Applications of Airborne and Portable LiDAR in the Structural Determination, Management, and Conservation of Southeastern U.S. Pine Forests

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APPLICATIONS OF AIRBORNE AND PORTABLE LIDAR IN THE STRUCTURAL DETERMINATION, MANAGEMENT, AND CONSERVATION OF SOUTHEASTERN U.S. PINE FORESTS

by

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ABSTRACT

Active remote sensing techniques, such as Light Detection and Ranging (LiDAR), have transformed the field of forestry and natural resource management in the last decade. Intensive assessments of forest resources and detailed structural assessments can now be accomplished faster and at multiple landscape scales. The ecological applications of having this valuable information at-hand are still only being developed. This work explores the use of two active remote sensing techniques, airborne and portable LiDAR for forestry applications in a rapidly changing landscape, Southeastern Coastal Pine woodlands. Understanding the strengths and weaknesses of airborne and portable LiDAR, the tools used to extract structural information, and how to apply these to managing fire regimes are key to conserving unique upland pine ecosystems. Measuring habitat structure remotely and predicting habitat suitability through modeling will allow for the management of specific species of interest, such as threatened and endangered species.

Chapter one focuses on the estimation of canopy cover and height measures across a variety of conditions of secondary upland pine and hardwood forests at Tall Timbers Research Station, FL. This study is unique since it uses two independent high resolution small-footprint LiDAR datasets (years 2002 and 2008) and extensive field plot and transect sampling for validation. Chapter One explores different tools available for metric derivation and tree extraction from discrete return airborne LiDAR data, highlighting strengths and weaknesses of each. Field and LiDAR datasets yielded better correlations for stand level comparisons, especially in canopy cover and mean

height data extracted. Individual tree crown extraction from airborne LiDAR data significantly under-reported the total number of trees reported in the field datasets using either Fusion/LVD and LiDAR Analyst (Overwatch).

Chapter two evaluates stand structure at the site of one of the longest running fire ecology studies in the US, located at Tall Timbers Research Station (TTRS) in the southeastern U.S. Small footprint high resolution discrete return LiDAR was used to provide an understanding of the impact of multiple disturbance regimes on forest structure, especially on the 3-dimensional spatial arrangement of multiple structural elements and structural diversity indices. LiDAR data provided sensitive detection of structural metrics, diversity, and fine-scale vertical changes in the understory and mid-canopy structure. Canopy cover and diversity indices were shown to be statistically higher in fire suppressed and less frequently burned plots than in 1- and 2-year fire interval treated plots, which is in general agreement with the increase from 2- to 3-year fire return interval being considered an" ecological threshold" for these systems (Masters et al. 2005). The results from this study highlight the value of the use of LiDAR in evaluating disturbance impacts on the three-dimensional structure of pine forest systems, particularly over large landscapes.

Chapter three uses an affordable portable LiDAR system, first presented by Parker et al. (2004) and further modified for extra portability, to provide an understanding of structural differences between old-growth and secondary-growth forests in the Red Hills area of southwestern Georgia and North Florida. It also provides insight into the strengths and weaknesses in structural determination of ground-based portable systems in contrast to airborne LiDAR systems. Structural plot metrics obtained from airborne and portable LiDAR systems presented some similarities (i.e. canopy cover), but distinct differences appeared when measuring canopy heights (maximum and mean heights) using these different methods. Both the airborne and portable systems were able to provide gap detection and canopy cover estimation at the plot level. The portable system, when compared to the airborne LiDAR sensor, provides an underestimation of canopy cover in open forest systems (<50% canopy cover), but is more sensitive in detection of cover in hardwood woodland plots (>60% canopy cover). The strength of the portable LiDAR system lies in the detection of 3-dimensional fine structural changes (i.e. recruitment, encroachment) and with higher sensitivity in detecting lower canopy levels, often missed by airborne systems.

Chapter four addresses a very promising application for fine-scale airborne LiDAR data, the creation of habitat suitability models for species of management and conservation concerns. This Chapter uses fine scale LiDAR metrics, such as canopy cover at various height strata, canopy height information, and a measure of horizontal vegetation distribution (clumped versus dispersed) to model the preferences of 10 songbirds of interest in southeast US woodlands. The results from this study highlight the rapidly changing nature of habitat conditions and how these impact songbird occurrence. Furthermore, Chapter four provides insight into the use of airborne LiDAR to provide specific management guidance to enhance the suitable habitat for 10 songbird species.

The collection of studies presented here provides applied tools for the use of airborne and portable LiDAR for rapid assessment and responsive management in southeastern pine woodlands. The advantages of detecting small changes in three-dimensional vegetation structure and how these can impact habitat functionality and suitability for species of interest are explored throughout the next four chapters. The research presented here provides an original and important contribution in the application of airborne and portable LiDAR datasets in forest management and ecological studies.

I dedicate this achievement to my family, especially my husband Bill and son Stefan, who have always supported me in this long effort and had to share years of quality family time with my research. To my many friends and colleagues, who have provided encouragement and stimulated great ideas when I needed them most. I also dedicate this work to my mother's memory, Clara, who always encouraged me to pursue what looked like the most difficult path, and placed so much belief in my abilities.

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INTRODUCTION

With the rapid loss of ecosystems and their inherent biodiversity, there is a great need for tools that enhance conservation and management to take place at multiple spatial scales. Furthermore, these methods must be rapid and accurate, providing fine scale information over broad landscapes. Remote sensing is one way to evaluate and apply many of the key ecological concepts, such as the relationship of biodiversity to structural habitat (MacArthur and MacArthur, 1961;Karr and Roth, 1971) and Niche-Gestalt (James, 1971), to conservation decisions. Passive remote sensing techniques, especially with multispectral and hyperspectral sensors, have yielded scientists with direct and indirect species and ecosystem health information (Turner et al., 2003b), even in rugged terrain. The advent of active remote sensing, such as LiDAR and, to some extent, Radar, has added a third component or vertical dimension to ecosystem level data collection. The advantages of these new sensors are difficult to dismiss, especially when both horizontal and vertical heterogeneity can be assessed simultaneously at varying spatial scales.

Airborne LiDAR was a breakthrough technology, particularly in the field of forestry 15 years ago. Applications range from forest inventories and stand characterization, and fire behavior modeling (Akay *et al.*, 2009), to microclimate modeling (Chen et al., 1999;Zimble et al., 2003) and species habitat suitability modeling (Vierling *et al.*, 2008). The number of ecological applications for airborne LiDAR is expanding, as costs have decreased and validation has been substantiated across a variety of ecosystems.

The advantages of being able to use this active remote sensing tool are numerous: 1) it is much more cost- and time-effective to collect structural data, particularly fine-scale vertical data 2) allows the data to be extracted and analyzed at multiple spatial scales (i.e. individual tree, plot, stand, landscape) that might be best appropriate for different applications 3) provides more detailed spatial distribution information (dispersal/clumpiness of vegetation) than practical to collect using conventional vegetation sampling techniques on the ground, and 4) provides an alternative for collecting data in difficult to access terrain, a particularly common problem in areas with complex structures and high biodiversity.

This study provides an overview of the use of LiDAR and highlights the potential ecological applications in southeastern pine woodlands. The type of ecosystem was selected due to four reasons: 1) pine forests, particularly old-growth longleaf pine forests, have been dramatically reduced to less than 2% of the original extent (Noss et al., 2001), and many of the remaining forests are now secondary old pine-oak woodlands 2) southern pine ecosystems are highly disturbance driven (Masters, 2007), with a frequent fire presence, therefore tools are necessary for very active management and monitoring to be successful 3) this ecosystem contains many wildlife species of management and conservation concern (Masters et al., 2002;Masters et al., 2006), for which appropriate steps have to be applied to assure perpetuity 4) extensive history of management at the ecosystem level and scientific studies have been conducted in this ecosystem (Hermann, 1995).

The goal of the research, as a whole, is to advance the value of airborne and portable LiDAR in forest management and species conservation. Ultimately, 21st century adaptive management of ecosystems in flux will require incorporating remotely sensed data to minimize field inventory efforts, especially in large landscapes or hard to reach areas. To provide a better understanding of how LiDAR can be incorporated in management, this research study first confirmed the relationship of airborne LiDAR versus field derived canopy cover metrics at fine and large spatial scales (individual tree-plot-stand scales) using an extensive network of over 2000 field plots, then, examined how specific tools for LiDAR extraction performed. Secondly, two independent sets of airborne LiDAR were applied to plots with varying fire regimes to demonstrate the sensitivity of these data to portray fine scale 3-dimensional differences in structure, particularly shrub encroachment and recruitment. This second portion of the study highlights the advantages and limitations of airborne LiDAR in making spatially explicit management decisions, such as the application of fire regimes, to forested ecosystems. Thirdly, the use of a portable LiDAR unit, first presented by (Parker et al., 2004) is explored for its potential in providing fine-scale mid-story structural information for monitoring and providing time-sensitive information for management decisions. Comparisons between portable and airborne systems focus on the limitations, strengths, and future advantages in fusing both sensors to provide an accurate, complete, and comprehensive understanding of all vertical layers in a forest or woodland.

Finally, the last chapter of this research links vertical and horizontal structural heterogeneity to habitat suitability of woodland songbird species. Fine and coarse scale structural measures extracted from airborne LiDAR are used to model habitat suitability of ten selected species, including species of management and conservation priority (i.e. Bachman's Sparrow, Northern Bobwhite, and Red-headed Woodpecker). The fourth chapter brings the focus back to the ecological need for advanced technology, such as airborne LiDAR, to provide the best understanding of how to manage biodiversity, by managing structural parameters. It also provides promising models that, parsimoniously, explain the preferences of ten species that are currently under active management in southeastern pine-woodlands. Upon further validation or refinement with additional, independent datasets, these could provide clear measurable goals for land managers to implement.

This work will facilitate the use of airborne and portable LiDAR in understanding fine-scale vertical structure in forested ecosystems, and how structural changes can be measured and quantified for conservation success. This research will also benefit land managers by providing specific guidelines to enhance the habitat of 10 important woodland bird species in southeastern pine forests of the US. Finally, this work can be a precursor in establishing habitat suitability models, using exclusively LiDAR data, to model the occurrence of species that require immediate conservation and recovery efforts.

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CHAPTER ONE - ESTIMATION AND GROUND VALIDATION OF SOUTHERN PINE FOREST CANOPY STRUCTURE USING SMALL FOOTPRINT LiDAR

Abstract

Estimation of canopy cover and height measures across large areas is of great value for forestry and natural resource management, with key structural attributes being directly linked to target goals for wildlife and ecosystem level management. In this study, we evaluated two independent high resolution small-footprint LiDAR datasets (years 2002 and 2008) at Tall Timbers Research Station, FL. Basic canopy metrics (cover, mean and maximum heights) were validated across a variety of conditions of secondary upland pine and hardwood forests using extensive field plot and transect sampling. Two methods were examined in the extraction of canopy metrics from LiDAR: a raw GIS and the Fusion/LDV software (USDA Forest Service) approach. The asynchronous nature of the field and LiDAR datasets resulted in low plot-level correlations for most variables, but Fusion/LDV stand estimation of canopy cover and heights, were within 15%, and 2 m, respectively, of field mean data. In general, the Fusion/LDV approach yielded better canopy cover and stand height estimates than the raw GIS method.

Individual tree crown locations including tree height, height to base of live crown, and crown width, were extracted from 2008 LiDAR data using both LiDAR Analyst (Overwatch) and Fusion/LDV software packages. Both methods significantly under-reported the total number of trees extracted from LiDAR data compared to field data,

with the LiDAR Analyst outperforming Fusion/LDV's algorithm in denser canopy areas (>60% cover) and Fusion/LDV capturing more of the trees in open field conditions (<40% cover). Management treatments, i.e. major thinning, applied after the field inventory (2003-2004) and LiDAR data collection events (2008), could justify a percentage of the tree under-representation in the later year.

Introduction

Airborne LiDAR has rapidly become a powerful technology in forestry and natural resource management. This active remote sensing technique has demonstrated the ability to characterize forest stands and approximate forest inventory data with canopy height (Lovell et al., 2003;Clark et al., 2004;Coops et al., 2007), basal area, aboveground biomass (Drake et al., 2002a;Drake et al., 2002b;Lefsky et al., 2002a), and leaf area (Roberts et al., 2003;Lefsky et al., 2005). In addition, one of the most promising ecological applications of small footprint LiDAR is the direct acquisition of vertical foliage distribution (Kao et al., 2005;Coops et al., 2007), which provides detailed information of the forest subcanopy elements. Field methods for foliage profile characterization involve quantifying the horizontal and vertical distribution of vegetation, either using a line method (MacArthur and Horn, 1969) or laser point-quadrat method (Radtke and Bolstad, 2001), both of these are very field intensive.

This paper focuses on estimation of simple canopy structure variables, such as canopy height (mean and maximum height) and cover, which have been found to be in general agreement to field data across ecosystems types (Naesset and Okland, 2002;Lim et al., 2003), from boreal (Magnussen et al., 1999) to tropical (Drake et al., 2002a) ecosystems. In some studies, individual tree height errors have been found to be less than 1.0 m (Persson et al., 2002) and plot based estimated errors of maximum and mean canopy heights were less than 0.5 m (Naesset, 2002). Other LiDAR studies have found errors of up to 3 m in height to be common when estimating field heights (Coops et al., 2004). Small footprint LiDAR is known to underestimate canopy height at the plot or stand level (Gaveau and Hill, 2003;Coops et al., 2007), due to the low likelihood that the beam hits the tree tops. Other common problems when using LiDAR to estimate field canopy heights are related to difficulty to pinpoint ground elevations in certain conditions (Lefsky et al., 2002a). Misclassified understory returns as ground returns, more likely to occur in complex canopy systems, induces a negative bias in the derived tree canopy height.

As LiDAR data collection becomes more affordable and its strengths become apparent for structural characterization, the choice of processing options and off-the shelf software has expanded. Careful planning is needed when selecting the methodology employed for analysis, either off-the-shelf software or custom. Equivalent to the variety of definitions of field stand "top height" - seven, according to (Sharma et al., 2002)- canopy metrics from LiDAR point cloud data metrics can assume distinctively different definitions, and, thus, provide different results.

Individual tree extraction from LiDAR datasets, including tree height, height to the base of live crown, and crown width, is another area of recent high interest. There are a variety of options - in terms of proprietary software with customizable algorithms - to allow trees to be located and attributed from point cloud datasets. Success in the detection of subcanopy or non-isolated dominant trees has been very limited (Lee and Lucas, 2007), unless optical imagery is used (Palace et al., 2008). Most of the algorithms currently available to the user, such as implemented in TreeVaW software (Kini and Popescu, 2004) and Fusion/LDV (McGaughey, 2010) were developed for a very specific ecosystem, Pacific Northwest Douglas-fir forest. This study implements two currently available methods - ESRI ArcGIS or Fusion/LDV - for tree extraction for the same LiDAR dataset, and compares the success of these two against field data.

The first objective of this study was to ground validate two independent LiDAR datasets based on a densely sampled network of field plots and transects that cover a variety of ecosystems and forest conditions. Secondly, this study highlights strengths and weaknesses of using different methods for extracting common structural plot metrics and individual tree information. Both of these objectives provide a foundation for important ecological applications of airborne LiDAR data: forest dynamics analyses (Birnbaum, 2001), wildlife habitat modeling and mapping (Davenport et al., 2000;Hinsley et al., 2002), light penetration modeling (Zimble et al., 2003), and carbon and energy exchange modeling (Lefsky et al., 1999;Clark et al., 2004;Lefsky et al., 2005).

<u>Methods</u>

Tall Timbers Research Station

This study took place at Tall Timbers Research Station, which is located within the Red Hills region of southwestern Georgia and northwestern Florida (Figure 1). This region occupies approximately 300,000 ha between Thomasville, Georgia and Tallahassee, Florida and is home to over 230 rare types of plants and animals and over 27 federally listed threatened and endangered species (Masters et al., 2007). The Red Hills area is comprised of a mixture of young and old growth longleaf pine forests, natural and planted loblolly (*Pinus taeda*) and shortleaf (*Pinus echinata*) pine forests primarily in an old field context, mixed hardwood and pine forests, forested and herbaceous wetlands, agricultural fields, and residential/urban land cover types .

The Tall Timbers Research Station (TTRS) covers 1600 ha within the Red Hills Region, and is located just north of Tallahassee, FL. Until 1895 the upland pine ecosystems at TTRS were dominated by pristine savanna uplands, but have been highly disturbed by agriculture, and are currently dominated by a mixed canopy of loblolly pine (*Pinus taeda*), shortleaf (*Pinus echinata*) and longleaf (*Pinus palustris*) (Masters et al., 2005). The groundcover at the study site is dominated by many legumes and composite family members and interspersed with grasses (broomsedge bluestem, *Andropogon virginicus*, primarily), but lacking the wiregrass typical of pristine longleaf pine savanna ecosystems (Hermann, 1995).

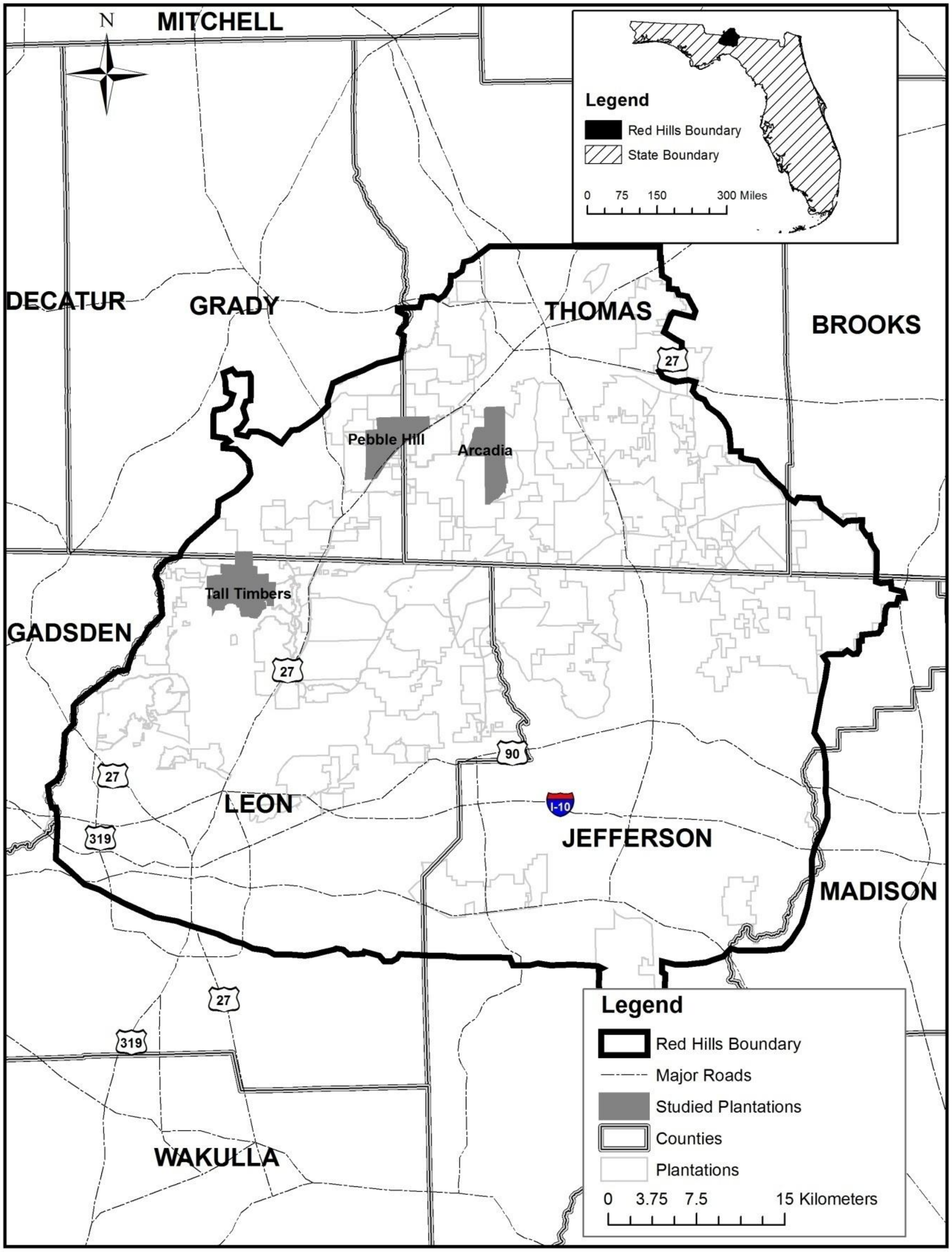

Figure 1. Location of Tall Timbers Research Station (TTRS) within the Red Hills area.

