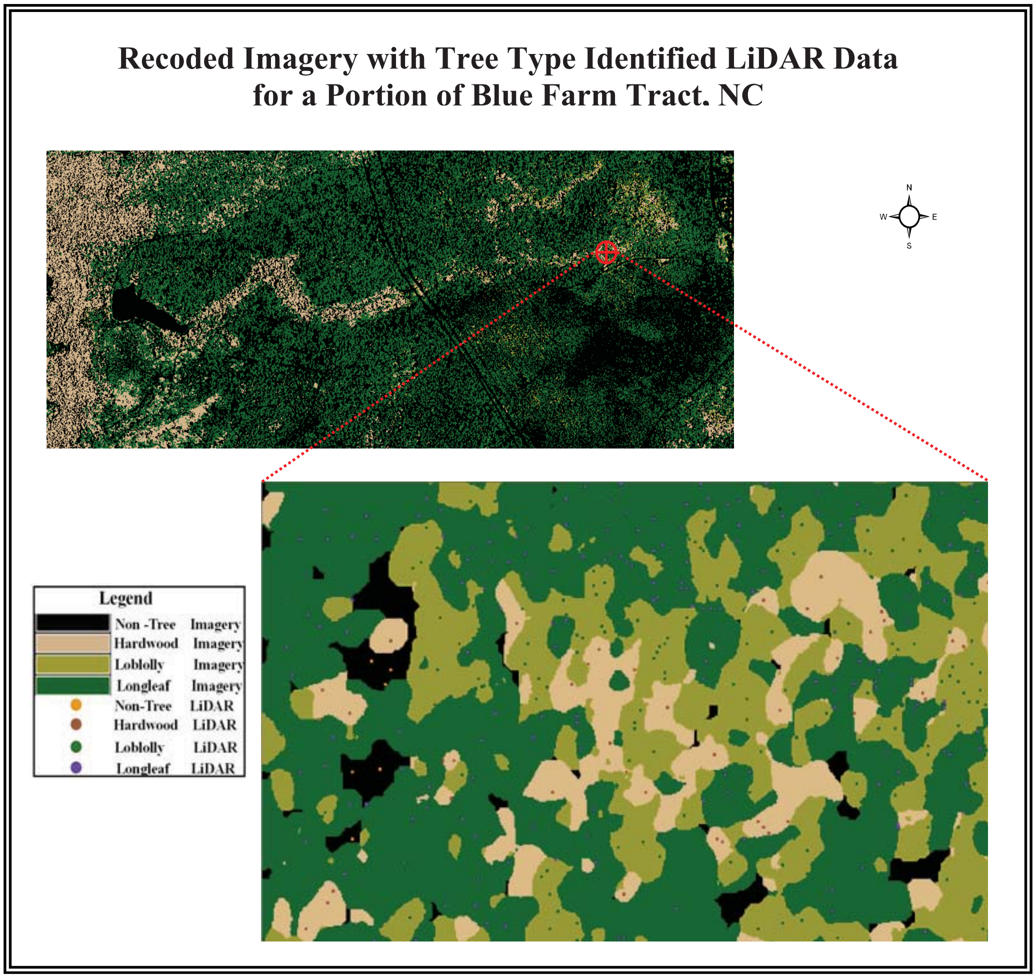

Figure 3.9 Recoded object-based classified multi-spectral imagery of Blue Farm Tract (upper left) and, a zoomed in portion of the Blue Farm Tract with results of LiDAR identified by tree type and recoded classified multi-spectral imagery (center bottom).

Average Height, DBH, BA and Stem Density per Plot

Categorized by Diameter Class Output

Average pine height, DBH, BA and stem density per plot for each diameter class based on the RCW Recovery Guidelines were assessed for LiDAR and field data for the canopy values. For all three tracts (Table 3.14), average height per plot for matched trees ranged from 13.4 – 28.1 m, combined total average tree heights ranged from 11.3 – 27.9

m, and both missed and commission tree heights ranged from 9.7 – 27.4 m. Mean DBH for all three tracts for matched trees ranged from 18.5 – 41.6 cm, combined total average tree diameters ranged from 13.6 – 41.5 cm, and both missed and committed trees ranged from 11.6 – 40.9 cm diameter. Mean BA for all three tracts (Table 3.14) for matched trees ranged from 1.2 – 6.7m^2/ha, combined total average BA ranged from 2.5 – 8.9 m^2/ha, and both missed and committed BA ranged from 0.8 – 3.0 m^2/ha. Mean stem density for all three tracts (Table 3.14) for matched trees ranged from 42.3 – 75.7 trees/ha, combined total average mean stem density ranged from 28.0 – 143.9 stems/ha, and both missed and committed mean stem density ranged from 6.5 – 101.5 stems/ha.