TTRS is focused on research and management issues of longleaf pine savanna, pine woodlands, and other ecosystems of the Red Hills area, including management for game birds (such as the Northern bobwhite, *Colinus virginianus*) and threatened and endangered species (such as the red cockaded woodpecker, *Picoides borealis*). This Research Station provides a "model working landscape" that engages landowners (under the Land Conservancy, TTLC) to ensure the future health of the Red Hill area's forests and wetlands.

The unique heterogeneity of the landscape, on-site long-term research history, and availability of two sets of LiDAR data, allowed for an ideal study area for ground validation and estimation of forest canopy structure.

Forestry Plots and Transects

Two sets of field data (plots and transects) are used to provide insight into structural variables that can be extracted from small-footprint airborne LiDAR datasets. Forestry plots 0.04 ha in area (11.3 m radius) have been setup by TTRS field staff in a dense 61 by 61 m grid throughout the entire uplands of the station, excluding bottomland hardwoods, fields, and wetlands (Figure 2). GPS location of the plot center, tree canopy cover (9 sighting scope readings), individual tree species and corresponding DBH (for trees and saplings >1.27cm DBH) were collected for all 2572 plots. Canopy cover was collected at the plot center and all 4 cardinal directions at 2 and 4 m from the plot center. In addition, for about one fifth of the plots (422 plots), tree top height and height to the base of live crown were obtained for all trees within the plot area. The forestry data collection took place by TTRS forestry staff in two phases, the first completed in 2003, and the second one in 2004.

Additionally, sixteen transects of 250 m in length and 10 m in width (0.25 ha) designed for further field data collection were strategically placed throughout the TTRS (Figure 3). The transect approach was selected in addition to the dense network of forestry plots for validation, increasing the representation of diverse land cover types and natural variation present at TTRS. Furthermore, this transect approach also allowed a more detailed ground validation analysis, since accurate (1-2 m) geolocations for all trees were obtained.

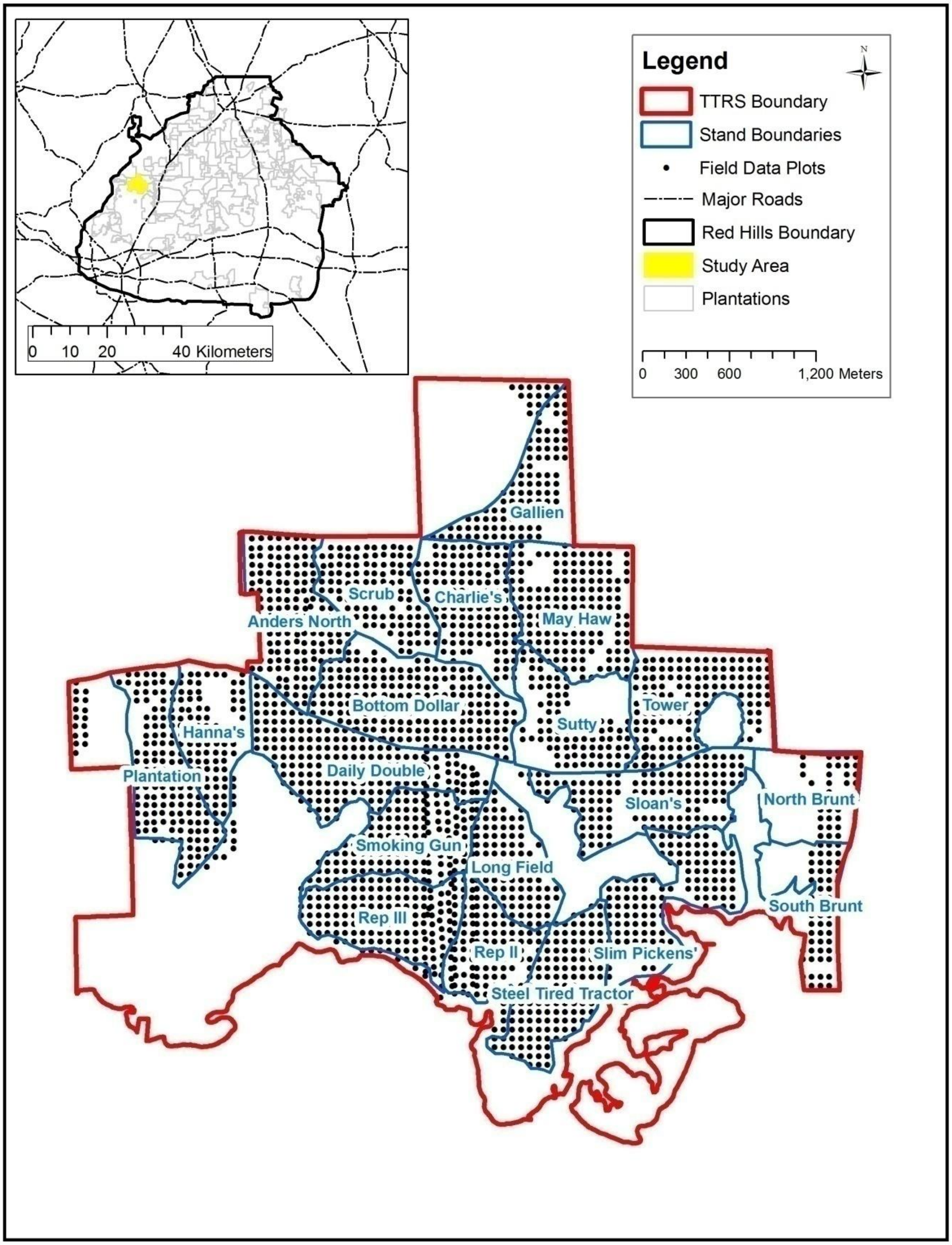

Figure 2. Location of the Extensive Forestry Field Plot Network within the Tall Timbers Research Station.

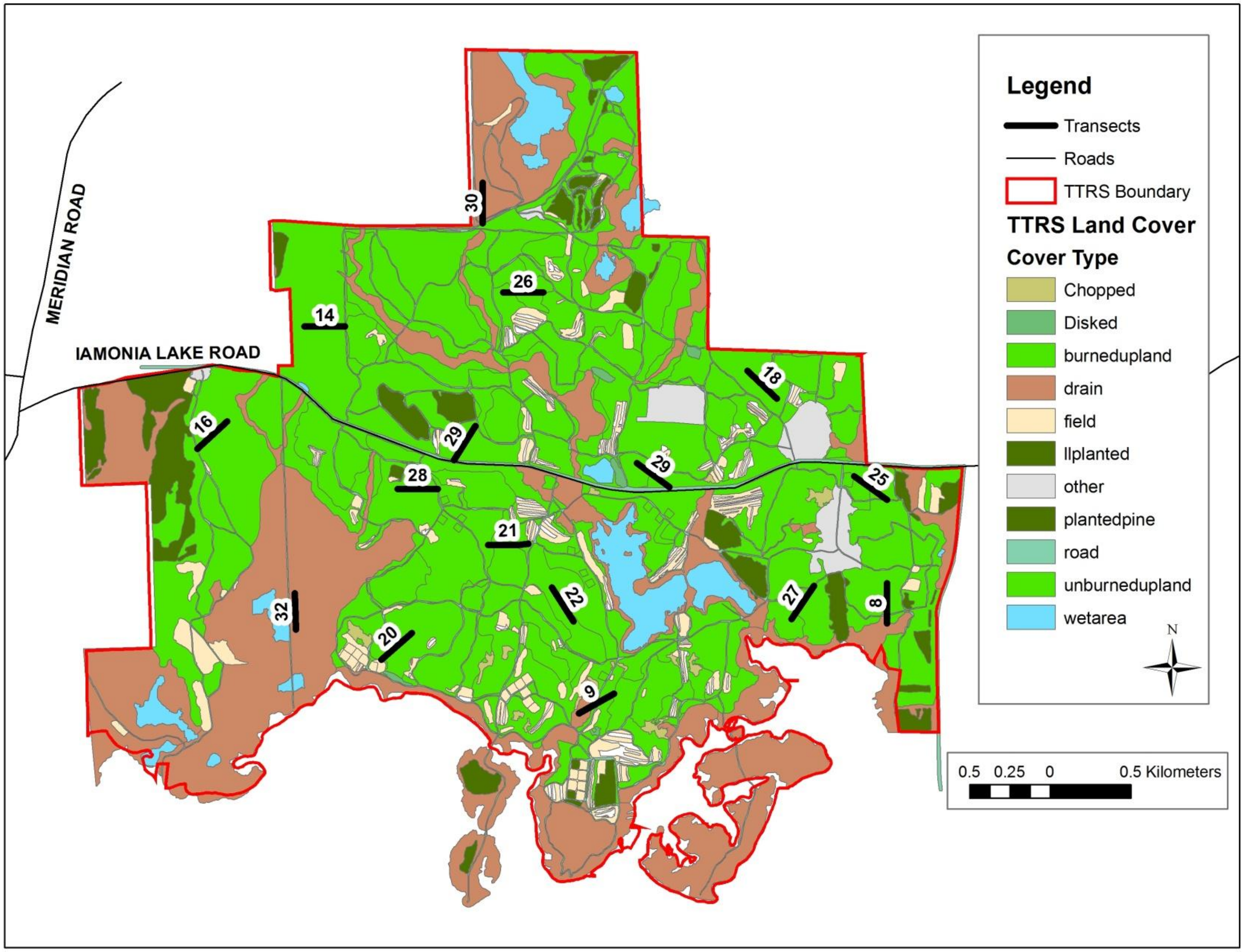

Figure 3. Location of the 16 Field Transects and their Represented Land Cover in the Tall Timbers Research Station.

Transect selection was based on a variety of factors and carefully planned in a GIS environment. Land use land cover 2002-2004 coverage (Noble, 2006) and 2004 digital orthophotos (www.labins.org) were used to verify natural variability and allow appropriate transect placement. From the 2001 land use land cover information, it was clear that almost 50% of TTRS should be excluded from sampling, consisting of open fields, developed areas, loblolly planted areas, roads, and wetlands. Further areas of exclusion consisted of the northern portion of TTRS (located outside Leon County and for which no airborne LiDAR data are available) and the Stoddard experimental fireplots. The 16 transects were placed scattered in the upland pine area, varying direction, road interference (11 out of 16 crossed minor roads), ecotone representation (2 represented a clear transition between cover types),attempting to achieve some degree of spatial dispersion (Figure 3).

Three point spatial layers were collected using customized data dictionaries with a Trimble GeoXT for each transect: canopy cover/ shrub layer, tree locations, and photograph point locations. For the first layer, binary canopy cover measurements (0% vs. 100%) were recorded using a densiometer at 5 m intervals along the transect line. Additionally, height estimates and species of shrub and small trees (<2m) were collected at the same location. Height estimates for shrubs will fall within one of the following categories: >40, 40-60, 60-80, 80-100, 100-120, 120-140, 140-160, 160-180, and 180-200 cm classes.

The tree layer included the exact location of all trees > 5 cm in DBH within the 10 m wide swath (5 m on each side of the transect line) of each of the 16 transects. Data collected for the individual trees included the species, DBH, top height, crown height (height to base of live crown), and maximum crown diameter. Height data were collected using a LTI Impulse laser rangefinder. Dead trees were also included in the tree layer, and clearly identified as such.

LiDAR Data

Two datasets of small footprint multiple return LiDAR (Light Imaging and Ranging) were obtained from the Tallahassee-Leon County Geographic Information Systems (GIS) Department. These datasets included raw LAS files for the entire Leon County in both 2002 and 2008 transitional seasons (February and March, respectively) with the goal of creating countywide detailed floodplain mapping. The first set (2002) was collected using the ALS40 (Leica Geosystems) scanner by Merrick & Co. in February 2002, and has a mean and minimum point spacing of 1.39 and 1.05 m, respectively. The 2008 dataset was collected using a Leica ALS50 Geosystem in March 2008, and has a mean and minimum point spacing of 1.55 and 1.19 m, respectively. Horizontal accuracies were 0.55 and 0.52 m RMSE for the 2002 and 2008 LiDAR datasets and vertical accuracy was 0.10 m RMSE for both datasets.

Point cloud data were obtained in the LAS 1.0 format for the 2002 data which specified ground vs. non-ground data, but not any additional return numbers. The point cloud data were converted to multipoint files and interpolated using an inverse distance weighted (IDW) approach in the 3D Analyst ArcGIS (ESRI) environment to a Digital Elevation Model (DEM) - ground point - and a Digital Canopy Height Model (DSM) - for all non-ground points (Zimble et al., 2003). The Canopy Height Model (DCHM) was extracted from the difference between the DSM and the DEM.

For 2008, the newer LAS 1.1 format was used, which included both the class (ground versus non-ground) and multiple return numbers. Similar to the 2002 dataset, the 2008 point cloud data were converted to multipoint files. After the construction of the DEM using an IDW second degree interpolation of ground returns, the DCHM model was similarly extracted from the difference between the DSM (constructed using first returns only) and the DEM. All IDW interpolations performed were second power interpolations with a variable search of up to 12 neighbors and a 1 meter grid output size (instead of a much smaller 0.2 m grid used by (Zimble et al., 2003). Post processing of all the raster products was used to fill most, if not all, empty cells, with nearby interpolated values. The DEM heights were assigned to all point cloud data, allowing the computation of height above ground for every data point.

LiDAR data with above ground heights were extracted for the forestry plots by selecting point cloud data within a 12 m buffer around point center. Similarly, LiDAR data within the transects' area were extracted and further identified with the transect unique identifier in the ESRI ArcGIS environment. Data management for these large datasets took place in ESRI ArcGIS using geodatabases for the extracted LiDAR plots and transect 2002 and 2008 datasets. No co-registration between LiDAR datasets took place, since the RMSE vertical and horizontal errors were strictly controlled by the vendor, and insignificant for plot and stand level comparisons.

Data Analyses

The two goals of the data analyses were: 1) to obtain LiDAR derived structural variables, using two different methods (raw GIS and Fusion/LDV) and datasets (2002 and 2008), and use field plot and transect data for validation 2) to test two different tree extraction methods from airborne LiDAR and compare these results to field collected data.

Plot and Transect Data Analyses

The field plot data measurements for canopy cover were averaged from the 9 sighting readings and converted to percentage from the 0-9 scale. Individual tree data collected for each plot were linked to the plot id, and height statistics (average, maximum, minimum, standard deviation) were calculated per plot. While canopy cover and basal area were available for all 2572 plots, tree height variables were only available for a subset of these (422 plots).

The transect data measurements for canopy cover were averaged per transect from the 50 binomial readings (0/100%). In contrast to the plot data, individual tree data were collected with associated high accuracy locations and available for all 16 transects. Height variables, similar to the plot field data ones, were calculated for each transect. The first method of LiDAR data extraction of structural variables of interest -raw GIS extraction- was used for both the 2002 and 2008 datasets. This method used only ESRI ArcGIS and Spatial Analyst's built-in tools, along with database queries, for the creation of elevation and canopy height models, attribution of x, y, z LiDAR points with heights above ground (see "LiDAR Data"), and extraction of variables of interest per plot and stand.

For appropriate validation of the field data, x,y,z LiDAR data points with heights above ground were clipped to the appropriate area of interest. For the plot validation, a 12 m buffer was used around the forestry plot center location, and for the transects, a 5 m buffer around each side of the transect were used. The clipping allowed the correspondence of the airborne LiDAR datasets to the field collected data.

The variables of interest extracted using the first method included canopy cover, canopy height (maximum, minimum, mean, and standard deviation), basal area, and tree count. Canopy height and cover indices were extracted using similar methodology (Lim et al., 2003;Lovell et al., 2003) for discrete return LiDAR, with slight modification from the 20X20m window used by others (Lovell et al., 2003;Coops et al., 2007). For the canopy heights, instead of using a 20X20 m window to obtain the highest canopy point as the maximum height, the individual forestry plots or transect buffer area were used. Maximum mean height corresponded to the highest LiDAR canopy classified return (within the entire plot), and mean canopy height used an average of all canopy returns over 2 m, and is expected to underestimate the average field tree heights (Lim et al., 2003). Canopy cover was measured by redefining closed canopy returns as only the ones over 2 m and dividing the total number of these returns in each plot by all discrete returns in the same plot. The proportion of canopy returns is a standard canopy cover index (Lim et al., 2003), which, for this study, has been slightly modified to exclude the herbaceous and lower shrub layers.