Table 3.14 Summary of mean tree height, mean DBH, mean BA, and mean stem density for both the field and LiDAR pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) samples per plot for the entire forest canopy for the combined tracts (McCain, Blue Farm, and Fort Bragg Tracts) in Hoke County, North Carolina in 2007.

All Three Tracts - 69 Plots						
	Matched Trees		**All Identified Trees**		**Commission**	**Omission**
	Field	**LiDAR**	**Field**	**LiDAR**	**Field**	**LiDAR**
Mean Height (m) / Plot						
DBH < 24.5 cm	14.6	13.4	11.3	11.3	9.7*	9.9*
DBH 24.5 - 35 cm	21.5	22.0	21.2	21.9	21.7*	20.2*
DBH >= 35 cm	24.9	28.1	24.3	27.9	27.4*	21.2*
Mean DBH (cm) / Plot						
DBH < 24.5 cm	18.5	18.7	13.6*	15.9*	13.6*	11.6*
DBH 24.5 - 35 cm	31.0	31.1	30.7*	30.9*	31.6*	30.0*
DBH >= 35 cm	41.6	39.7	41.5*	39.5*	38.8*	40.9*
Mean BA (m²/ha) / Plot						
DBH < 24.5 cm	1.2	1.3	2.6*	2.5*	1.1*	1.3*
DBH 24.5 - 35 cm	4.0	5.8	5.3*	8.9*	3.0*	1.3*
DBH >= 35 cm	6.7	2.7	7.9*	3.5*	0.8*	1.2*
Mean Stem Density (stems/ha) / Plot						
DBH < 24.5 cm	42.3	45.2	143.9	102.2	57.0	101.5
DBH 24.5 - 35 cm	51.7	75.7	69.6	116.2	40.5	17.9
DBH >= 35 cm	48.4	21.5	57.0	28.0	6.5	8.6
Note: Means followed by an * are significantly different at an alpha of 0.05.						

For the McCain Tract (Table 3.15), average height per plot for matched trees ranged from 13.5 – 28.4 m, combined total average tree heights ranged from 10.1 – 28.2 m, and both missed and commission tree heights ranged from 7.7 – 27.6 m. Mean DBH for McCain Tract for matched trees ranged from 18.3 – 42.1 cm, combined total average tree diameters ranged from 11.4 – 42.1 cm, and both missed and commission diameter trees ranged from 8.6 – 41.6 cm. Mean BA for McCain Tract (Table 3.15) for matched trees ranged from 1.0 – 10.9 m²/ha, combined total average BA ranged from 1.7 – 11.7 m^2/ha, and both missed and invented BA ranged from 0.7 – 3.7 m²/ha. Mean stem density for McCain Tract (Table 3.15) for matched trees ranged from 32.6 – 88.9 stems/ha, combined total average mean stem density ranged from 76.5 – 140.6 stems/ha, and both missed and invented mean stem density ranged from 5.6 – 100.4 stems/ha.

Table 3.15 Summary of mean tree height, mean DBH, mean BA, and mean stem density for both the field and LiDAR pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) samples per plot for the entire forest canopy on the McCain Tract in Hoke County, North Carolina in 2007.

McCain Tract - 22 Plots	Matched Trees		All Identified Trees		Commission	Omission
	Field	**LiDAR**	**Field**	**LiDAR**	**Field**	**LiDAR**
Mean Height (m) / Plot						
DBH < 24.5 cm	16.5	13.5	10.3	10.1	7.7*	7.7*
DBH 24.5 - 35 cm	23.0	22.6	22.6	22.6	22.6*	20.7*
DBH >= 35 cm	27.1	28.4	27.0	28.2	27.6*	25.7*
Mean DBH (cm) / Plot						
DBH < 24.5 cm	18.3	18.9	11.4*	14.2*	10.8*	8.6*
DBH 24.5 - 35 cm	31.3	31.9	31.2*	39.9*	31.9*	30.5*
DBH >= 35 cm	42.1	40.2	42.1*	16.7*	39.0*	41.6*
Mean BA (m^2/ha) / Plot						
DBH < 24.5 cm	1.2	1.0	2.0*	1.7*	0.7*	0.8*
DBH 24.5 - 35 cm	4.9	7.2	5.9*	11.0*	3.7*	1.0*
DBH >= 35 cm	10.9	7.6	11.7*	9.7*	2.2*	0.8*
Mean Stem Density (stems/ha) / Plot						
DBH < 24.5 cm	40.5	32.6	140.6	78.8	46.1*	100.4*
DBH 24.5 - 35 cm	63.0	88.9	76.5	135.0	46.1*	13.5*
DBH >= 35 cm	76.5	58.5	82.1	76.5	18.0*	5.6*

Note: Means followed by an * are significantly different at an alpha of 0.05.

For the Blue Farm Tract (Table 3.16), average height per plot for matched trees ranged from 14.6 – 25.9 m, combined total average tree heights ranged from 11.2 – 26.0 m, and both missed and committed tree heights ranged from 7.9 – 26.3 m. Mean DBH for the Blue Farm Tract for matched trees ranged from 18.1 – 40.6 cm, combined total average tree diameters ranged from 14.8 – 40.7 cm, and both missed and committed diameter trees ranged from 11.1 – 41.7 cm. Mean BA for the Blue Farm Tract (Table 3.16) for matched trees ranged from 0.8 – 7.9 m²/ha, combined total average BA ranged from 1.0 – 10.3 m²/ha, and both missed and invented BA ranged from 0.5 – 2.3 m²/ha. Mean stem density for the Blue Farm Tract (Table 3.16) for matched trees ranged from 7.2 – 104.2 stems/ha, combined total average mean stem density ranged from 9.3 – 135.1 stems/ha, and both missed and committed mean stem density ranged from 2.1 – 59.8 stems/ha.

Table 3.16 Summary of mean tree height, mean DBH, mean BA, and mean stem density for both the field and LiDAR pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) samples per plot for the entire forest canopy on the Blue Farm Tract in Hoke County, North Carolina in 2007.

Blue Farm Tract - 24 Plots						
	Matched Trees		All Identified Trees		Commission	Omission
	Field	LiDAR	Field	LiDAR	Field	LiDAR
Mean Height (m) / Plot						
DBH < 24.5 cm	15.9	14.6	12.8	11.2	7.9*	11.4*
DBH 24.5 - 35 cm	20.9	21.9	21.1	21.9	21.8*	22.2*
DBH >= 35 cm	22.9	25.9	22.9	26.0	26.3*	23.4*
Mean DBH (cm) / Plot						
DBH < 24.5 cm	18.1	20.5	14.8	15.7	11.1*	13.3*
DBH 24.5 - 35 cm	30.8	30.9	30.7	30.8	30.7*	30.2*
DBH >= 35 cm	40.6	36.5	40.7	36.7	37.2*	41.7*
Mean BA (m²/ha) / Plot						
DBH < 24.5 cm	0.8	1.1	1.7*	1.6*	0.5*	1.0*
DBH 24.5 - 35 cm	5.3	7.9	6.3*	10.3*	2.3*	1.0*
DBH >= 35 cm	6.0	0.8	6.9*	1.0*	0.2*	0.9*
Mean Stem Density (stems/ha) / Plot						
DBH < 24.5 cm	26.8	30.9	86.6	62.9	32.0	59.8
DBH 24.5 - 35 cm	70.1	104.2	83.5	135.1	30.9	13.4
DBH >= 35 cm	45.4	7.2	51.6	9.3	2.1	6.2

Note: Means followed by an * are significantly different at an alpha of 0.05.

For the Fort Bragg Tract (Table 3.17), average height per plot for matched trees ranged from 12.7 – 26.2 m, combined total average tree heights ranged from 11.3 – 26.2 m, and both missed and invented tree heights ranged from 0.0 – 20.7 m. Mean DBH for the Fort Bragg Tract for matched trees ranged from 17.8 – 42.0 cm, combined total average tree diameters ranged from 14.5 – 41.4 cm, and both missed and committed trees had diameters from 0.0 – 40.2 cm. Mean BA for Fort Bragg Tract (Table 3.17) for matched trees ranged from 0.1 – 3.5 m^2/ha, combined total average BA ranged from 0.1 – 5.4 m^2/ha, and both missed and committed BA ranged from 0.0 – 3.1 m^2/ha. Mean stem density for Fort Bragg Tract (Table 3.17) for matched trees ranged from 1.1 – 72.1 stems/ha, combined total average mean stem density ranged from 1.1 – 206.6 stems/ha, and both missed and invented mean stem density ranged from 0.0 – 146.4 stems/ha.

Table 3.17 Summary of mean tree height, mean DBH, mean BA, and mean stem density for both the field and LiDAR pine species (loblolly pine Pinus taeda L. and longleaf pine Pinus palustris Mill.) samples per plot for the entire forest canopy on the Fort Bragg Tract in Hoke County, North Carolina in 2007.