The second method of LiDAR data extraction -FUSION/LDV extraction- was also used, for comparison purposes, to analyze the 2008 dataset only (for both the plots and transects). The lack of return information and the older LAS file format for the 2002 dataset prevented its use in the Fusion/LDV software version 2.9 (McGaughey, 2010). The freely available Fusion/LDV software from the USDA Forest Service uses LAS files and associated orthophotography to allow data analysis and visualization. In order to extract height variable and canopy cover information, a number of command line programs have to be run, including "PolyClipData" (clips the cloud data to user specific polygons using an ArcGIS shapefile), "GridSurfaceCreate" (allow the creation of interpolated surfaces using user selected LAS files and parameters), "CanopyModel" (created a CHM using LAS files), "Cover"(creates a canopy cover raster file), and "CloudMetrics" (McGaughey, 2010). Resulting metric information were combined with interpolated ground elevation values for each plot or transect to obtain height above ground metrics. Cloud metrics for height data provided by Fusion/LDV are extensive and include percentile values, means, minima and maxima, variance and skewness variables. Canopy cover is estimated by Fusion/LDV using the first returns, as default, and results correspond to the canopy closure (0-100%) in a grid output format. For consistency, only canopy first returns over 2 m were selected as canopy returns for the estimation of the proportion of canopy returns from all LiDAR returns.

Extracted raw GIS and Fusion/LDV LiDAR-derived structural information were compared to field-derived variables (canopy cover, mean, median, and maximum tree height) through scatterplots and visual representation at the plot, transect, and stand level. Stand level analysis included both aggregating the field and LiDAR plot data into stand statistics, as well as spatial analysis of the differences in canopy cover and heights across the study area. For the spatial distribution maps, ArcGIS 3D Analyst was used to create IDW interpolations of the field versus LiDAR canopy cover and maximum plot heights, and subsequent percent differences between these grids were calculated. Difference maps always represent the subtraction of LiDAR derived data (ArcGIS raw method) from the corresponding field values.

Tree Extraction

Individual tree extraction utilized the 2008 LiDAR dataset and was conducted independently using two sets of tools for a subset of the Tall Timbers area: the LiDAR Analyst extension (Overwatch Geospatial, 2009), and Fusion/LDV software (USDA Forest Service, 2010). For the entire area that covers both the 2572 field plots and the 16 transects, tree extraction was completed only using the Fusion/LDV software tools. Tree extraction using LiDAR Analyst was completed for a subset of the study area, to enhance performance and avoid license limitations. Both methods require a digital terrain model and canopy height model to be created prior to extraction tree location and associated height information.

The LiDAR Analyst toolset provides automatic methods of extracting individual tree locations based on the LiDAR DEM, along with tree height, crown width, and stem diameter. The proprietary tree extraction algorithm allows users to define certain features as trees, by providing minimum tree height and degree of vertical curvature. For the Fusion/LDV toolset, a combination of command line programs had to be completed prior to running the "CanopyMaxima" program. This latter one uses a CHM to identify local maxima, based on a local algorithm with a variable-size window. The algorithm used in Fusion/LDV is similar to that reported in (Popescu et al., 2002) and (Kini and Popescu, 2004) and implemented in the TreeVaW software (Kini and Popescu, 2004). The tree variable window algorithm uses a window that changes dependent on the height of the CHM for that particular region, and is geared to providing dominant tree height information. The extracted trees from this method include tree height, crown height, and minimum and maximum crown width (McGaughey, 2010).

Extracted tree location and height information were compared and contrasted between the two tree extraction methods for the same area, using visual plots and general statistics. Furthermore, tree height information available from the Fusion/LDV method for all plots and transects were compared to field collected tree information. Location of the tree locations could only be compared to the transect collected tree data, since these were individually geolocated in the field.

Results and Discussion

Forest Plots

Stand Analysis

Overall, aggregating plot-level information into stands distributed across TTRS, highlighted the wide range of conditions across Tall Timbers. Field canopy cover mean values for the stands range between 28% (Tower and Rep III) to 56% (Scrub), with an overall mean for all plots within Tall Timbers around 39% (Table 1). The 2002 and 2008 LiDAR canopy cover percentages (extracted using ArcGIS tools) have a similar range to the field results, between 27% (Anders North and Bottom Dollar) and 53% (Daily Double). However, the stands representing the highest or lowest canopy cover in one dataset did not consistently present the same pattern in the other datasets (LiDAR or Field). It was expected that differences would occur between both LiDAR datasets, since a selective thinning treatment occurred in 2007 for all stands with the exception of the Gallien, Van Brunt, and Hanna Hammock. Thinning can account for some of the canopy cover reductions observed between 2002 and 2008.

While mean canopy cover percentage values for all the plots were around 4% higher when comparing field to 2002 LiDAR data, the 2008 LiDAR canopy cover mean was 5% higher than the field collected data. It is important to note that the plot field data were collected asynchronously from either LiDAR data collection events: field data were collected 1-2 years after the 2002 LiDAR data collection, and 4-5 years before the 2008

LiDAR data collection. Cumulative rainfall differences prior to the data collection event can have an impact on the canopy cover differences (Masters, pers. communication) encountered among the three sets of data (43%, 39%, and 34% in 2002 LiDAR, 2004 field, and 2008 LiDAR datasets, respectively). The 2002 LiDAR derived canopy cover values correspond to a well above average rainfall year (150 cm), while both 2004 (field) and 2008 (LiDAR) data collection events corresponded to below average rainfall years (97 and 115 cm, respectively). Furthermore, forestry data collection for the plots did take place in a range of seasons, depending on the stand, from dormant to late transitional. In contrast, both LiDAR datasets took place in the transitional season (February-March) for all the study area. The impact of seasonality in canopy cover measurements is obvious in hardwood woodlands, but also important in secondary upland pine forest, where there is a significant hardwood encroachment component.

Table 1. Stand Level Field and Raw Airborne LiDAR (2002 and 2008) Results for the Tall Timbers Forestry Plots.

Stand Name	Conventional Forestry				Airborne Lidar						Difference (Conventional-Lidar)					
					2002			2008			2002			2008		
	%Cover	TreeCount	MaxHT[1]	MeanHT[1]	%Cover	MaxHT[1]	MeanHT[1]	%Cover	MaxHT[1]	MeanHT[1]	ΔCover	ΔMaxHT[1]	ΔMeanHT[1]	ΔCover	ΔMaxHT[1]	ΔMeanHT[1]
N/A	29.58	178	32.92	15.43	45.72	36.10	14.42	38.47	36.57	16.60	-16.14	-3.18	1.01	-8.89	-3.65	-1.17
Anders North	40.34	861	28.06	6.26	35.52	36.50	13.91	27.09	36.69	15.65	4.83	-8.44	-7.65	13.25	-8.62	-9.39
Bottom Dollar	35.76	357	32.89	12.07	42.63	37.33	14.74	27.99	37.33	16.70	-6.87	-4.44	-2.67	7.77	-4.44	-4.63
Charlie's	50.41	142	31.62	16.16	46.12	35.13	16.45	32.66	35.22	17.85	4.29	-3.51	-0.28	17.75	-3.60	-1.69
Daily Double	33.34	301	35.36	17.67	52.58	35.12	16.26	34.60	34.15	18.82	-19.24	0.24	1.40	-1.26	1.21	-1.16
Gallien	45.34	57	32.61	20.54	50.44	34.78	16.07	41.45	34.12	19.27	-5.11	-2.17	4.47	3.88	-1.51	1.28
Hanna's	45.62	175	28.83	12.53	38.68	29.66	14.14	35.16	30.30	17.72	6.95	-0.84	-1.61	10.46	-1.47	-5.19
Long Field	36.29	76	43.59	19.14	44.43	38.26	16.02	29.34	38.32	18.44	-8.14	5.32	3.12	6.95	5.27	0.70
May Haw	33.13	118	43.89	20.26	41.33	42.62	18.61	31.31	40.16	20.20	-8.20	1.27	1.65	1.82	3.73	0.05
North Brunt	49.16	24	33.83	19.44	37.02	28.64	13.57	52.34	29.45	15.31	12.14	5.19	5.86	-3.18	4.38	4.13
Plantation	53.10	470	30.60	14.02	52.98	28.63	12.86	41.50	29.61	15.76	0.11	1.97	1.15	11.60	0.98	-1.75
Rep II	29.00	124	38.40	16.41	41.66	37.82	14.09	29.83	38.37	17.04	-12.66	0.59	2.32	-0.83	0.03	-0.63
Rep III	27.98	162	42.06	20.71	48.80	36.77	15.38	29.75	36.57	17.61	-20.82	5.29	5.33	-1.77	5.50	3.10
Scrub	56.00	127	32.31	12.87	40.41	34.44	15.88	28.99	34.85	17.23	15.59	-2.13	-3.01	27.01	-2.54	-4.37
Slim Pickens'	37.94	123	43.28	19.52	47.07	38.14	19.09	40.96	37.83	20.64	-9.13	5.14	0.43	-3.02	5.45	-1.12
Sloan's	32.37	136	39.93	16.15	42.40	36.28	15.84	33.45	35.97	17.94	-10.03	3.65	0.31	-1.08	3.96	-1.79
Smoking Gun	32.49	173	52.43	18.23	50.62	42.03	18.18	35.25	41.94	19.73	-18.13	10.40	0.05	-2.76	10.48	-1.50
South Brunt	51.09	34	22.25	17.43	31.51	22.96	10.79	42.33	24.88	14.35	19.58	-0.71	6.64	8.76	-2.63	3.08
Steel Tired Tractor	32.68	123	42.06	16.08	48.51	41.95	14.79	34.10	39.25	16.95	-15.83	0.11	1.28	-1.42	2.81	-0.88
Sutty	41.98	84	43.75	15.85	36.46	39.51	16.59	30.78	39.25	19.02	5.51	4.24	-0.74	11.20	4.50	-3.17
Tower	27.92	89	41.97	11.28	35.43	37.22	15.39	28.50	36.76	17.59	-7.51	4.76	-4.10	-0.58	5.21	-6.31
Stand Mean	39.12	187.33	36.79	16.10	43.35	35.71	15.38	34.56	35.60	17.64	**-4.23**	**1.08**	**0.71**	**4.56**	**1.19**	**-1.54**

[1] Units are in meters

Spatial patterns of differences between airborne and field canopy cover are distinct, indicating stands located in northeastern Tall Timbers (Anders North, Scrub and Charlie's) with higher field canopy cover values, and a section of the southern central study area (Daily Double, Smoking Gun, and Rep III) having greater LiDAR values in comparison to field collected ones (Figure 4).

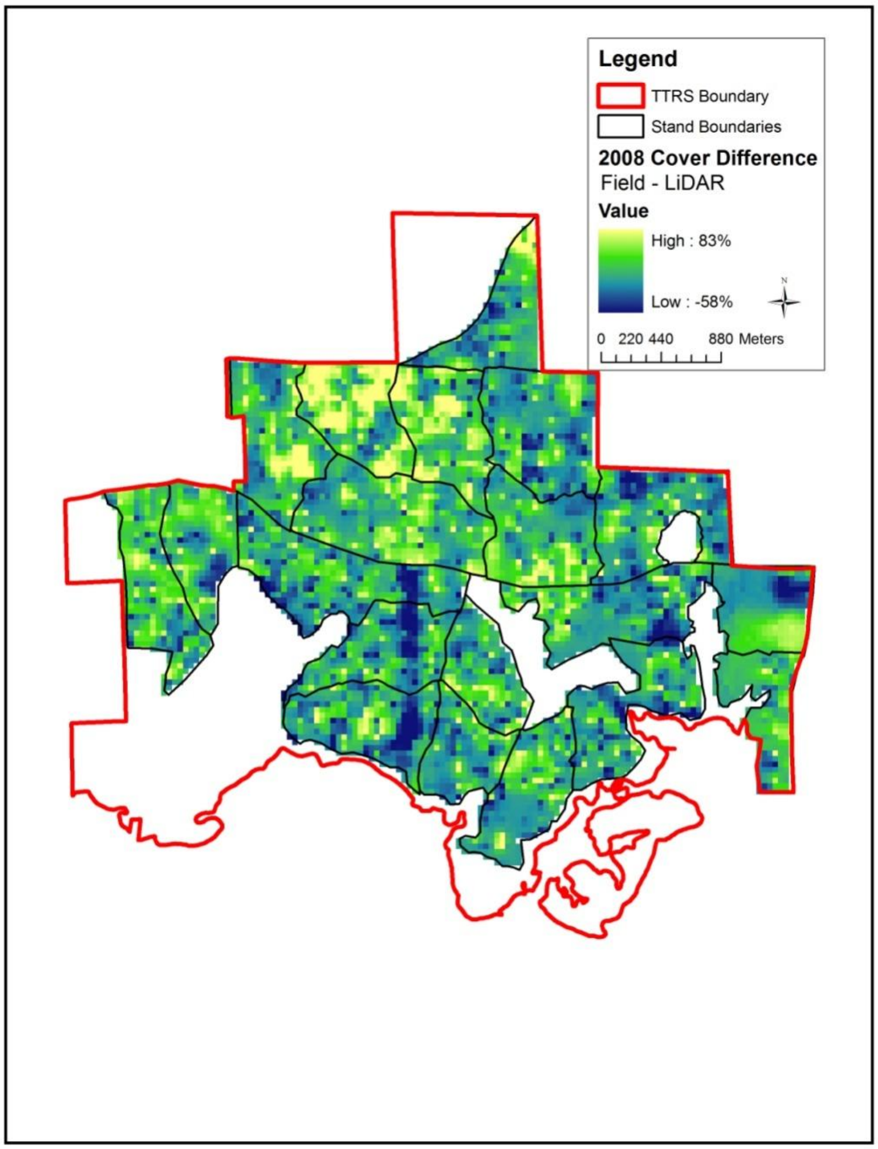

Figure 4. Spatial Interpolation of Canopy Cover Differences across Tall Timbers (Field - LiDAR derived canopy cover).

Height variables, mean and maximum height for the forest stands are more consistent for both sets of airborne LiDAR data, with an across the board increase in mean stand height in the later year (17.64 m for 2008 instead of 15.38 m for 2002). This is consistent with an increase in height from 6 years of vegetation growth and, additionally, the effects of selective thinning of the smaller trees. Field collected maximum stand height is overall 1 m higher than airborne LiDAR maximum stand height, but differences range between 10 m higher to 8m lower than LiDAR measurements (Table 1). There is a consistent bias towards slightly lower top tree elevations (portrayed in the maximum heights) common to LiDAR datasets, since it is easy for first returns to miss the highest point of the tree. Mean heights derived from LiDAR datasets can under-report field mean heights substantially, since the former includes the height through all the tree crown and not only average tree top height, as collected in the field.

Spatial interpolations of maximum canopy heights yielded clear differences across the stands (Figure 5), with the northwestern stands (Anders North and Scrub), which had significant less detected canopy cover using LiDAR than field methodologies, presenting greater maximum heights using LiDAR data. Over-representation of maximum heights using LiDAR were located where field sampling was reduced, such as portions of Gallien and Tower stands, or in stands where thinning took place in 2007 (Gallien, Hannah's Hammock and the Van Brunt stands). Across most of the other areas, the pattern still indicated a slight bias towards lower maximum heights captured by remotely sensed data, when compared to field acquired heights.

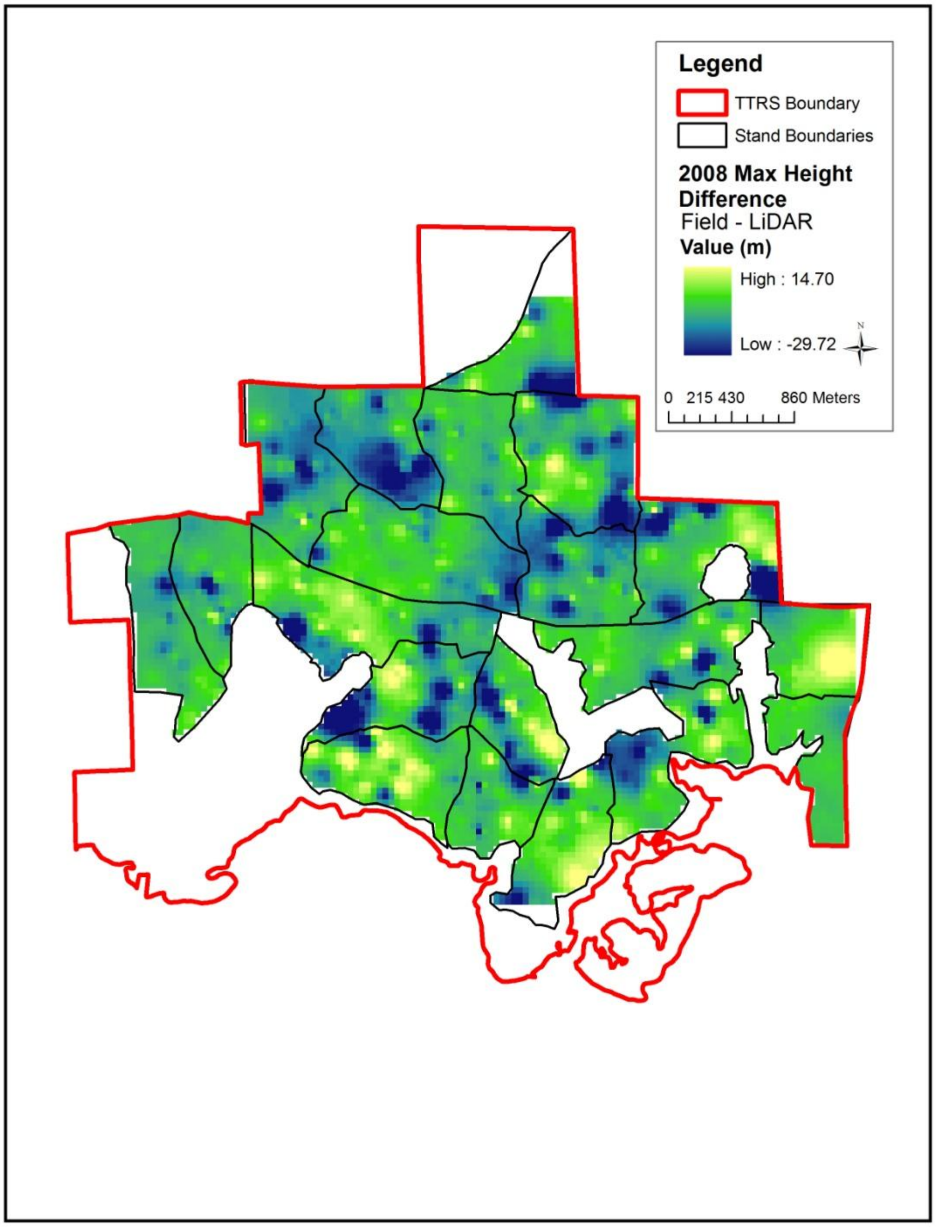

Figure 5. Spatial Interpolation of Maximum Canopy Height Differences across Tall Timbers (Field - LiDAR derived maximum canopy height).

Mean crown height from field data varied between 6 m (Anders North) to 21 m (Rep III), with a stand average of 16 m. These height measurements are the result of averaging field plots individual tree measurements, and include saplings 0.5 cm DBH or greater.