Fort Bragg Tract - 23 Plots	Matched Trees		All Identified Trees		Commission	Omission
	Field	LiDAR	Field	LiDAR	Field	LiDAR
Mean Height (m) / Plot						
DBH < 24.5 cm	12.7	12.7	11.3	11.9	11.4*	10.7*
DBH 24.5 - 35 cm	19.4	21.1	19.1	20.9	20.7*	18.8*
DBH >= 35 cm	22.0	26.2	20.7	26.2	0.0*	18.5*
Mean DBH (cm) / Plot						
DBH < 24.5 cm	18.8	17.8	14.5*	16.7*	15.9*	12.7*
DBH 24.5 - 35 cm	30.6	29.7	30.1*	29.4*	29.1*	29.7*
DBH >= 35 cm	42.0	37.1	41.4*	37.1*	0.0*	40.2*
Mean BA (m^2/ha) / Plot						
DBH < 24.5 cm	1.8	1.9	4.0*	4.1*	2.2*	2.3*
DBH 24.5 - 35 cm	1.6	2.4	3.5*	5.4*	3.1*	1.9*
DBH >= 35 cm	3.5	0.1	5.3*	0.1*	0.0*	1.8*
Mean Stem Density (stems/ha) / Plot						
DBH < 24.5 cm	60.3	72.1	206.6*	165.7*	93.6*	146.4*
DBH 24.5 - 35 cm	21.5	33.4	48.4*	78.6*	45.2*	26.9*
DBH >= 35 cm	24.8	1.1	38.7*	1.1*	0.0*	14.0*

Note: Means followed by an * are significantly different at an alpha of 0.05.

For all three tracts (Table 3.14), McCain (Table 3.15), Blue Farm (Table 3.16), and Fort Bragg (Table 3.17)] significant differences were found in the omission and commission values for height, DBH, and BA. McCain (Table 3.15) and Fort Bragg (Table 3.17) had a significant difference in omission and commission values for stem density. For all identified trees, significant differences were found in DBH and BA values for all tracts combined (Table 3.14), McCain (Table 3.15), Blue Farm (Table 3.16), and Fort Bragg (Table 3.17) as well as for stem density in Fort Bragg (Table 3.17).

Summary Statistics for Pine Height, DBH, BA, and Stem Density per Plot

Regression analysis, p-values, and RMSE values were used to compare the LiDAR to field measurements for the entire canopy of matched trees, all trees, and unmatched canopy pine trees per plot for the height, DBH, BA, and stem density. For DBH the R^2 was 0.73 and for BA the R^2 was 0.54. For all three tracts - 69 Plots (Table 3.18), height samples had an R^2 of 0.53, DBH samples had an R^2 of 0.24, BA samples had an R^2 of 0.29, and stem density had an R^2 of 0.30. The unmatched height samples had an R^2 of 0.03, R^2 for DBH was 0.13, BA had an R^2 of 0.04, and stem density had an R^2 of 0.16.

For the McCain Tract - 22 Plots (Table 3.19), height samples, R^2 was 0.98 for DBH samples, the R^2 was 0.59, BA the R^2 was 0.55. For all trees matched and unmatched combined, height samples had an R^2 of 0.60, DBH samples had an R^2 of 0.28, BA samples had an R^2 of 0.36, and stem density had an R^2 of 0.36. The unmatched height samples had an R^2 of 0.00, R^2 for DBH was 0.00, BA had an R^2 of 0.05, and stem density had an R^2 of 0.06.

For the Blue Farm Tract - 24 Plots (Table 3.20), height samples, R^2 was 0.95 for DBH samples, the R^2 was 0.38, BA the R^2 was 0.25. For all trees matched and unmatched combined, height samples had an R^2 of 0.44, DBH samples had an R^2 of 0.11, BA samples had an R^2 of 0.12, and stem density had an R^2 of 0.59. The unmatched height samples had an R^2 of 0.11, R^2 for DBH was 0.06, BA had an R^2 of 0.05, and stem density had an R^2 of 0.18.

For the Fort Bragg Tract – 23 Plots (Table 3.21), height samples, R^2 was 0.96, for DBH samples, the R^2 was 0.81, BA the R^2 was 0.63. For all trees matched and unmatched combined, height samples had an R^2 of 0.32, DBH samples had an R^2 of 0.16, BA samples had an R^2 of 0.16, and stem density had an R^2 of 0.10. The unmatched height samples had an R^2 of 0.1, R^2 for DBH was 0.05, BA had an R^2 of 0.00, and stem density had an R^2 of 0.19.

Table 3.18 Summary statistics of comparing field to LiDAR mean tree height, mean DBH, mean BA, and mean stem density for both the field and LiDAR pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) samples per plot for the entire forest canopy for the Combined Tracts (McCain, Blue Farm, and Fort Bragg Tracts) Hoke County, North Carolina in 2007.

All Three Tracts - 69 Plots			
	Matched Trees	**All Identified Trees**	**Unmatched Trees**
Mean Height (m) / Plot			
R-square	0.97	0.53	0.03
RMSE	1.05	3.75	7.81
Mean DBH (cm) / Plot			
R-square	0.73	0.24	0.13
RMSE	4.93	6.84	11.17
Mean BA (m/ha) / Plot			
R-square	0.54	0.29	0.04
RMSE	0.57	0.65	0.83
Mean Stem Density (ha) / Plot			
R-square	-	0.30	0.16
RMSE	-	101.91	76.49

Table 3.19 Summary statistics of comparing field to LiDAR mean tree height, mean DBH, mean BA, and mean stem density for both the field and LiDAR pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) samples per plot for the entire forest canopy on the McCain Tract in Hoke County, North Carolina in 2007.