Stands with a high number of saplings or shrub encroachment, such as Anders North with a tree count of 861 (twice as high as any other stand), are heavily biased by this new growth (mean height 40% of the mean stand height). In contrast, LiDAR derived mean stand heights correspond to all returns over 2 m, and are more heavily influenced by the entire crown structure of the trees, rather than just measures of the top crown. In most stands (15 out of 21), the mean height measures of field versus LiDAR were within 3 m of each other, even when considering the distinctly different nature of these measures. Stands with the greatest differences in field heights were characterized by extreme conditions, either very dense or sparse tree counts. Stands with a high amount of saplings (Anders North) were heavily biased in the field by the heights of small shrubs, and thus, lower than LiDAR portrayed heights (8 to 9 m below LIDAR mean heights). Stands with a low number of trees (North and South Brunt, 24 and 34 trees, respectively) had between 3-7 m higher field mean heights than LiDAR mean heights. The low number of tree top heights from the field in comparison from returns from the entire crown of the trees represented with the LiDAR explains the bias in these stands.

Fusion/LDV derived data from the 2008 airborne dataset produced more consistent canopy cover and mean height stand values compared to the field measurements (Table 2), than did the raw GIS extraction of the same LAS data. Overall average canopy cover data for the stands was only 1% lower for the Fusion/LDV values than the field, but individual stand differences did reach almost 22% for the Scrub Stand. With the exception of four stands, however, canopy cover differences between the Fusion/LDV and Field methods were within 10%. Considering the variability of canopy cover measurements with the number of samples taken in the field (Jennings et al., 1999) and the asynchronous nature of the datasets used in this validation, cover differences of 10% are encouraging. This difference could also be a direct result of the management treatments occurring at the station, including burning and especially thinning that took place in 2007, a year prior to the 2008 LiDAR data acquisition.

Fusion/LDV derived maximum and mean height variables averaged about 2 m lower than the height variables obtained using the raw GIS processes (Table 1 and Table 2). Differences in maximum stand height between LiDAR and field datasets were greater using the Fusion/LDV (4.02 m) than the raw GIS methodology (1.19 m), whereas differences in mean stand heights were more subdued using Fusion/LDV (0.57 m) than raw GIS (1.54 m). Stand mean heights were, as an average, only 0.6 m higher in the field data than the Fusion/LDV metrics (Table 2), and the range of differences was reduced from the raw to the Fusion/LDV LiDAR processes. With the exception of three stands, mean Fusion/LDV derived heights were within 1-3 m of the field results.

Overall, crown height maximum and mean heights extracted from the airborne LiDAR datasets closely approximated field heights, with mean stand differences at or below 1.5 m: mean and maximum crown height differences were 1.08 and 0.71 m for the 2002 LiDAR and 1.19 and -1.54 m for the 2008 LiDAR dataset (Table 1).

Table 2. Stand Level Field versus Fusion/LDV Derived Metrics (2008 LIDAR) Results for the Tall Timbers Forestry Plots.

Stand Name	Conventional Forestry				Fusion Metrics			Field - Fusion		
	%Cover	TreeCoun	MaxHT[1]	MeanHT[1]	%Cover	MaxHT[1]	MeanHT[1]	ΔCover	ΔMaxHT[1]	ΔMeanHT[1]
N/A	29.58	178	32.92	15.43	25.54	28.67	17.40	4.04	4.25	-1.97
Anders North	40.34	861	28.06	6.26	33.73	29.33	9.64	6.62	-1.26	-3.38
Bottom Dollar	35.76	357	32.89	12.07	29.41	35.49	14.66	6.35	-2.60	-2.59
Charlie's	50.41	142	31.62	16.16	34.69	31.73	13.76	15.72	-0.11	2.41
Daily Double	33.34	301	35.36	17.67	40.06	33.45	16.16	-6.72	1.91	1.51
Gallien	45.34	57	32.61	20.54	50.78	31.54	18.73	-5.45	1.08	1.82
Hanna's	45.62	175	28.83	12.53	N/A		N/A	N/A	N/A	N/A
Long Field	36.29	76	43.59	19.14	31.24	39.10	13.14	5.05	4.49	6.00
May Haw	33.13	118	43.89	20.26	33.10	39.87	17.57	0.03	4.02	2.69
North Brunt	49.16	24	33.83	19.44	60.10	23.81	12.69	-10.94	10.03	6.75
Plantation	53.10	470	30.60	14.02	N/A		N/A	N/A	N/A	N/A
Rep II	29.00	124	38.40	16.41	29.00	33.31	14.28	0.00	5.09	2.13
Rep III	27.98	162	42.06	20.71	31.56	33.13	18.50	-3.58	8.94	2.20
Scrub	56.00	127	32.31	12.87	34.00	33.31	18.29	22.00	-1.00	-5.42
Slim Pickens'	37.94	123	43.28	19.52	45.14	37.19	18.12	-7.20	6.09	1.40
Sloan's	32.37	136	39.93	16.15	33.04	35.07	15.31	-0.67	4.86	0.84
Smoking Gun	32.49	173	52.43	18.23	39.32	41.65	22.01	-6.83	10.78	-3.78
South Brunt	51.09	34	22.25	17.43	59.95	22.27	14.46	-8.86	-0.02	2.97
Steel Tired Tractor	32.68	123	42.06	16.08	29.44	35.02	14.23	3.24	7.04	1.84
Sutty	41.98	84	43.75	15.85	29.48	36.12	18.15	12.49	7.63	-2.30
Tower	27.92	89	41.97	11.28	28.20	36.75	13.46	-0.28	5.23	-2.18
Stand Mean	39.12	187.33	36.79	16.10	36.73	33.52	15.82	**1.32**	**4.02**	**0.57**

[1] Units are in meters

Plot Level Analysis

Plot level comparison of field versus 2002 and 2008 LiDAR canopy cover percentages (raw GIS methodology) presented a large amount of scatter, with a low r^2 of 0.22 to 0.27, respectively (Figure 6). A large portion of this scatter was found in plots that were recorded in the field as having no canopy cover (from the nine field measurements per plot), but had a wide ranging percentage of crown returns using either LiDAR datasets. As a matter of fact, some of these plots did have tree height data recorded, highlighting the difficulty estimating canopy cover in the field for a plot based on a small sample of points. According to Jennings et al. (1999), canopy cover differences, unless major, cannot be discerned with less than 100 samples per plot. Previous suggestions of 20 sample points per plot now seem to be insufficient to provide an accurate characterization of canopy cover plot differences. The high field sampling effort required to provide greater confidence in structural measurements is a keypoint in the utility of using active remote sensing techniques, such as airborne LiDAR, in the assessment of forest structures.

The relationship between mean field versus airborne LiDAR derived heights for the 422 plots at Tall Timbers is slightly stronger (r^2 of 0.28 and 0.32 for 2002 and 2008 LiDAR, respectively), but still presents some scatter, especially with plots with lower field height estimates (Figure 7). These plots are concentrated in the Anders North Stand and present a high percentage of saplings, potentially not present in other data collection years (due to fire management approaches).

The best relationship encountered at the plot level corresponds to the maximum height, with an r^2 of 0.33 and 0.42 for 2002 and 2008 datasets, respectively. The majority of the scatter is present in plots with field maximum heights of 2 and 20 m, with airborne LiDAR capturing higher crowns in the majority of these plots (Figure 8). Excluding these plots, the maximum height difference between field and airborne LiDAR methods is within the 3 m range, which could be easily explained by either geolocation errors in plot centers or field height collection errors. Investigations of the outliers plots using orthophotography from the field data collection year indicated that canopy cover estimated from LiDAR datasets appear to better represent the actual field conditions.

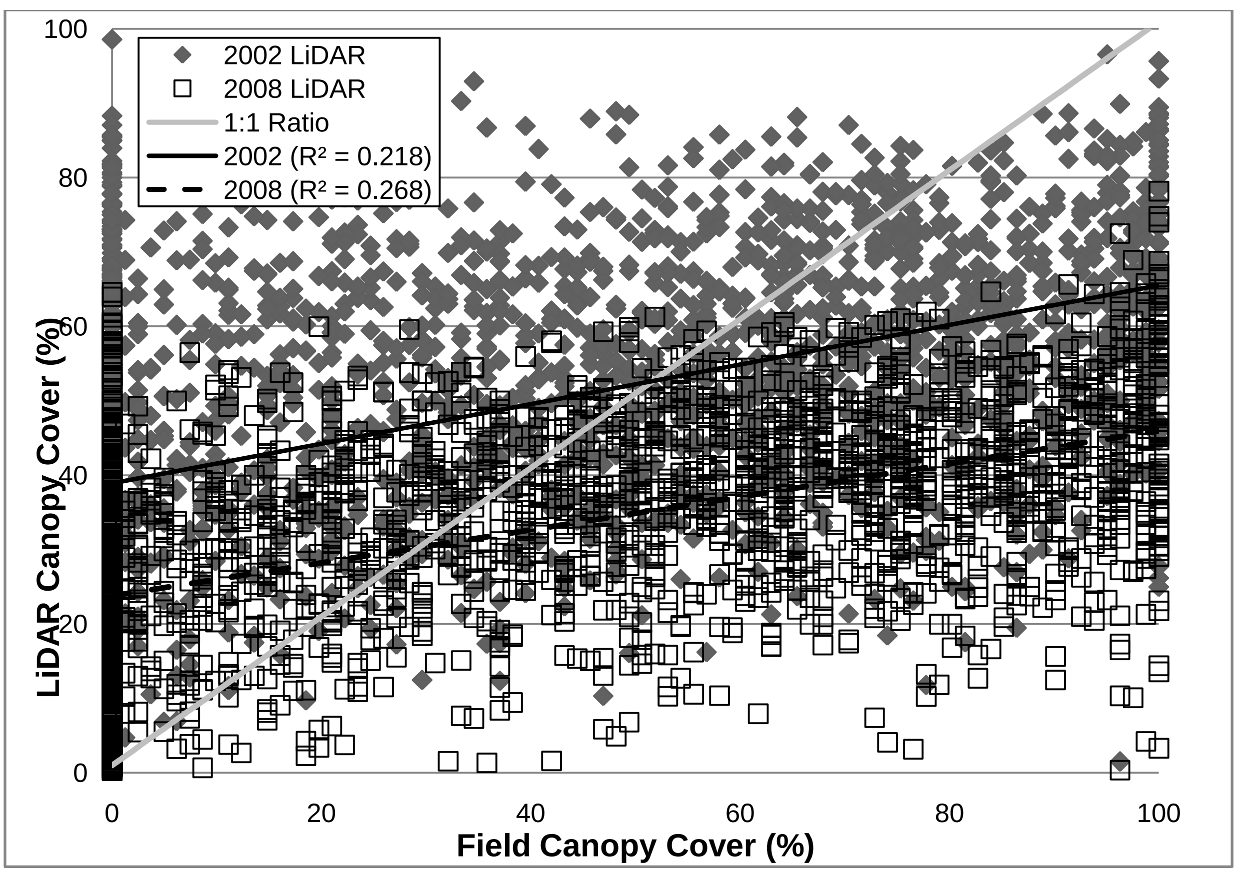

Figure 6. Scatterplot of Field versus Airborne LiDAR (2002 and 2008) derived Canopy Cover for individual forest plots at Tall Timbers.

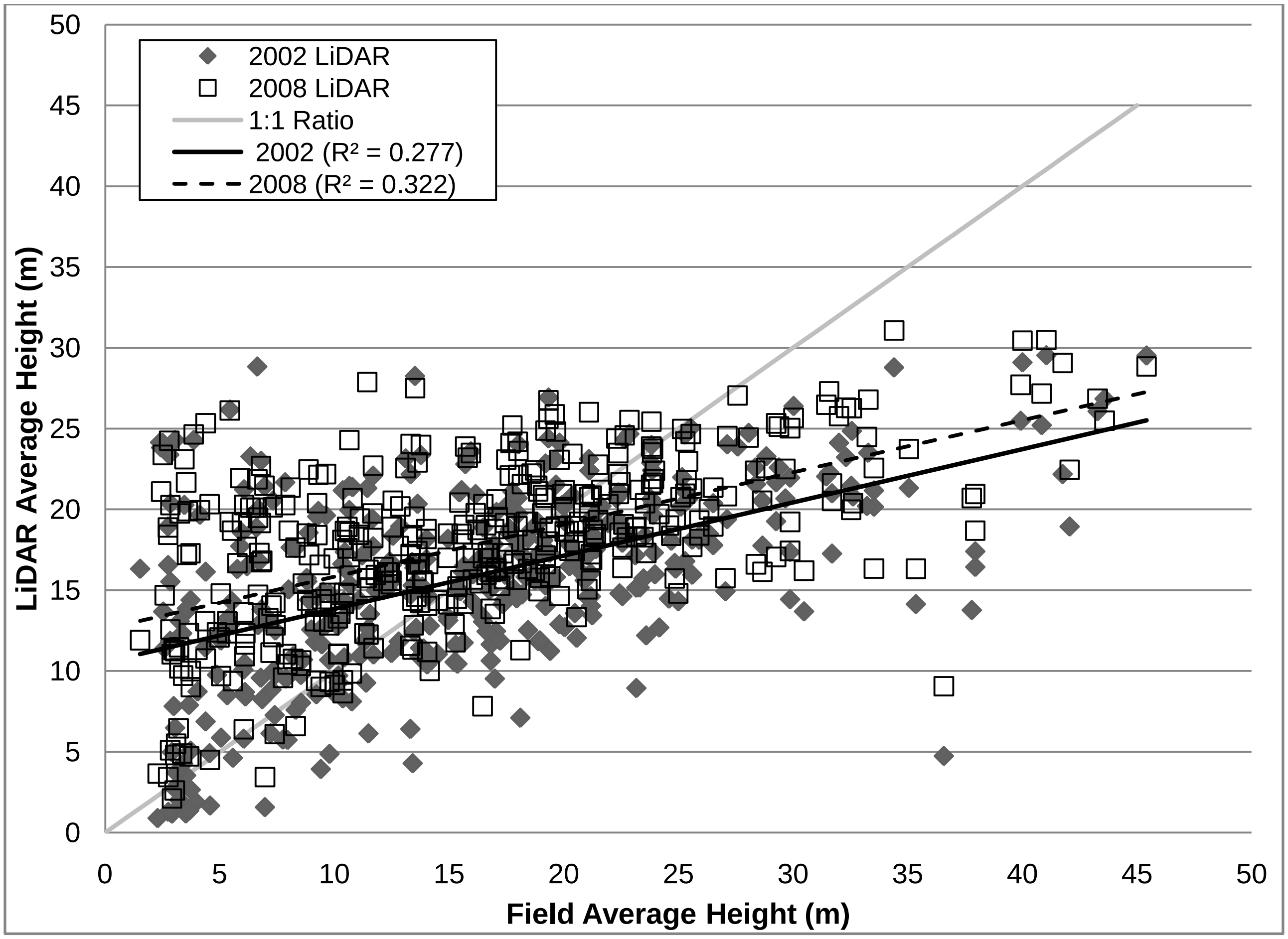

Figure 7. Scatterplot of Field versus Airborne LiDAR (2002 and 2008) derived Mean Crown Height for individual forest plots at Tall Timbers.

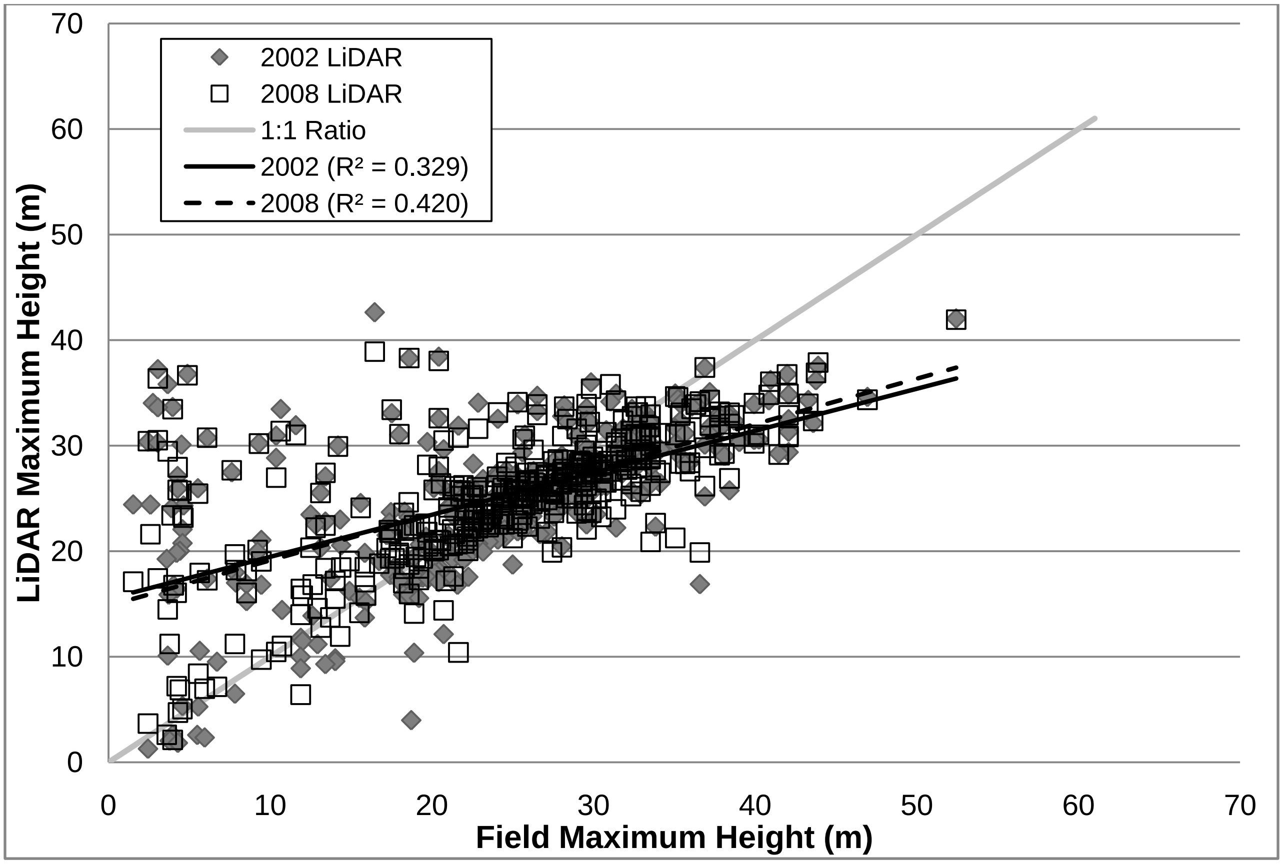

Figure 8. Scatterplot of Field versus Airborne LiDAR (2002 and 2008) derived Maximum Crown Height for individual forest plots at Tall Timbers.

Investigating the plots with dramatic differences in canopy cover (Figure 6) and mean canopy height (Figure 7) using imagery (2004 DOQQs), indicated that most of the plots with zero or low canopy cover in the field dataset had a visible amount of crown cover, in closer agreement with the LiDAR cover extraction. The weaker than expected relationships between field and LiDAR derived metrics could be, in part, explained by field plot geolocation errors.

Transect

Transect field canopy cover percentages are visibly higher for most transects than 2008 LiDAR canopy cover metrics (Table 3). The difference between field versus LiDAR cover is much smaller when these latter values were derived using Fusion/LDV than the raw GIS methodology (11% versus 25% difference, respectively). Higher canopy cover percentages were expected for the 2006 field collected transect data, since the preceding 12 month rainfall was just above average (154 cm), while the rainfall preceding the 2008 LiDAR data collection was well below average (115 cm).

Additionally, the majority of the field work took place in April and May, two months later in the year than the timing of the airborne LiDAR data collection. The difference in canopy cover metrics between two extraction types of the same raw LiDAR dataset is accentuated in transects that either represent hardwood ecosystems or ecotones between upland pine and hardwood areas (transects 8, 9, 30, and 32). The end product of both methods is different, which could have an impact in the differences observed: Fusion/LDV created a standard 15 by 15 m grid of cover values using first return only, whereas the raw GIS metrics provided cover value as the proportion of all canopy returns within the transect buffer area. In dense areas, the Fusion/LDV method provided higher canopy cover returns, which seemed more consistent with field canopy cover results (Table 3).

Table 3. Comparison of Conventional Forestry (Field), GIS-derived and Fusion/LDV-derived LiDAR metrics (2008 data) for the Transects located throughout Tall Timbers Research Station.

Transect ID	Cover Type	Field Data			GIS Metrics			Fusion Metrics			Field - GIS			Field - Fusion		
		%Cover	MaxHT[1]	MeanHT[1]	%Cover	MaxHT[1]	MeanHT[1]	%Cover	MaxHT[1]	MeanHT[1]	ΔCover	ΔMaxHT[1]	ΔMeanHT[1]	ΔCover	ΔMaxHT[1]	ΔMeanHT[1]
8	Hardwood & Pine	80.00	32.92	15.43	50.14	24.26	12.71	79.20	38.64	15.41	29.86	8.66	2.72	0.80	-5.72	0.02
9	Hardwood & Pine	67.50	28.06	6.26	26.25	32.37	14.51	50.59	37.71	13.00	41.25	-4.31	-8.25	16.91	-9.65	-6.74
14	Pine	38.30	32.89	12.07	21.07	20.56	10.22	31.31	22.98	10.72	17.23	12.33	1.85	6.99	9.91	1.35
18	Pine	23.64	31.62	16.16	7.95	29.95	15.61	17.40	33.06	6.57	15.69	1.67	0.56	6.24	-1.44	9.59
20	Pine	58.54	35.36	17.67	31.63	28.45	14.56	36.54	33.67	20.13	26.90	6.90	3.11	21.99	1.69	-2.47
21	Pine	35.42	32.61	20.54	23.53	33.03	17.16	26.55	35.46	9.54	11.89	-0.42	3.38	8.87	-2.84	11.01
22	Pine	25.49	28.83	12.53	13.46	30.70	16.70	23.42	34.59	14.67	12.03	-1.87	-4.17	2.07	-5.77	-2.15
25	Pine	31.94	43.59	19.14	26.91	30.57	15.81	30.61	33.41	15.38	5.03	13.02	3.32	1.34	10.18	3.76
26	Pine	66.67	43.89	20.26	31.62	28.27	12.78	44.64	28.72	15.27	35.05	15.63	7.47	22.02	15.17	4.99
27	Pine	50.98	33.83	19.44	30.20	31.65	15.64	49.91	36.55	19.05	20.78	2.18	3.80	1.07	-2.72	0.39
28	Pine	63.46	30.60	14.02	37.42	29.85	13.90	42.85	33.42	15.61	26.04	0.75	0.12	20.61	-2.82	-1.60
29	Pine	52.73	38.40	16.41	25.64	28.27	14.96	29.36	33.36	9.04	27.09	10.13	1.45	23.37	5.05	7.37
30	Hammock	96.08	42.06	20.71	46.20	30.00	14.97	71.79	32.43	19.79	49.88	12.06	5.74	24.28	9.63	0.92
31	Pine	51.72	32.31	12.87	31.02	30.27	13.69	40.02	33.26	18.38	20.70	2.04	-0.82	11.70	-0.95	-5.51
32	Hammock	100.00	43.28	19.52	62.82	31.98	16.51	97.75	33.89	20.35	37.18	11.30	3.01	2.25	9.39	-0.83
Transect Mean		56.16	35.35	16.20	31.06	29.35	14.65	44.80	33.41	14.86	**25.11**	**6.00**	**1.55**	**11.37**	**1.94**	**1.34**

[1] Units are in meters

Some of the differences encountered in the canopy cover estimated between Fusion/LDV and raw GIS could correspondent to vegetation under 2 m not captured by the raw GIS method (which includes canopy returns above this threshold only). Transects representing ecotones (8 and 9) and hammocks (30 and 32) have a significant presence of shrubs (0.5-2.0 m) which would only be captured by the Fusion/LDV methods. Canopy cover differences in these 4 transects are extremely high, with the raw GIS method removing the shrub component and yielding 30-50% less cover than the Fusion/LDV results.

Maximum and mean crown height present the usual LiDAR underestimation bias due to missed top tree returns, but overall differences are minimized by the use of Fusion/LDV metrics, instead of raw GIS values. Overall, field maximum heights are 6m higher than raw GIS derived LiDAR values, but only 2 m higher when using Fusion/LDV metrics. The differences are smaller for the mean crown height values, with 1.6 m versus 1.3 m higher field mean heights than for raw GIS and Fusion/LDV metric LIDAR heights, respectively. Transects with much higher maximum field heights than LiDAR maximum heights are, in general, the most open upland pine representatives (transects 25 and 26). A simple small geolocation error could explain missing these unique examples of very tall loblolly pine (*Pinus taeda*) trees of over 43 m in height.

Tree Detection

The variable-window tree extraction algorithm used in the Fusion/LDV software was designed to extract individual tree information from relatively open conifer-type forests with dominant and co-dominant trees (McGaughey, 2010). Without modification of the window size coefficients, the number of trees extracted for all the forestry plots located at Tall Timbers was minimal compared to the field tree count (Table 4). Field derived tree counts per stand ranged between 24 and 861 trees, with an average count of 188 trees. In contrast, Fusion/LDV only extracted data from the most dominant trees and was able to derive between 7-36 trees per stand, with an average tree count of 19 per stand. Since only the largest and most isolated trees were detected by Fusion/LDV, average tree height is much higher for the tree extraction than for field tree data collection (extracted mean heights are consistently between 2 and 14 m higher than mean stand field heights). Maximum tree heights per stand were similar (<4 m difference) for both field and Fusion/LDV methods, with differences easily accounted for by plot geolocation errors described above (see plot level analysis).

It is very important to note that tree extraction methods, including Fusion/LDV, require a minimum of 4 returns per meter to perform adequately, while the 2008 LiDAR datasets had only a maximum of 1 return per meter. Newer LiDAR datasets acquired for forestry applications can easily meet or exceed these specifications, and individual tree extraction would be significantly improved. Additional management treatments between field and LiDAR data collection, such as the thinning in 2007, might also have an impact on tree detection: some of the non-dominant trees might be under-reported in 2008 because these were removed in 2007 by the treatment. Another potential cause for the differences in maximum canopy height are field sampling error: heights, particularly from very tall trees, are difficult to obtain with a great accuracy. The impact of under or over-reporting one tree per stand would have immediately impact in the differences reported.

Similar results from tree extraction using the Fusion/LDV software were encountered for the transects across Tall Timbers: most transects, especially the ones with 60% or higher canopy cover (transects 8, 9, 26, 30-32), were grossly misrepresented by the Fusion/LDV tree extraction results (Table 5). These are transects either completely within the hardwood woodlands and hammocks or ecotones between these are upland pine areas. Tree extraction for transects with lower canopy cover conditions and dominated by upland pine (Figure 9) performed better, but still underrepresented the trees on-site by about 50%, and over-reported the mean average height by about 6 m (Table 5). Since Fusion/LDV assigns height to base of live crown and crown width as fixed proportions of the extracted tree height (50% and 16%, respectively), both of these variables were overestimated by 5 m and 9 m, respectively, when comparing to field values.

Table 4. Stand Level Comparison of Fusion/LDV Tree Extraction Results from 2008 Airborne LiDAR with Field Collected Tree Data for the Forestry Plots at Tall Timbers.

Stand Name	Conventional Forestry (Field)				Fusion Tree Extraction				Field - Fusion			
	TreeCount	MaxHT[1]	MeanHT[1]	MeanCrHT[1]	TreeCount	MaxHT[1]	MeanHT[1]	MeanCrHT[1]	ΔCount	ΔMaxHT[1]	ΔMeanHT[1]	ΔMeanCrHT[1]
Anders North	861	28.06	6.26		20	27.37	20.20	10.10	841	0.69	-13.94	N/A
Bottom Dollar	357	32.89	12.07		34	35.43	19.36	9.68	323	-2.54	-7.28	N/A
Charlie's	142	31.62	16.16		23	32.46	23.63	11.81	119	-0.84	-7.46	N/A
Daily Double	301	35.36	17.67	10.79	36	31.28	24.38	12.19	265	4.08	-6.71	-1.40
Gallien	57	32.61	20.54	13.46	15	30.42	25.74	12.87	42	2.19	-5.19	0.59
Hanna's	175	28.83	12.53		3	22.84	20.98	10.49	172	5.99	-8.45	N/A
Long Field	76	43.59	19.14	11.29	12	32.88	24.21	12.10	64	10.71	-5.07	-0.81
May Haw	118	43.89	20.26	11.58	17	37.85	27.84	13.92	101	6.04	-7.58	-2.34
North Brunt	24	33.83	19.44	13.91	8	23.47	17.10	8.55	16	10.36	2.34	5.36
Plantation	470	30.60	14.02						N/A	N/A	N/A	N/A
Rep II	124	38.40	16.41	13.59	13	33.06	21.65	10.82	111	5.35	-5.24	2.76
Rep III	162	42.06	20.71	13.54	28	32.71	25.75	12.87	134	9.35	-5.04	0.66
Scrub	127	32.31	12.87	6.84	20	33.18	24.42	12.21	107	-0.87	-11.55	-5.37
Slim Pickens'	123	43.28	19.52	13.56	20	37.43	28.67	14.34	103	5.85	-9.15	-0.78
Sloan's	136	39.93	16.15	9.64	28	30.68	21.44	10.72	108	9.25	-5.29	-1.08
Smoking Gun	173	52.43	18.23	12.63	32	41.80	28.85	14.43	141	10.62	-10.62	-1.80
South Brunt	34	22.25	17.43	7.48	7	22.31	20.33	10.17	27	-0.06	-2.90	-2.69
Steel Tired Tractor	123	42.06	16.08	11.11	19	34.97	22.41	11.21	104	7.10	-6.34	-0.09
Sutty	84	43.75	15.85	6.77	18	36.97	27.22	13.61	66	6.78	-11.37	-6.84
Tower	89	41.97	11.28	6.36	15	36.73	23.12	11.56	74	5.25	-11.84	-5.21
Stand Mean	188	36.99	16.13	10.84	19	32.31	23.54	11.77	**154**	**5.02**	**-7.30**	**-1.27**

[1] Units are in meters
[2] MeanCrHT is the mean to the base of live crown height

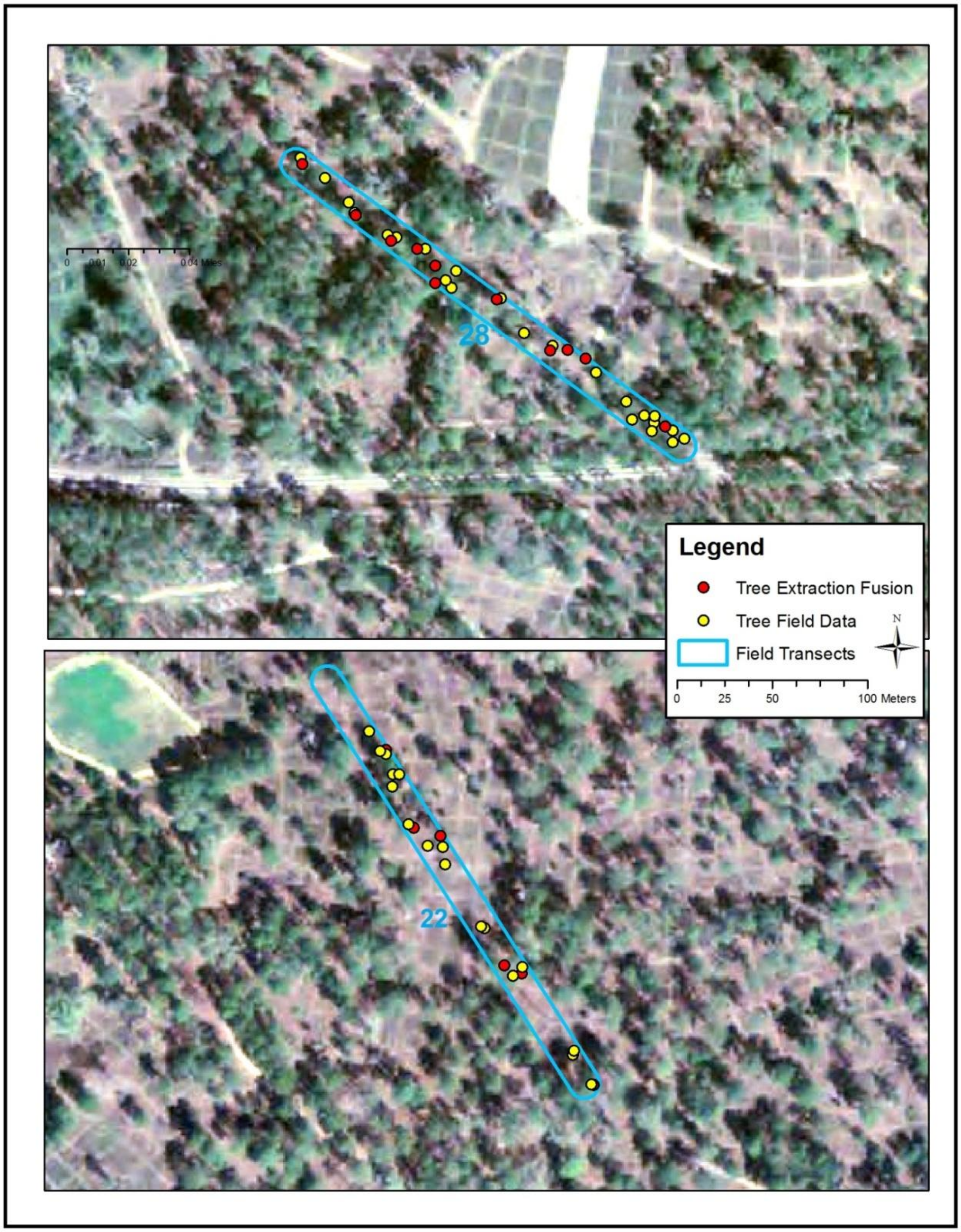

Figure 9. Tree Extraction Results: a comparison of Fusion/LDV Tree Extraction Algorithms with Field Collected Tree Data for selected transects (transect 28, top, transect 22, bottom) within Tall Timbers.

Table 5. Comparison of Fusion/LDV Tree Extraction Results from 2008 Airborne LiDAR with Field Collected Tree Data for the Transects at Tall Timbers.

Transect ID	Cover Type	**Conventional Forestry (Field)**					**Fusion Tree Extraction**					**Field - Fusion**				
		Count	MaxHT[1]	MeanHT[1]	MCrHT[1,2]	MCrWD[1,3]	Count	MaxHT[1]	MeanHT[1]	MCrHT[1,2]	MCrWD[1,3]	ΔCount	ΔMaxHT[1]	ΔMeanHT	ΔMCRHT[1,2]	ΔMCrWD1,3
8	Hardwood & Pine	67	34.18	15.96	4.80	6.75	6	28.45	24.72	12.36	19.22	91	5.73	-8.76	-7.56	-12.46
9	Hardwood & Pine	35	34.95	21.42	6.67	7.68	9	33.64	28.67	14.33	16.88	26	1.31	-7.25	-7.66	-9.20
14	Pine	41	22.87	17.74	7.39	5.43	12	21.86	19.48	9.74	13.73	29	1.01	-1.74	-2.35	-8.31
18	Pine	7	30.55	24.82	9.18	11.09	1	34.73	34.73	17.36	13.07	6	-4.18	-9.90	-8.18	-1.98
20	Pine	27	33.85	20.63	8.04	9.35	12	30.01	22.92	11.46	14.54	15	3.84	-2.28	-3.42	-5.19
21	Pine	20	39.73	26.87	9.74	9.65	9	34.32	30.52	15.26	13.86	11	5.41	-3.66	-5.52	-4.21
22	Pine	17	37.74	19.33	6.57	8.93	6	32.78	30.24	15.12	17.50	11	4.96	-10.92	-8.55	-8.57
25	Pine	14	44.15	24.73	10.95	7.53	8	32.91	24.05	12.03	14.09	6	11.24	0.68	-1.07	-6.56
26	Pine	72	31.48	18.59	8.29	6.04	12	32.60	21.94	10.97	16.50	60	-1.12	-3.35	-2.68	-10.47
27	Pine	39	33.40	20.25	10.47	5.92	10	33.78	30.03	15.02	20.38	29	-0.38	-9.78	-4.55	-14.46
28	Pine	23	30.96	23.69	8.52	10.17	11	31.23	26.24	13.12	11.75	12	-0.27	-2.55	-4.60	-1.58
29	Pine	25	32.98	23.10	9.29	8.44	15	31.12	22.25	11.13	13.79	10	1.86	0.85	-1.84	-5.35
30	Hammock	98	32.10	19.40	7.93	6.81	10	31.75	29.06	14.53	22.20	88	0.35	-9.66	-6.60	-15.40
31	Pine	47	32.97	18.98	8.54	7.67	10	32.69	24.31	12.15	15.28	37	0.28	-5.33	-3.61	-7.61
32	Hammock	82	37.50	21.17	7.28	8.20	7	33.60	31.20	15.60	26.21	75	3.90	-10.03	-8.32	-18.01
Transect Mean		41	33.96	21.11	8.24	7.98	9	31.70	26.69	13.35	16.60	**34**	**2.26**	**-5.58**	**-5.10**	**-8.62**

[1] Units are in meters
[2] MCRHT is the mean to the base of live crown height
[3] MCRWD is the mean width of the tree crown

Automated tree extraction resulted in contrasting results depending on the choice of methodology, with LiDAR Analyst extracting more trees than Fusion/LDV in heavily wooded areas (Figure 10). Fusion/LDV had the advantage of capturing some of the small trees and shrubs interspersed in open field areas.