McCain Tract - 22 Plots			
	Matched Trees	**All Identified Trees**	**Unmatched Trees**
Mean Height (m) / Plot			
R-square	0.98	0.60	0.00
RMSE	0.77	4.01	8.29
Mean DBH (cm) / Plot			
R-square	0.59	0.28	0.00
RMSE	5.10	7.86	12.46
Mean BA (m/ha) / Plot			
R-square	0.55	0.36	0.05
RMSE	0.64	0.78	1.01
Mean Stem Density (ha) / Plot			
R-square	-	0.36	0.06
RMSE	-	126.79	79.85

Table 3.20 Summary statistics of comparing field to LiDAR mean tree height, mean DBH, mean BA, and mean stem density for both the field and LiDAR pine species (loblolly pine Pinus taeda L. and longleaf pine Pinus palustris Mill.) samples per plot for the entire forest canopy on the Blue Farm Tract in Hoke County, North Carolina in 2007.

Blue Farm Tract - 24 Plots			
	Matched Trees	**All Identified Trees**	**Unmatched Trees**
Mean Height (m) / Plot			
R-square	0.95	0.44	0.11
RMSE	0.77	3.65	8.74
Mean DBH (cm) / Plot			
R-square	0.38	0.11	0.06
RMSE	3.83	6.53	12.68
Mean BA (m/ha) / Plot			
R-square	0.25	0.12	0.05
RMSE	0.44	0.54	0.87
Mean Stem Density (ha) / Plot			
R-square	-	0.59	0.18
RMSE	-	60.50	47.68

Table 3.21 Summary statistics of comparing field to LiDAR mean tree height, mean DBH, mean BA, and mean stem density for both the field and LiDAR pine species (loblolly pine *Pinus taeda* L. and longleaf pine *Pinus palustris* Mill.) samples per plot for the entire forest canopy on the Ft. Bragg Tract in Hoke County, North Carolina in 2007.

Fort Bragg Tract - 23 Plots			
	Matched Trees	**All Identified Trees**	**Unmatched Trees**
Mean Height (m) / Plot			
R-square	0.96	0.32	0.05
RMSE	1.56	3.92	5.76
Mean DBH (cm) / Plot			
R-square	0.81	0.16	0.00
RMSE	4.85	5.99	8.22
Mean BA (m/ha) / Plot			
R-square	0.63	0.16	0.00
RMSE	0.42	0.50	0.59
Mean Stem Density (ha) / Plot			
R-square	-	0.10	0.19
RMSE	-	96.60	91.00

CHAPTER IV

DISCUSSION

Image Classification Accuracy Assessment

Overall, accuracy assessment results (Tables 3.1-3.4) for the object-based classification showed relatively high accuracies and Kappa values when separating longleaf from loblolly pines and hardwood canopy trees. Oruc et al. (2004), using Landsat - 7 spectral imagery in Zonguldak, Turkey, compared classic pixel–based versus object–based classifications and found the object-based approach to have better results in accuracy. In the present study, separating pines from hardwoods showed a higher accuracy at 80.8% with a Kappa of 73.3 versus a lower accuracy at 73.7% and Kappa of 0.7 (The Kappa measures the proportion of correctly classified pixels after the probability of chance agreement has been removed Congalton 1991.) when separating the two pine classes from each other. The decrease in percent accuracy was attributed to pines having more similarities to each other in the NIR spectral reflectance band which created overlap in the membership functions thus difficulties in correctly labeling individual canopy pine tree species.

Individual class accuracies and associated Kappas indicated 90.8% of the known reference locations used to classify longleaf were correctly identified (producers accuracy). Of all sites visited in the field (user's accuracy) that were labeled on the classification as longleaf, 58.9% were found to be longleaf (Table 3.2). This confusion was mainly due to software misclassifying 31 longleaf trees as loblolly and 24 longleaf trees as hardwoods. The associated Kappa value was 0.9. The confusion between the pine classes might have occurred because loblolly and longleaf pines have similar morphology resulting in similar reflectance properties of the tree species.

Individual class accuracies and associated Kappas indicated 61.5% of the known reference locations used to classify loblolly were correctly identified (producer's accuracy). Of all sites visited in the field (user's accuracy) that were labeled on the classification as loblolly, 69.1% were found to be loblolly (Table 3.2). Most of the confusion was due to mislabeling 22 loblolly trees as hardwoods and 8 as longleaf trees. The Kappa value calculated at 0.5 suggested a higher chance of random correctness than was seen for longleaf.