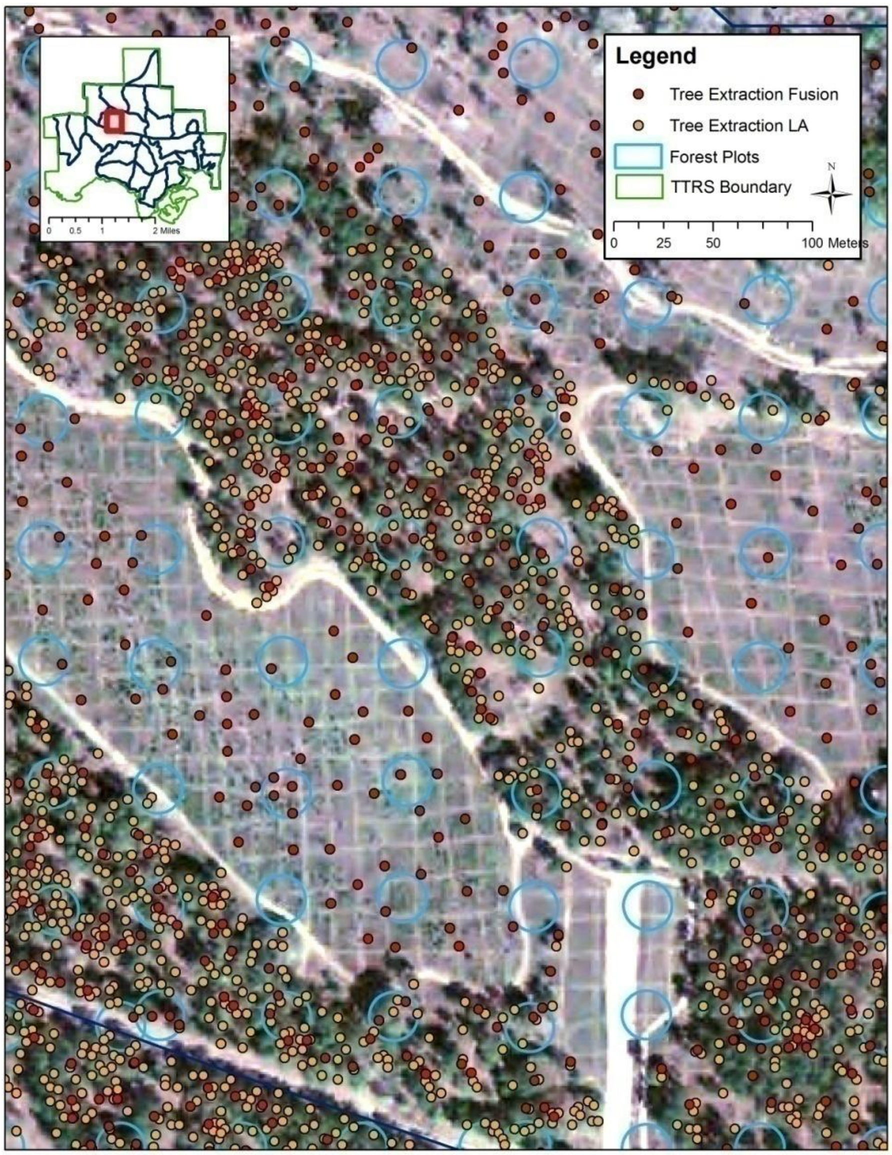

Figure 10. Tree Extraction Results: a comparison of LiDAR Analyst and Fusion/LDV Tree Extraction Algorithms for selected plots within Tall Timbers. Red line is zoomed extent.

Generally, however, both methods did under-represent tree data captured in the field, which could be due to two independent causes: 1) the point density of the LiDAR dataset used was too low (1-1.5 returns/meter) to obtain reliable results with any attempted tree extraction software and 2) a heavy thinning treatment was applied in 2007, a year prior to the LiDAR data collection, heavily reducing the number of trees.

Without modification, LiDAR Analyst performed better at delineating trees in denser canopy conditions, especially when these were dominated by hardwoods. On the other hand, Fusion/LDV, without any modifications, is particularly more sensitive when extracting evergreen trees in open conditions. While very limited user-input is allowable using the LiDAR Analyst tree extraction application, Fusion/LDV is customizable, and the algorithm based on a variable window first presented in (Popescu et al., 2002) and (Kini and Popescu, 2004) can be calibrated with field crown height and width information. Providing appropriate calibration data for the ecosystem of interest would increase the ability of appropriately detecting, at a minimum, most of the dominant trees with isolated crowns. Most importantly, using a higher density LiDAR dataset, with a minimum of 4-6 returns/m would further enhance the ability of extracting individual tree crowns accurately.

Conclusion

Advances in active remote sensors, reduction in the commercial cost, and improvements in the off-the-shelf available software for data analyses and management, have intensified the need to understand the value of the use of these tools in forestry, conservation biology, and natural resource management applications. For the use of multiple return LiDAR to replace or minimize field data collection efforts, validation of this technology, and especially of different strategies of data extraction have to be explored. The potential applications of LiDAR in forest management include forest inventory estimations - gross-merchantile volume or fine-scale stratified inventories (Lim et al., 2003) - and site quality assessments using canopy height/age data (Dean et al., 2009). Ecological applications for the use of LiDAR data include the prioritization of areas of high biodiversity, prediction of species distributions, ecological species or assemblage modeling, and anthropogenic change detection (Turner et al., 2003a). This study provides an in-depth look at validation of two independent LiDAR datasets with an extensive grid of field plot data using a variety of analyses tools.

There is an inherent assumption, when validating data, that field data collection carries a smaller degree of error than remotely sensed data. Nevertheless, field measurements do include errors, which can be difficult to estimate, and should be acknowledged in a validation effort. In this study, the forestry field collected data certainly had errors in the measurement of both canopy cover and tree height, with field plot geolocation errors having a potential to be a large error source. Canopy cover percentages per plot, unless sampled extensively (approaching 100 replicates per plot), can produce gross errors (Jennings et al., 1999). Only nine point canopy cover samples were taken per plot, and about 25 per transect, which could have resulted in a very low confidence in the field canopy cover results per individual plot.

Correlations of individual plot field with LiDAR canopy cover measurements was, as a result, very low (r^2 <0.27), but stand level comparisons faired significantly better. Nevertheless, 15% difference in cover detection can have an important impact on ecological applications. On a landscape scale, land cover classification, important for circulation and carbon exchange models could incorrectly assign woodland classes to forests or shrubland, with a 15% error in canopy cover (Hansen et al., 2000). Light penetration modeling would be also dramatically skewed with a 15% error, and habitat suitability modeling for wildlife species could provide incorrect guidance to land managers (See Chapter 4).

Plot mean and maximum heights obtained from field measurements have inherent errors which would be more pronounced in either denser canopy conditions (bottomland hardwoods and hammocks) or isolated taller trees (Clark et al., 2004). In stands and transects representing these two extreme conditions at Tall Timbers, the discrepancy between LiDAR and field mean heights was the most obvious. Additionally, small footprint LiDAR datasets are well reported for the underestimation of canopy height due to failure of recording the top of trees (Gaveau and Hill, 2003). The underestimation of laser returns when determining maximum canopy height is clearly visible in most stands and transects at Tall Timbers, where an average negative bias of between 1-4 m was detected. Other studies detected negative bias ranging between 1 to 3.7 m (Gaveau and Hill, 2003;Clark et al., 2004). Overall, validation of both 2002 and 2008 LiDAR derived mean and maximum heights performed extremely well, with differences ranging between 0.5-1.5 m. These differences are negligible for modeling habitat preferences, a powerful application especially for avian woodland species (Davenport et al., 2000) and microclimate in forest ecosystems, crucial for floral and faunal diversity (Chen et al., 1999).

Other obvious sources of error are the temporal differences among all three datasets (the two LiDAR datasets) and the field data collection. Hardwood components are known to vary dramatically at Tall Timbers, not only due to senescence (seasonal variation), but also to active management. Differential treatment of stands, such as selective thinning in 2007 at most stands, added variability when detecting metric differences. Selective thinning directly impacts canopy cover and canopy heights by removing non-dominant, smaller trees from most stands. Furthermore, differences in cumulative annual rainfall prior to the data collection could impact the forest structure, especially the canopy cover of specific stands.

Potential causes for the weaker correspondence in LiDAR include field calibration and geolocation errors, LiDAR mean height underestimation bias, and most likely the asynchronous nature of the datasets. The field data collection was at least 2 years apart from either LiDAR data collection event, and significant rainfall differences and even seasonal differences could have impacted canopy cover and height. Reducing the bias of environmental (rainfall and seasonality differences) and anthropogenic factors (management treatments) in validation of the field data is difficult when datasets are not synchronous or at least within the same range of conditions.

The methodology used for LiDAR data metrics extraction and tree extraction does impact the results. As sensors improve, the point cloud data density increases while cost decreases, and more options will be available for automated data extraction from larger LiDAR datasets. The choice of processing methodologies, either off-shelf or custom software, should take the goal of the analysis, LiDAR dataset size, and on-site conditions into account. In this study, metrics derived from the raw GIS method were able to pinpoint the highest crown height better, for most plots, than Fusion/LDF software metrics did. For most other metrics, however, canopy cover and mean plot or transect heights, Fusion/LDV derived metrics outperformed GIS results. The nature of the analyses using point cloud data in ArcGIS preserves all individual returns, while the Fusion/LDV analysis relies heavily on grid interpolated values of canopy and ground heights to calculate its metrics. Similarly, tree extraction results were dramatically different when comparing LiDAR Analyst with Fusion/LDV's CanopyMaxima algorithm detection: LiDAR Analyst, without customization was more suitable for detection of trees in denser woodlands, whereas Fusion/LDV was superior in open canopy/field conditions.

Success in tree extraction results from LiDAR extraction is still very limited to a few studies (Hyppa et al., 2001;Leckie et al., 2003;Suarez et al., 2005;Lee and Lucas, 2007), mostly due to application of algorithms that were developed primarily for uniformly structured forests in areas that have a greater variety of crown sizes and subcanopy dominance. Success at tree extraction on a broad spatial scale is still best reported with the use of optical imagery (Palace et al., 2008). Fusion/LDV's "CanopyMaxima" algorithm used in this study was based on TreeVAW software (Kini and Popescu, 2004), and targeted eastern coniferous trees. In plots or transects with relatively open canopy (40% or under) and dominated by pine trees, this algorithm performed well. In hardwood dominated areas or transects representing ecotones with significant hardwood encroachment, a large percentage of the trees were not detected. Increasing the average point density of the LiDAR data acquired to a minimum of 4-6 returns/m should be priority when the data will be used for tree extraction. Additionally, modification of the algorithm used in Fusion/LDV's software, especially after calibrating it with field specific data, could enhance its tree extraction performance. LiDAR Analyst, however, doesn't provide as much flexibility in the implementation of the proprietary algorithm. The use of a complementary relative penetration index, Height-Scaled Crown Openness Index (HSCOI) developed for more complex forests (Lee and Lucas, 2007), might significantly improve the tree extraction results. Fusing optical with LiDAR imagery might further enhance tree extraction. Accurate tree extraction is important for forest managers, since it switched the emphasis back to the results conventional forestry uses for daily management tasks. On an ecological note, appropriate detection of crowns across broad landscapes will broaden the applications even further: it would enhance species suitability modeling to an even finer scale level, and potentially allow canopy gap modeling. Canopy gaps are crucial in forest recruitment and succession, and key in understanding and protecting biodiversity, especially in tropical forests (Hamer et al., 2003).

To be used in forestry, LiDAR data should be acquired and processed with the specific goals in mind. For stand level canopy cover and mean height estimates, using Fusion/LDV software, which interpolates point cloud data, yields estimates closer to field inventory metrics. Pinpointing maximum crown height in plots, using the raw GIS method yields more appropriate results, since this method does not average or smooth individual returns. Tree extraction should only be attempted with very high density LiDAR datasets, with a minimum of 4-6 returns/m. High density sampling is also crucial to reduce the underestimation bias airborne LiDAR datasets commonly present, by reducing the likelihood of missing treetops.

The approximation of field structural variables by the use of high resolution LiDAR data doesn't fully highlight the value and benefits of the use of active remote sensing techniques in natural resource management. Multi-return LiDAR provides the ability of characterizing forest structures three-dimensionally, even through large extents (Kao et al., 2005;Akay et al., 2009), enhancing forest monitoring and management (Lim et al., 2003).

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CHAPTER TWO - THE USE OF LIDAR MEASURES TO DETERMINE THE IMPACT OF VARYING FIRE REGIMES ON THE 3-D STRUCTURE OF A PINE-GRASSLAND WOODLAND

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Abstract

Once a dominant ecosystem in the Southeast, pine-grassland forest has been cleared to agriculture or converted to either closed canopy pine-hardwood forest or pine plantations, and requires active and responsive management for successful restoration. These forests depend on a frequent (1-3—year fire return), low- to moderate-intensity fire regime to prevent succession to mixed hardwood forests and maintain understory species diversity. This study evaluates stand structure at the site of one of the longest running fire ecology studies in the US, located at Tall Timbers Research Station (TTRS) in the southeastern U.S. Small footprint high resolution discrete return LiDAR was used to provide an understanding of the impact of multiple disturbance regimes on forest structure.

Height profiles and derived metrics - canopy cover, canopy heights, shrub height and cover were determined using 2002 and 2008 airborne LiDAR. The study plots consist of

three replicates each of four different fire treatments: 1-year, 2-year, 3-year fire return interval, and fire suppressed plots. The 3-dimensional spatial arrangement of multiple structural elements was used to assess hardwood encroachment.   Canopy cover and diversity indices were shown to be statistically higher in fire suppressed and less frequently burned plots than in 1- and 2-year fire interval treated plots, which is in general agreement with 3-year fire return interval being considered an” ecological threshold” for these systems (Masters et al. 2005). The results from this study highlight the value of the use of LiDAR in evaluating disturbance impacts on the three-dimensional structure of pine forest systems.

Introduction

In the last decade, LiDAR remote sensing, both in waveform and discrete returns (as in this study), has been explored as a tool in the field of forestry. Besides providing predominant height, canopy cover, and even derived basal area information that is analogous to field data (Lefsky et al. 1999; Means et al. 1999; Dubayah and Drake 2000; Lovell et al. 2003; Coops 2007), this active remote sensing technique allows the direct measurement of canopy height profiles, or the three dimensional distribution of plant material in space, including subcanopies (Lefsky 2002). LiDAR has been demonstrated to be an effective tool to characterize stand structure including above-ground biomass and carbon storage- (Lefsky et al. 2005), forest inventory and management (Lim et al. 2003; Akay et al. 2009,), and fire behavior and bird population modeling (Lim et al. 2003). LiDAR provides a means to evaluate the three-dimensional forest structure (Zimble et al 2003), with a much reduced effort and cost than ground based measurements, particularly over large areas. In fact, field constraints, such as accessibility, lack of objective and efficient measurement techniques, and high personnel and equipment costs, have quickly made the use of LiDAR remote sensing more attractive to land managers and conservation ecologists.

Small footprint LiDAR allows the rapid characterization of habitat structure, which is so crucial for determining habitat suitability and consequent community richness (Lefsky et al. 2002) from plot to landscape scales (Lefsky et al. 2002; Zimble et al. 2003). Its use brings scientists and land managers together and enhances their understanding of forest structure over large landscapes (Kao et al. 2005). As steadily improving sensors increase the number of surface returns captured, a further decrease in overall costs is expected, and more detailed three dimensional models can be constructed quickly and affordably. This cost and time savings has been demonstrated in the development of forest fuel management plans at half the cost and with 3.5 times less time with airborne LiDAR than with the traditional alternative (Akay et al. 2009).

The application of a high resolution LiDAR to a study site with a long-term study design, consistent implementation, and well known structural differences – the Stoddard Fire Plots on Tall Timbers Research Station (TTRS) - allowed a better understanding of the strengths and weaknesses of this new technique. The study sites (TTRS and two surrounding plantations) are representative of pine savanna ecosystems in the southeastern U.S., that led to a concerted conservation effort.

Historically, most of the upland areas of the Southeast Coastal Plain were dominated by pine savanna (Vogl 1973) or pine-grassland woodlands (Masters et al. 2005), which can be described as very open pine-dominated ecosystems with a rich grassland understory. The role of fire in shaping the composition and understory species richness of these communities is well established in the literature (Walker and Peet 1983; Allen and Wyleto 1983; Mehlman 1992; Waldrop et al.1992; Gliztenstein et al. 2003; Glitzenstein et al. 2008). Fire is a mechanism that controls multiple components in this ecosystem; it maintains a relatively low canopy cover (Waldrop et al. 1992; Masters et al 1995; Masters et al. 2005), reduces hardwood shrub encroachment and litter (Garren

1943; Ahlgren and Algren 1960; Vogl 1972; Masters et al. 1998), and it enhances pine recruitment by creating canopy gaps and seedling success (Vogl 1972; Platt et al. 1988; Myers 1990). While increasing canopy openness is relatively easy in management, enhancing understory heterogeneity and maintaining the balance between reduction of hardwood midstory components and increasing pine recruitment remains a challenge to land managers.

Succession of pine-dominated ecosystems to dense mixed pine-hardwood forests with reduced understory species richness is largely a consequence of fire suppression (Masters et al. 1995, 2007; Sparks et al. 1998, Glitzenstein et al 2008). Additionally, the large-scale conversion of pine dominated upland areas to agriculture and short-rotation forestry plantations have further decimated this once prevalent landscape to fragmented remnants of the once abundant pine savannas. One of the most studied pine savanna ecosystems, the longleaf pine (*Pinus palustris*) savanna, is now considered one of the "most endangered ecosystems" in the world (Noss et al. 1995), after being reduced to less than 2% of its original extent (Ware et al. 1993).

The historical fire regime of southeastern pine woodlands or savannas, derived by fire history studies (Chapman 1926, Frost 1998, Huffman 2006) and landform-slope mapping (Hammond 1964; Frost 1998), consists of very frequent (1-3 year) low intensity fires predominantly during the growing season of May-October (Gliztenstein et al. 2003). Other studies focusing specifically on Florida indicate an earlier start of the fire season, February and March (Myers and Ewel 1990). The fire return frequency is the result of high incidence of lightning strikes during the natural fire season (Chen and Gerber 1990) and, historically, has been attributed to the widespread use of fire by Native Americans (Vogl 1972; Gliztenstein et al. 2003). Many researchers suggest that original fire frequency of the upland Southeastern pine forest was as high as annually (Komarek 1964; Lotti 1971; Perkins 1971), and that the predicted 1-3 year fire return is a conservative estimate (Frost 1998). Recent work by Huffman (2006) suggest that a 2 year interval may be the norm with periodic longer intervals.

Traditional management efforts in the southeastern US have attempted, to a certain extent, to mimic the original pre-settlement fire regime in frequency and intensity. However, the traditional goal of land management was game management (Robbins and Myers 1992) rather than ecosystem management, which led to a pattern of very frequent 1-2 year dormant season (November through February) burns. Seasonality and frequency of fires have an impact of species composition and structure. Researchers have evaluated how the modification of seasonality from growing to dormant seasons reduces the impact on woody species encroachment and the long-term ability of native herbaceous species survival (Gliztenstein et al. 1995, Robbins and Myers 1995). Other studies, specifically at Tall Timbers, have shown how an annual burning regime suppresses pine basal area growth and seedling establishment (Masters et al. 2005).

The objective of this study was to determine the ability of airborne LiDAR for fine scale determination of vegetation structure on an experimental area of known treatment differences.

Methods

Study area

This study took place at Tall Timbers Research Station, historically the Henry Beadel Plantation, which is located within the Red Hills area of southwestern Georgia and northwestern Florida, USA (Figure 11). This region occupies approximately 300,000 ha between Thomasville, Georgia and Tallahassee, Florida and is home to over 230 rare types of plants and animals and over 27 federally listed threatened and endangered species (Masters et al., 2007). The Red Hills area is comprised of a mixture of young and old growth longleaf pine forests, natural and planted loblolly (*Pinus taeda*) and shortleaf (*Pinus echinata*) pine forests primarily in an old field context, mixed hardwood and pine forests, forested and herbaceous wetlands, agricultural fields, and residential/urban land cover types .

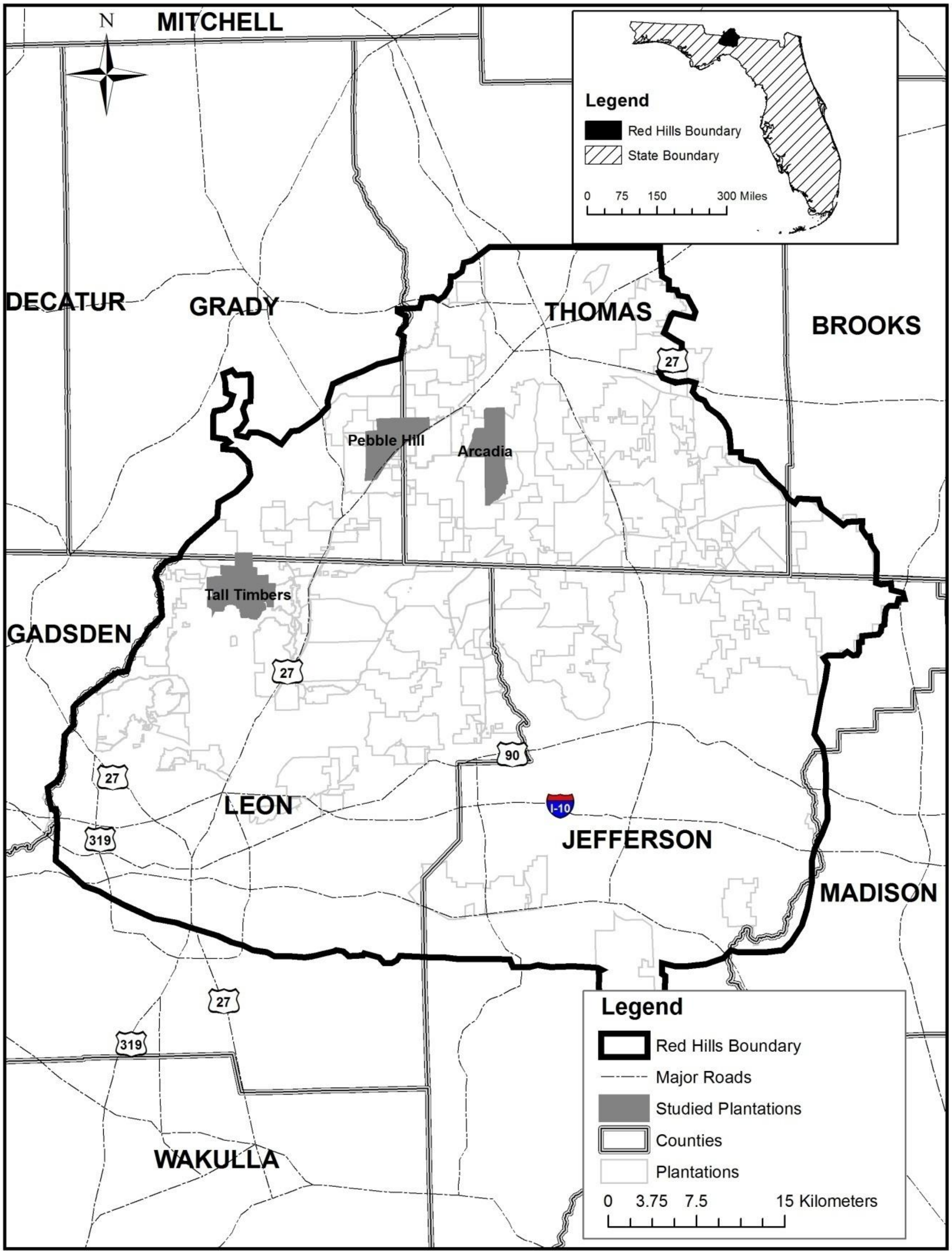

Figure 11. Location Map of the Red Hills Area and Tall Timbers Research Station.

The Tall Timbers Research Station (TTRS) covers 1600 ha within the Red Hills area, and is located just north of Tallahassee, FL (Figure 11). Prior to 1895, the area now occupied by the Research Station, was dominated by pristine pine savanna uplands interspersed with hardwoods and some hammocks at lower elevations along drainages. After 1897, the area was converted to Hickory Hill Plantation, a corn and cotton producing plantation, but was soon devoted to agriculture and wildlife management as early as the 1920's when it became known as Tall Timbers Plantation. The upland pine ecosystems at TTRS have been highly disturbed by agriculture, and are dominated by a mixed canopy of loblolly pine (*Pinus taeda*), shortleaf (*Pinus echinata*) and longleaf (*Pinus palustris*) (Masters et al. 2005). The groundcover at the study site is dominated by many legumes and sunflower family members and interspersed with grasses (primarily broomsedge bluestem, *Andropogon virginicus*), but lacking the wiregrass typical of pristine longleaf pine savanna ecosystems (Hermann 1995).

TTRS is focused on research and management issues of longleaf pine savanna, pine woodlands, and other ecosystems of the Red Hills area, including the management of forests for game birds (such as the Northern bobwhite, *Colinus virginianus*) and threatened and endangered species (such as the red cockaded woodpecker, *Picoides borealis*). This Research Station provides a "model working landscape" that engages landowners (under the Land Conservancy, TTLC) to ensure the future health of the Red Hill area's forests and wetlands.

The TTRS has been actively managing its secondary upland pine forest using prescription fire of low intensity transition season treatments with a return interval of 1-2 years (applied in a heterogeneous small-scale pattern). It is important to note that the upland pine woodlands for this study are formerly old field sites (Herman 1995) and no longer have a natural fire regime. Furthermore, scientists at the station had realized for many decades the importance in studying the role of fire in the restoration and maintenance of its upland pine ecosystem. In 1959, the Stoddard fire plots were established using three replicates of four fire treatments (1-, 2-, 3-, and 4-year fire return intervals) and a set of three control or fire suppressed plots, among others. The specifically mentioned Stoddard fire plots are the focus of this research project.

Description of Stoddard Fire Plots

The 12 Stoddard fire plots (named after Herbert Stoddard, prominent conservationist who established these) and three additional control plots are 20 by 20 m (Table 6), occupy about 0.3 ha in area and were randomly placed throughout the central upland area of TTRS (Figure 12). There are replicates (A, B, and C) for each of the four fire returns studied, W1, W2, W3, and W4 correspond to the 1-, 2-, 3-, and 4-year fire return interval treatments. The control plots (UA, NB66, and W75B) have been fire suppressed since 1959 except for NB66 which has been fire suppressed since winter 1967.

Table 6. Stoddard Fire Plots Description: Treatment Type, Dimensions, Soil Type, Fire and Land Use History (extracted from 1930s Imagery)

Plot Name	Fire Treatment	Perimeter	Acres	Soil Type	Burn Date (prior to 2002 LiDAR)	Burn Date (prior to 2008 LiDAR)	Out of Rotation	Forested, natural (%)	Forested Dense Canopy	Total Forested (%)	Roads, unpaved (%)	Cleared (%)	Total Non-Forested	Alteration Ratio (Non-Forested/Forested
W1A	1 year	180.16	0.50	Faceville 8-12	3/22/2001	3/23/2008	No	43.75	0	43.75	0	56.25	56.25	1.29
W1B	1 year	181.58	0.51	Orangeburg 2-5	3/23/2001	3/23/2008	No	27.46	32.44	59.89	4.41	35.7	40.11	0.67
W1C	1 year	183.53	0.52	Faceville 5-8	3/22/2001	3/23/2008	No	0	51.98	51.98	0	48.02	48.02	0.92
W2A	2 year	180.41	0.50	Faceville 5-8	3/22/2001	4/5/2007	No	86.67	0	86.67	0	13.33	13.33	0.15
W2B	2 year	181.00	0.51	Orangeburg 2-5	3/23/2001	4/5/2007	No	0	46.52	46.52	41.52	11.96	53.48	1.15
W2C	2 year	183.54	0.52	Faceville 5-8	3/22/2001	4/5/2007	No	11.97	0	11.97	0	88.03	88.03	7.35
W3A	3 year	181.21	0.51	Fuquay 0-5	3/27/2001	3/29/2007	No	46.02	0	46.02	0	53.98	53.98	1.17
W3B	3 year	179.47	0.50	Orangeburg 8-12	3/23/2001	3/29/2007	No	63.05	0	63.05	11.47	25.48	36.95	0.59
W3C	3 year	180.41	0.51	Pelham 5-8	3/22/2001	4/5/2007	No	0	67.24	67.24	0	32.76	32.76	0.49
W4A	4 year*	181.47	0.51	Faceville 5-8	3/22/2000	3/29/2007	1999-2007	0	67.69	67.69	0	32.31	32.31	0.48
W4B	4 year*	187.99	0.54	Orangeburg 2-5	3/21/2000	4/5/2007	1999-2007	8.21	37.28	45.49	0	54.51	54.51	1.2
W4C	4 year*	190.96	0.56	Faceville 5-8	3/23/2000	4/5/2007	1999-2007	71.34	0	71.34	21.73	6.93	28.66	0.4
NB66	Suppressed	180.78	0.51	Orangeburg 8-12	None	None	No	0	24.62	24.62	35.23	40.15	75.38	3.06
UA	Suppressed	183.13	0.52	Faceville 5-8	None	None	No	61.42	0	61.42	27.77	10.81	38.58	0.63
W75B	Suppressed	185.52	0.53	Faceville 2-5	None	None	No	77.8	0	77.8	22.2	0	22.2	0.29

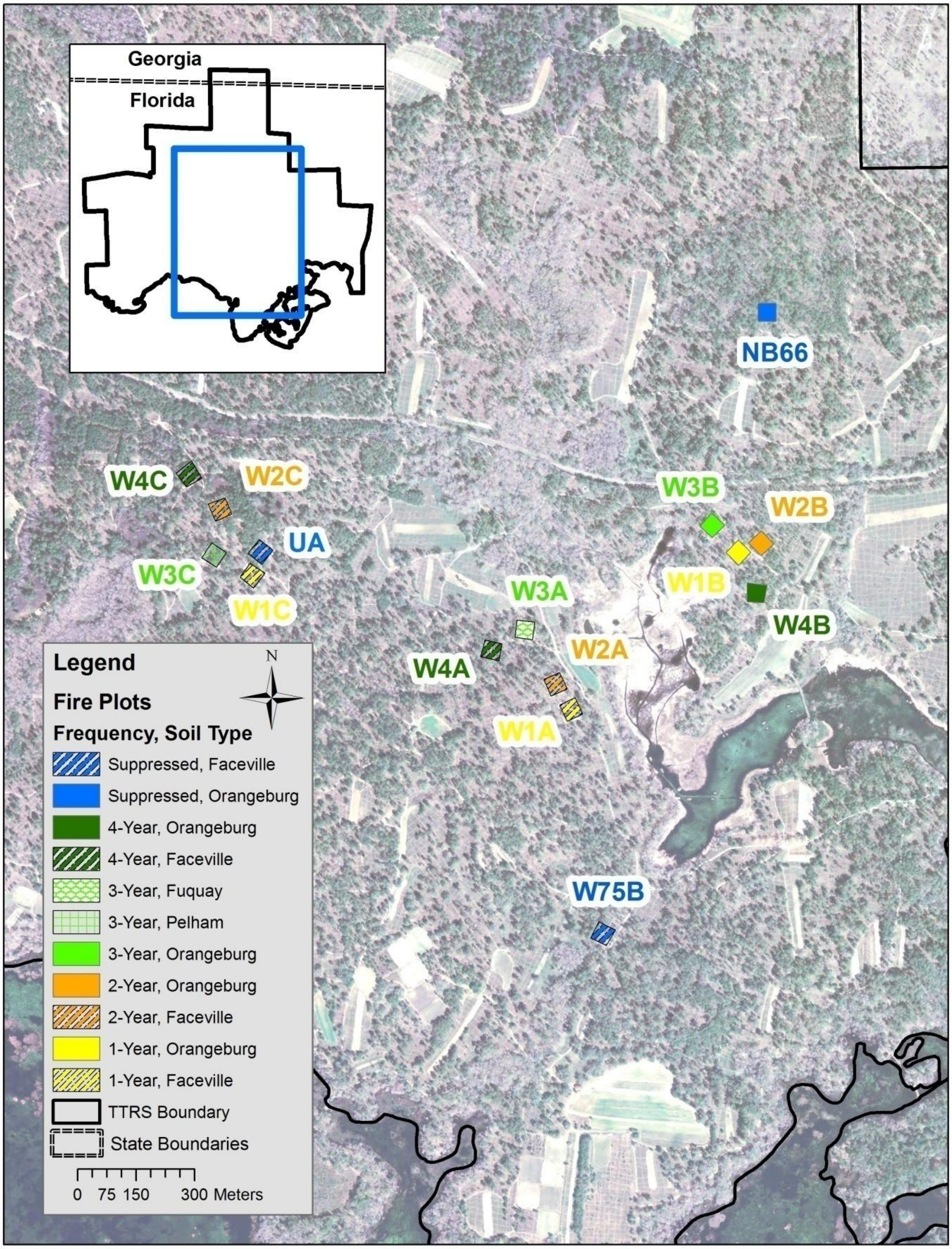

Figure 12. Location, Fire Treatment and Location, Fire Frequency, and Soil Type of the Stoddard Fire Plots at TTRS.

Differences in soil type and past land use (Figure 12, Table 6) for the Stoddard plots have been explored. Historical photography from the 1930s was obtained and the areas of open canopy, dense forest, cleared land, and roads clearings were digitized for all the Stoddard plots. An alteration ratio for each plot was calculated as the total percentage of cleared land to the total forested percentage (Table 6).

All the treated plots were burned using low intensity fires during the transitional season (between the dormant and growing season or March-April) at their dedicated fire rotation for 50 consecutive years. The only treated plots out of rotation for a period of time were the 4-year fire return Stoddard plots (W4 A, B, and C). These latter plots were treated as 2-year fire return interval plots during the 1999-2007 period before being returned to the 4-year interval.

Canopy cover was collected for all 12 Stoddard fire plots starting in 2004. These plots were sampled on April, August, October, and December 2004, all months of 2005, January-March 2006, and April 2010. For the canopy cover assessment, 8 permanent point locations within each fire plot were established. These permanent plots were located at 10 m intervals on two randomly located lines perpendicular to the fire plot boundary. To avoid bias caused by influences from adjacent treatment units, no sampling took place within 10-m of any edge. Overstory canopy cover was determined using a 9-point grid in a sighting tube with vertical and horizontal levels. Cover was determined at each plot center and the four cardinal points at 2-m and 4-m from each permanent plot location. The yearly basal area assessment was determined by the variable radius plot method. Basal areas of trees/stems with ≥ 5 cm in DBH were quantified with a 10-factor wedge prism at each of the 8 permanent plot locations that were used for collecting canopy cover.

LiDAR remote sensing

Two datasets of small footprint multiple return LiDAR (Light Imaging and Ranging) were obtained from the Tallahassee-Leon County Geographic Information Systems (GIS) Department. These datasets included raw LAS files for the entire Leon County in both 2002 and 2008 transitional seasons (February and March, respectively) with the goal of creating countywide detailed floodplain mapping. The first set (2002) was collected using the ALS40 (Leica Geosystems) scanner by Merrick & Co. in February 2002, and has a mean and minimum point spacing of 1.39 and 1.05 m, respectively. The 2008 dataset was collected using a Leica ALS50 Geosystem in March 2008, and has a mean and minimum point spacing of 1.55 and 1.19 m, respectively. Horizontal accuracies were 0.55 and 0.52 m RMSE for the 2002 and 2008 LiDAR datasets and vertical accuracy was 0.10 m RMSE for both datasets.

Point cloud data were obtained in the LAS 1.0 format for the 2002 data which specified ground vs. non-ground data, but not any additional return numbers. The point cloud data were converted to multipoint files and interpolated using an inverse distance weighted (IDW) approach in the 3D Analyst ArcGIS (ESRI) environment to a Digital

Elevation Model (DEM) - ground point - and a Digital Canopy Height Model (DSM) - for all non-ground points (Zimble et al., 2003). The Canopy Height Model (DCHM) was extracted from the difference between the DSM and the DEM.

For 2008, the newer LAS 1.1 format was used, which included both the class (ground versus non-ground) and multiple return numbers. Similar to the 2002 dataset, the 2008 point cloud data were converted to multipoint files. After the construction of the DEM using an IDW second degree interpolation of ground returns, the DCHM model was similarly extracted from the difference between the DSM (constructed using first returns only) and the DEM. All IDW interpolations performed were second power interpolations with a variable search of up to 12 neighbors and a 1 meter grid output size (instead of a much smaller 0.2 m grid used by (Zimble et al., 2003). Post processing of all the raster products was used to fill most, if not all, empty cells, with nearby interpolated values. The DEM heights were assigned to all point cloud data, allowing the computation of height above ground for every data point.

LiDAR data with above ground heights were extracted for the forestry plots by selecting point cloud data within a 12 m buffer around point center. Similarly, LiDAR data within the transects' area were extracted and further identified with the transect unique identifier in the ESRI ArcGIS environment. Data management for these large datasets took place in ESRI ArcGIS using geodatabases for the extracted LiDAR plots and transect 2002 and 2008 datasets. No co-registration between LiDAR datasets took place, since the RMSE vertical and horizontal errors were strictly controlled by the vendor, and insignificant for plot and stand level comparisons.