Individual class accuracies and associated Kappas indicated 57.8% of the known reference locations used to classify hardwoods were correctly identified (producer's accuracy). Of all sites visited in the field (user's accuracy) that were labeled on the classification as hardwoods, 80.8% were found to be hardwoods (Table 3.2). The confusion mainly came from mislabeling 11 trees as loblolly and 2 as longleaf. The associated Kappa value for hardwoods was found to be at 0.5 suggesting again a higher chance of random correctness. A possible reason for the class confusion may have been due to the closeness in reflectance values between the hardwoods and loblolly resulting in the software having a difficult time in distinguishing between trees in the high crown density areas.

For the combined pine class, 94.0% of the reference trees were identified with 77.4% of the locations on the map actually being pines (Table 3.4). Confusion came mainly from the hardwood class with 46 mislabeled as pine and 12 trees mislabeled as herbaceous (Table 3.3). The confusion with the herbaceous class occurred because young longleaf pines were not easily distinguishable from the herbaceous background due to image resolution. The associated Kappa for the pine class was found to be at 0.9 suggesting a high chance of actual correctness.

The other three cover classes: herbaceous, non-vegetation, and shadow were important in helping to separate out the canopy tree types of interest. The accuracy of separating out the canopy tree species from each other, and from the other cover classes, was illustrated in Tables 3.1-3.4. The shadow class had 70 of its 75 samples correctly identified with a user's accuracy of 81.4%, a producer's accuracy of 93.3%, and a Kappa of 0.9. This class was ambiguous in that it changes depending upon time of day and year the imagery was collected. The shadow class was interpreted from images only and, the interpreter would not be able to field validate the work it was done at the same instant images were acquired since shadows continuously change over time. The non-vegetation class had 60 of its 75 samples correctly identified with a user's accuracy of 95.2%, a producer's accuracy of 80.0%, and a Kappa of 0.8. Again, this class was ambiguous to some degree in areas where the imagery was collected frequently experienced prescribed burning or other disturbances. This accuracy assessment often exposed what appeared to be non-vegetation, yet in many cases, had those areas not been burned, they would be labeled as herbaceous. Therefore, in areas other than roads or deep sand, the classification process misclassified areas as either non-vegetation or shadow when those areas were no longer shadow or non-vegetation due to field data being collected a year after the imagery was flown allowing vegetation changes to occur. The herbaceous class had 48 of its 75 samples correctly identified with a user's accuracy of 80.0%, a producer's accuracy of 64.0%, and a Kappa of 0.6. In identifying this class, many samples were confused with young longleaf pines coming out of the grass stage, shadow, and a few non-vegetation locations. In many areas, there was longleaf pine regeneration ranging from the grass stage to the sapling size. To adequately identify individual trees using object-based classification, the crowns must be image segments composed of multiple pixels that are spectrally distinct from the background classes. Sampling young longleaf pines from herbaceous was not possible due to image resolution.

Tree Finding Model

Results from this research suggested the methodology used by McCombs et al 2003 was successful in classifying canopy trees and identifying canopy trees using LiDAR. The comparison of canopy plot trees to LiDAR-identified trees revealed some inconsistencies in the tree identification model's ability to detect all trees. One problem was in collecting field data measurements a year after the imagery was acquired allowing ample time to pass for vegetation change in the landscape. Another issue was acquiring matches on all canopy trees due to some positional accuracy imprecision in both the ground-based tree locations and the LiDAR data. This was largely attributed to assumed errors in GPS fixes on plot locations and measurement errors in tree location establishment relative to these GPS positions. Comparison of the LiDAR-derived canopy surface, the corresponding multi-spectral imagery, and output from the tree-finding algorithm visually illustrated the general successful performance of the models (Figure 3.9.

Overall omission/commission errors for the longleaf and loblolly pine classes showed longleaf had the least amount of omission/commission errors than loblolly (Table 3.5). The longleaf class having fewer errors compared to loblolly may have been partly due to location and density of the trees. Most of the areas were longleaf pines were measured were in areas of lower density and more open stands. Many of the loblolly pines measured were in areas of higher crown densities with less spacing between trees. Assessment of omission/commission errors per tract for longleaf and loblolly, indicated that Blue Farm had the fewest errors, McCain was intermediate and Fort Bragg had the largest errors. Blue Farm and McCain having fewer errors for the pine classes may have been due to a more intensive timber management practices on both tracts with Blue Farm having a more intensive management for timber and parts of McCain managing for pine straw and less for timber. The Fort Bragg Tract instead used prescribed burning without any timber management (Tables 3.6-3.8). The tree finding model worked better at finding trees that were in lower densities in more open stands found in the Blue Farm Tract versus more natural stands with higher density found on McCain and Fort Bragg Tracts. For the upper 25% (tallest trees), the tree finding model worked better having lower omission/commission errors (as expected) since these trees tended to stand out from the lower canopy trees (Tables 3.9-3.12).

Pine Size Class Determination

As of 2000, the McCain Tract was a state-owned conservation area that managed for RCWs with five active clusters (USFWS 2003). Activities primarily engaged in include prescribed burning, hunting/camping, and pine straw research. Given these land uses, it was not surprising that a large proportion of pine trees would be older and have larger diameters whereby many of the pine stems fell in the large DBH class (Table 3.13) since timber harvesting was not part of the main management practices. The older trees that became flat topped due to damages over time would have probably been removed had McCain had a more active management for timber as compared to the other two tracts. Flat-topped trees reduce the tree finding model accuracy because they lack a distinctive apex. These trees tend to have large diameters with a disproportionately shorter height than similar diameter pine trees exhibiting a normal apex shoot. Thus, predicting a relationship between diameter and height class was difficult for those trees. A possible way of compensating for this in the future may be to simply separate those trees from the rest of the sample and run separate analyses along with a combined analysis to compare the influence these flat-topped trees have on the relationships between the measured variables (height, DBH, BA, stem density). Additionally, there may still be challenges particularly in finding methods of excluding flat-topped trees from the remotely sensed data even though these trees can be separated from the rest of the field data relatively easy. The Fort Bragg summaries (Table 3.13) showed many of the pine stems falling in the smaller DBH class. This part of Fort Bragg is practicing intense management for RCWs, using prescribed burning as a way of opening up stands and retarding hardwood growth while favoring pine trees. As of 2000, there were roughly 350 active clusters on the entire installation (USFWS 2003). The Blue Farm summaries (Table 3.13) depicted most of the pine samples falling in the 24.5 – 35 cm diameter size class. This was consistent with Blue Farm management practices both for timber and pine straw production and RCW management. There were not many RCW clusters on Blue Farm because most of the land was on various timber harvest rotations.

Average Height, DBH, Basal Area and Stems per Plot

Mean tree height, DBH, BA, and stem density per plot were calculated for both the field and LiDAR values for matched, unmatched, and combined matched and unmatched trees. The matched height values resulted in LiDAR underestimating the number of smaller trees and overestimating the larger trees when compared to the field data. In this case, the elevation or ground surface model may have been slightly underestimated which would have resulted in overestimated values in the LiDAR (Lefsky et al. 2002). In previous studies LiDAR has commonly been shown to underestimate mean tree height (Hyyppa and Inkinen 1999; Naesset 1997; Naesset and Bjerknes 2000; McCombs et al. 2003; Roberts et al. 2005; Young 2000).

The field-derived relationship used to apply DBH estimates to the LiDAR tended to underestimate DBH and BA when compared to the field data whereas, stem density was overestimated compared to the average field data values. The underestimation of DBH and BA values may have been due to many of the pine trees having missing or broken tops. Since many of the pine trees had broken tops resulting in unnaturally shorter heights compared to their DBH size the regression equation was not able to predict DBH values for those trees. Trees with spreading crowns, particularly in areas of high crown closure tend to result in more false stem locations from LiDAR and thus inflate the stem density estimates.

Regression analysis performed between field and LiDAR showed there were significant differences found between the omission/commission errors for canopy height, DBH, and BA. Stem density overall and on Blue Farm tract showed no significant difference because on that tract the model was able to better identify those trees most likely due to increased spacing between trees (Tables 3.14-3.17). Additionally R^2 and RMSE were recorded for the trees per tract for canopy height, DBH, BA, and stem density values (Tables 3.18-3.21). Overall the R^2 suggested the model predicted height for matched trees well along with fairly good accuracy. DBH and BA for matched trees were not predicted as well by the model and were found with less accuracy. The model however did predict stem density with moderate accuracy. Blue Farm and McCain tracts had very similar results most likely due to similar management for the pines. Both had fairly good accuracy and good prediction of height values. DBH and BA values had lower prediction values with less accuracy. Stem density for both tracts had fair accuracy and prediction values. Height, DBH, and BA had less accurate values with not so good predictions. There was most likely a higher occurrence of flat-topped trees on this tract from a lack of timber management to periodically thin out older trees. Stem density was found to have both fair accuracy and prediction by the model because individual trees were able to be identified well from the tree finding model.

CHAPTER V

SUMMARY AND CONCLUSIONS

Multi-spectral imagery was acquired in the summer of 2005 from the coastal plain within the sandhill region in Hoke County, North Carolina. An object-based classification was performed to identify canopy trees then validated using field data samples collected from the sandhill region in Hoke County, North Carolina. The classification was found to be satisfactory in providing identification of tree species important in evaluating RCW habitat for this region. A tree finding model developed by McCombs et al. 2003 was modified and used to locate canopy trees from LiDAR data. Tree type was labeled with the multi-spectral imagery then validated by assessing omission and commission errors. Since longleaf and loblolly pines had moderately good separation and pine-hardwoods had high accuracy, the cover type classification indicated effectiveness in identifying one of the important factors in successfully evaluating RCW habitat. The confusion between cover types was probably due to spectral similarities of some of the species at the time of year in which the imagery was taken. Confusion between the two pine classes was somewhat expected due to morphological similarities influencing their spectral response patterns. A regression equation was developed from the field data to use in predicting diameters for the LiDAR identified trees. From the matched LiDAR trees with field trees, diameter size classes for pine were separated out into appropriate diameter classes based on the USFWS RCW Recovery Guidelines. The majority of the matched trees were found in the 24.5-35 cm diameter size class suggesting most of the trees from all tracts combined fell into the medium size class. Since Blue Farm and McCain tracts used timber management practices most of the trees were expected to fall within the medium and large diameter classes with the rest of the trees falling into the smaller diameter classes.

Average stem density/ha and average BA m^2/ha were predicted per diameter size class. The matched LiDAR data to field data were then tested for significant differences using regression analysis to get a more complete landscape description. Results showed no significant differences occurred between the matched field to LiDAR samples for height, diameter, and BA even though the R^2 values for diameter and BA were below 0.5. Using LiDAR and multi-spectral imagery to evaluate species type, height, and BA of pines was found to have potential usefulness for assessing a portion of the minimum requirements provided by USFWS for assessing good quality habitat for RCWs. Evaluating the species type from the classification was able to give information on how much of the area was covered by hardwoods, loblolly, and longleaf pine. Applying height, DBH, BA, and stem density values from the LiDAR to the classification gave an even better output for determining not only what type of trees but how large and how many trees were covering the project area. This information on tree species along with attributes of size and quantity should prove useful in providing managers and biologists with information that help in developing and maintaining management plans for RCW habitat.

CHAPTER VI

RECOMMENDATIONS

Future Research

Recommendations to better facilitate the study objectives included, but were not limited to, collecting imagery which has been orthorectified to the LiDAR data, increasing the number of field data samples, and collecting all data at the same time. Field data needed to be collected at the same time of year as the flight data associated with LiDAR and multi-spectral imagery. This was important when classifying cover classes such as non-vegetation or herbaceous vegetation which are dynamic and may change reflectance values if enough time has lapsed between collecting field data and flying imagery, and LiDAR data pre-processed by the provider to project specifications such as overlap between flight lines, footprint size, and the project area being covered by the LiDAR. Increased LIDAR return densities from overlap in the LiDAR data between flight lines should be more thoroughly investigated for bias influence on results regarding the number of LiDAR trees found from the tree finding model.

Multi-spectral Imagery

Multi-spectral imagery, which had been orthorectified to the LiDAR canopy layer, would have potentially aided in a better classification (McCombs et al. 2003;

Popescu et al. 2003; and Hudak et al. 2002). Some spectral confusion occurred in classes where there was a distinct height difference. For example, some of the open grassy areas were being confused with the pine classes. Had the imagery and LiDAR data been orthorectified to each other, LiDAR canopy layers could have been fused with the classification to label the canopy trees by species type from the found LiDAR trees. Likewise, if the imagery had been orthorectified to the LiDAR, the determination of crown radii for each tree could have been investigated using objected oriented classification instead of being modeled with the tree finding model as in this study.

In addition to increased number of plots, gathering information such as individual tree age would better supplement the data collected to compare with RCW Recovery Guidelines. Collecting age data, determining better accuracy with the pine basal size estimates, and taking samples in RCW clusters would yield a more robust habitat evaluation of the areas of interest.

LiDAR

Identification of locations of hardwood trees may have been improved had the tree finding model been able to have tree parameters tailored to typical hardwood tree morphology such as crown and multiple stems unlike pines with a relatively cone shaped crown and typically one central stem. In future research, a separate tree finding model could be investigated specific only to hardwood trees.

When developing the equation for predicting diameter values from tree heights, only pine tree values were used. A separate equation for hardwoods needed to be developed to increase accuracy in hardwood height, diameter, and BA values.

Concerning the tree finding model some factors should be taken into consideration and possibly avoided if this methodology is repeated. For example, field data need to be collected at the same relative time as the imagery is acquired. This would likely improve the classification of the multi-spectral imagery. Analyzing an area with relatively few flat-topped trees, or analyzing those trees separately from the rest of the data, again may provide better results in regard to omission and commission errors while showing how much bias associated with total height and diameter was attributed to the flat-topped trees. Evaluating hardwood species similarly to the pines is important in RCW habitat because USFWS Recovery Guidelines indicate having sparse to no hardwoods in the mid-story.

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