Data Analyses

The goals of the data analyses were three-fold: 1) to obtain LiDAR derived structural variables and attempt to relate these to the fire-return interval 2) to provide a method to present and analyze fine-scale differences in the three-dimensional structure, particularly in the midlevel canopy, of a plot using LiDAR data, and 3) to understand if past land use, soil, and location of the plots has an impact on plot canopy structure.

Structural variables of interest for the 2002 and 2008 LIDAR data were extracted using database queries and histograms. The variables of interest included canopy cover, canopy height (maximum, minimum, mean, and standard deviation), shrub height (mean and standard deviation of returns between 0.34 and 2 m), shrub cover (proportion of 0.34-2 m returns), and height diversity and height evenness indices (HDI and HEI, respectively) (Table 7). Canopy height and cover indices were extracted using similar methodology described by Lim et al. (2003) for discrete return LiDAR, with slight modification from the 20X20m window used by Lovell et al (2003) and Coops et al. (2007). For the canopy heights, instead of using a 20X20 m window to obtain the highest canopy point as the maximum height, the entire Stoddard plots, which are only about 40X40m in dimension, were used. Maximum height corresponded to the highest LiDAR canopy classified return within the entire plot, and mean canopy height used an average of all canopy returns over 2m, and is expected to underestimate the average field tree top heights (Lim 2003). Canopy cover was measured by redefining closed canopy returns as only the ones over 2m and dividing the total number of these returns in each plot by all discrete returns in the same plot, including non-ground returns (Table 7). The proportion of canopy returns is a standard canopy cover index (Lim et al. 2003), which, for this study, has been slightly modified to exclude herbaceous and lower shrub layers.

Shrub Dominance Index (SDI), or the proportion of shrub returns (returns between 0.34-2 m in height) to all LiDAR returns, was developed to capture shrub encroachment and/or recruitment (Table 7). This is a similar measure as the shrub density index adopted by Clawges et al. (2008), with the exception of a narrower height class (0.5-2 m). The higher the relative shrub cover value (or SDI), the greater the amount of returns classified as canopy between 0.3 m and 2 m in height. Shrub encroachment, specifically of hardwood species, in the southeastern pine forest, is often considered undesirable and leads to ecosystem function alterations, with the elimination of fire being directly linked to the reduction of ecological and conservation values (Masters et al. 2007). The frequent use of moderate intensity fire attempts to reduce this hardwood shrub encroachment. Other studies, using the Stoddard Fire Plots, have reported 2-year fire interval burns suppressing woody vegetation, and 3-year fire return intervals slowing, but not suppressing woody understory encroachment (Herman 1995).

Table 7. Definitions of LiDAR-derived Structural Information.

Name	Acronym	Units	Description
Canopy Cover	CANCOV	%	(Count of Canopy Returns >2m/Count of All Returns) * 100
Mean Canopy Height	CANAVGHT	m	Average Height of all Canopy Returns (>2m in height)
Maximum Canopy Height	CANMAXHT	m	Maximum Height of all Canopy Returns (>2m in height)
Shrub Mean Height	SHAVGHT	m	Average Height of all Shrub Returns, which are defined as Canopy Returns > 0.34m and <2m in height
Shrub Dominance Index	SHINT	N/A	Total Shrub Returns/All Returns
Height Diversity Index	HDI	N/A	The Shannon Diversity Index (H') modified to calculate Foliage Height Diversity or Structural Diversity (MacArthur & MacArthur 1961).
Height Evenness Index or Equitability Height Index	HEI	N/A	Another measure of diversity that takes the total number of height classes into account (MacArthur & MacArthur 1961).

Numbers in italics are significantly different among fire treatments

In order to examine the Stoddard plot three-dimensional structure, histograms of the proportion of LiDAR returns per 1 m height interval were constructed. Additionally, the Height Diversity Index (HDI) and corresponding Height Evenness Index (HEI) were calculated (Table 7), using a finer scale interval of 0.5 m intervals. The Height Diversity Index (HDI) was calculated using the standard *Shannon-Height Diversity Index formula (H'):* $H' = -\sum_{i=1}^{S}(\mathrm{p_i} \ln p_i)$, and is equivalent to the foliage height diversity (FHD) used by Clawges et al. (2008). The Height Evenness Index (HEI) was calculated by using the following formula: $HEI = \frac{HDI}{\ln S}$, where S is the total number of foliage layers.

Linear regressions were used to compare field-derived canopy cover (using a gridded sighting tube) and LiDAR-derived canopy cover. Since field data were not coincident with the 2002 and 2008 LiDAR data collection events, the closest available data were used. Field data from April 2004 were compared to February 2002 LiDAR canopy cover data, and April 2010 field data were used to compare with March 2008 LiDAR data.

The impact of the frequency of fire and location of the plots on the different LiDAR extracted structural variables of interest were examined by using several One-Way ANOVAS. The dependent variables examined were canopy cover, mean and maximum canopy heights, shrub dominance (SDI), shrub mean height, height and evenness diversity indices (HDI and EDI). One of the independent variables, the fire return interval, included the 1-, 2-, 3- year fire return and the suppressed plots. The 4-year fire return plots were not included for the statistical analyses, since these were out of rotation between 1999 and 2007. The other independent variable, the location (i.e. block number) within the study area, included Block A (plots W1A-W4A and suppressed plot W75B), Block B (W1B-W4B and suppressed plot NB66), and Block C (plots W1C-W4C and suppressed plot UA). The different Blocks refer to locations within the study area, and were used to provide replicates of each treatment type within the Tall Timbers Research Station (Figure 12).

The dependent variables that were found to be significantly different among treatment groups using ANOVAs, were further tested to determine pairwise significant differences among means of treatment groups were the Fisher Least Significant Difference (LSD) and the Tukey's Honestly Significantly Different (HSD) post-hoc tests. The former test is the original test developed to pinpoint which groups have significant differences from each other, and the latter test aims to perform similar analyses and still maintain accurate alpha levels (which, at times gets reduced with the LSD test). The Tukey's test advantage of conserving alpha levels is accompanied with a decrease in detection power, when compared to most other post-hoc tests (Winer et al. 1991).

Finally, the relationship between some of the statistically significant structural variables and the historical land use variable alteration ratio (see above for description) was explored by linear regression and adding this variable as a covariate in analyses of variance. The goal of this analysis was to eliminate historical past land use as a factor in shaping the present structure of the Stoddard plots.

Results and Discussion

LiDAR Stoddard Plot Structural Data

LiDAR-derived canopy cover percentages (CC_{Li}) of the Stoddard Plots vary significantly across the different fire treatments (Table 8). The canopy cover increases with an extension in the fire return interval; 2002 and 2008 LiDAR-derived cover have means of 45% (2002) and 40% (2008), respectively, for one year fire return intervals, 54% and 48% for 2-year return plots, 71% and 57% for 3-year plots, and finally 77% and 68% for fire suppressed plots (Figure 13). These findings are in agreement with many previous studies, which describe how repeated fires maintain an open overstory canopy in upland pine systems (Vogl 1972; Waldrop et al. 1992; Masters et al. 2005). The only apparent exception to this pattern is the canopy cover of the 4-year fire return plots, with means of 57% (2002) and 44% (2008), similar to the 2-year fire return canopy cover means. The 4-year fire return plots were out of rotation and treated as 2-year fire return plots prior to and during the data collection (See Methods), and further highlights the impact of a short-term change in fire return on forest structure.

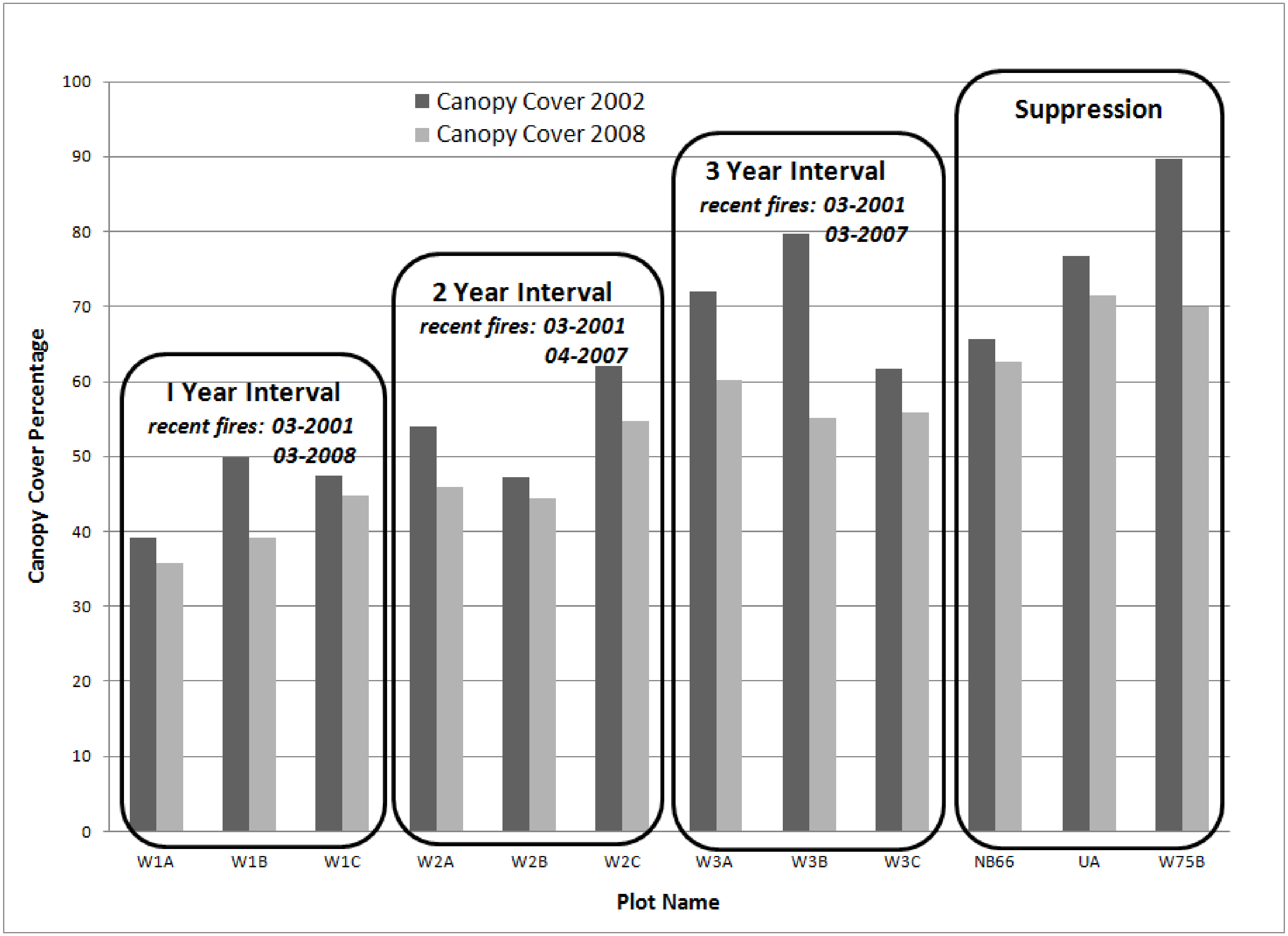

Figure 13. LiDAR-derived canopy cover percentages among Stoddard plots with multiple fire treatments and control plots.

Table 8. Derived Structural Canopy Information from the 2002 LiDAR dataset: Canopy Cover, Mean and Maximum Canopy Heights, Shrub Intensity, Height Diversity Index (HDI), Height Evenness Index (HEI).

Plot Name	Fire Treatment	Canopy Cover (%)		Mean Canopy Height (m)		Maximum Canopy Height (m)		Shrub Intensity		SHDI		EHI	
		2002	2008	[b]2002	[b]2008	2002	2008	2002	[b]2008	[b]2002	[b]2008	[b]2002	[b]2008
W1A	1 year	39.10%	35.73%	*15.53*	*11.99*	29.25	29.25	1.01		*2.25*	*1.99*	*0.55*	*0.50*
W1B	1 year	49.82%	39.23%	*15.75*	*16.84*	32.90	31.96	1.84		*2.77*	*2.18*	*0.66*	*0.54*
W1C	1 year	47.50%	44.73%	*20.25*	*22.12*	35.03	35.07	2.55	*0.10*	*2.72*	*2.46*	*0.64*	*0.59*
W2A	2 year	53.98%	45.87%	*16.91*	*9.75*	30.68	30.75	2.12	*0.22*	*2.91*	*2.50*	*0.70*	*0.61*
W2B	2 year	47.15%	44.34%	*16.39*	*17.04*	28.12	27.70	0.37		*2.45*	*2.24*	*0.61*	*0.60*
W2C	2 year	62.04%	54.76%	*16.05*	*18.67*	29.08	29.84	4.83	*0.15*	*3.21*	*2.71*	*0.79*	*0.69*
W3A	3 year	71.98%	60.22%	*15.00*	*15.20*	31.05	32.03	1.19	*0.20*	*3.47*	*3.01*	*0.84*	*0.73*
W3B	3 year	79.65%	55.08%	*16.46*	*18.56*	33.67	33.95	3.68	*0.60*	*3.87*	*2.93*	*0.92*	*0.70*
W3C	3 year	61.78%	55.85%	*16.41*	*18.53*	33.65	34.21	6.35	*0.82*	*3.39*	*2.97*	*0.80*	*0.70*
[a]W4A	4 year	51.38%	46.95%	*21.02*	*15.37*	32.90	33.80	3.74	*0.84*	*2.73*	*2.42*	*0.66*	*0.58*
[a]W4B	4 year	41.17%	39.40%	*16.72*	*18.42*	27.35	28.13	6.27	*2.01*	*2.38*	*2.11*	*0.60*	*0.55*
[a]W4C	4 year	78.74%	46.90%	*11.85*	*14.27*	32.46	32.91	3.51		*3.61*	*2.36*	*0.86*	*0.59*
NB66	Suppressed	65.62%	62.63%	*18.23*	*18.61*	30.82	30.99	0.21	*0.43*	*3.18*	*3.49*	*0.77*	*0.75*
UA	Suppressed	76.76%	71.48%	*18.03*	*17.36*	31.11	31.68	1.97	*2.14*	*3.61*	*3.50*	*0.87*	*0.85*
W75B	Suppressed	89.67%	70.02%	*21.25*	*19.00*	35.70	35.58	0.90	*0.33*	*4.01*	*3.07*	*0.94*	*0.82*

[a] Plots out of fire rotation between 1999-2007 (2 year fire return during this 8 year period)
[b] Metrics with statistically significant differences among fire treatment

Canopy cover in 2002 was, overall, higher than in 2008 across all Stoddard plots. Differences in canopy cover per treatment group varied between 6% and 14% lower in 2008 than in 2002. The overall mean for canopy cover of all Stoddard plots in 2002 was 61%, whereas the mean 2008 canopy cover was 52%. Similar, but more subdued differences in rainfall are visible in the field data collection between 2004 and 2006.The differences in canopy cover could likely be explained by a dramatic contrast in the cumulative and 2006 12 month and 24 month precipitation prior to the 2002 and 2008 data collection events (Tall Timbers, unpublished data). Whereas the cumulative 12 and 24 month precipitation prior to 2002 was at or near the 1969-2009 historical average (143 cm and 137 cm, respectively), the cumulative precipitations prior to 2008 was well below the average (99 cm and 97 cm, respectively) (Tall Timbers, unpublished data). Both 2006 and 2007 can be described as extreme drought years in North Florida, with values of 41 cm and 43 cm below the historic annual average of 140 cm. Loblolly pine needle fall – which would imply a decrease in canopy cover-, has been correlated to relative drought during the growing season, with precipitation effects lagging a year on these stands (Hennessey et al. 1992). Loblolly pine was the dominant canopy species on many of these plots (Masters et al. 2005).

Mean canopy height values varied between 11.85 m and 21.25 m (2002) and 9.75 m and 22.12 m (2008). There were no significant differences among treatment groups: 2002 and 2008 mean group heights varied only between 16 and 17m for 1-, 2-, 3-, and 4- year fire return treatments (Table 8). The only treatments with higher mean canopy heights are the unburned plots, with 19 m for 2002 and 18 m for 2008 data. The different fire treatments did not seem to influence the canopy height directly. Indirectly, the plots with much higher amount of shrub and canopy vegetation, such as the fire suppressed plots, had slightly higher mean heights, as a result of more tree cover. The mean canopy height (either derived by the average of all canopy points above 2 m or the average DCHM raster values per plot) is not equivalent to the average tree field height. LiDAR-derived data includes some midstory canopy and shrub returns into account, and would, therefore, be more easily biased than field heights of the dominant and co-dominant tree matrix.

The rainfall differences between 2002 and 2008 datasets also did not seem to have impacted the mean canopy heights of the Stoddard plots. The difference between the 2002 and the 2008 mean canopy height of all Stoddard and control plots is less than 1 m, namely between 17.06 m and 16.78 m, respectively.

Maximum canopy height values ranged between 27.5 m and 35.7 m (2002) and 27.7 m and 35.58 m (2008). Similar to the mean canopy heights, the maximum heights for both 2002 and 2008 did not show any discernable pattern among the different fire treatments: maximum heights are lowest in the 2 year fire return interval treatment (29 m), similar for all other treatment and control plots (31-33 m) (Table 8). The fire treatment did not seem to have an impact in the maximum canopy height of the Stoddard plots, with fire suppressed plots having essentially identical average heights (32.54 m or 32.75 m for 2002 and 2008, respectively) to the 1-year fire return treatment (32.4 m and 32.09 m, respectively).

The maximum canopy height data for the 2002 dataset were identical to the 2008 data, with total plot averages of 35.70 m for the canopy height of the first dataset and 35.58 m for the later dataset. The canopy height, represented by the highest return value in the plot, didn't seem to have been negatively affected by the extreme drought experienced in 2006 and 2007.

Relative shrub cover (or SDI) values range from 0.21 to 6.35% for the 2002 dataset and from 0.10 to 2.14% for the 2008 dataset (Table 8, Figure 14). The overall mean shrub cover of all the Stoddard and control plots was much higher in 2002 (2.7%) than in 2008 (0.71%). As a matter of fact, several of the more frequently burned Stoddard plots (W1A, W1B, and W2B) presented no return classified as shrub in the 2008 year (Figure 14). With similar point density (minimum 1.05-1.19 returns/m) and seasonality of data collection of both sets (February-early March), differences in the ability of shrub detection were not expected. Low numbers of shrub returns in 2008 could be a consequence of precipitation differences described previously (indicating a lack of shrub growth after a prolonged drought) as average Keetch-Byram Drought Index values for the burns in the previous years (2001 and 2007) were considerably different (22 vs. 435) and likely reflect more intense fire behavior on the plots in the later burns.

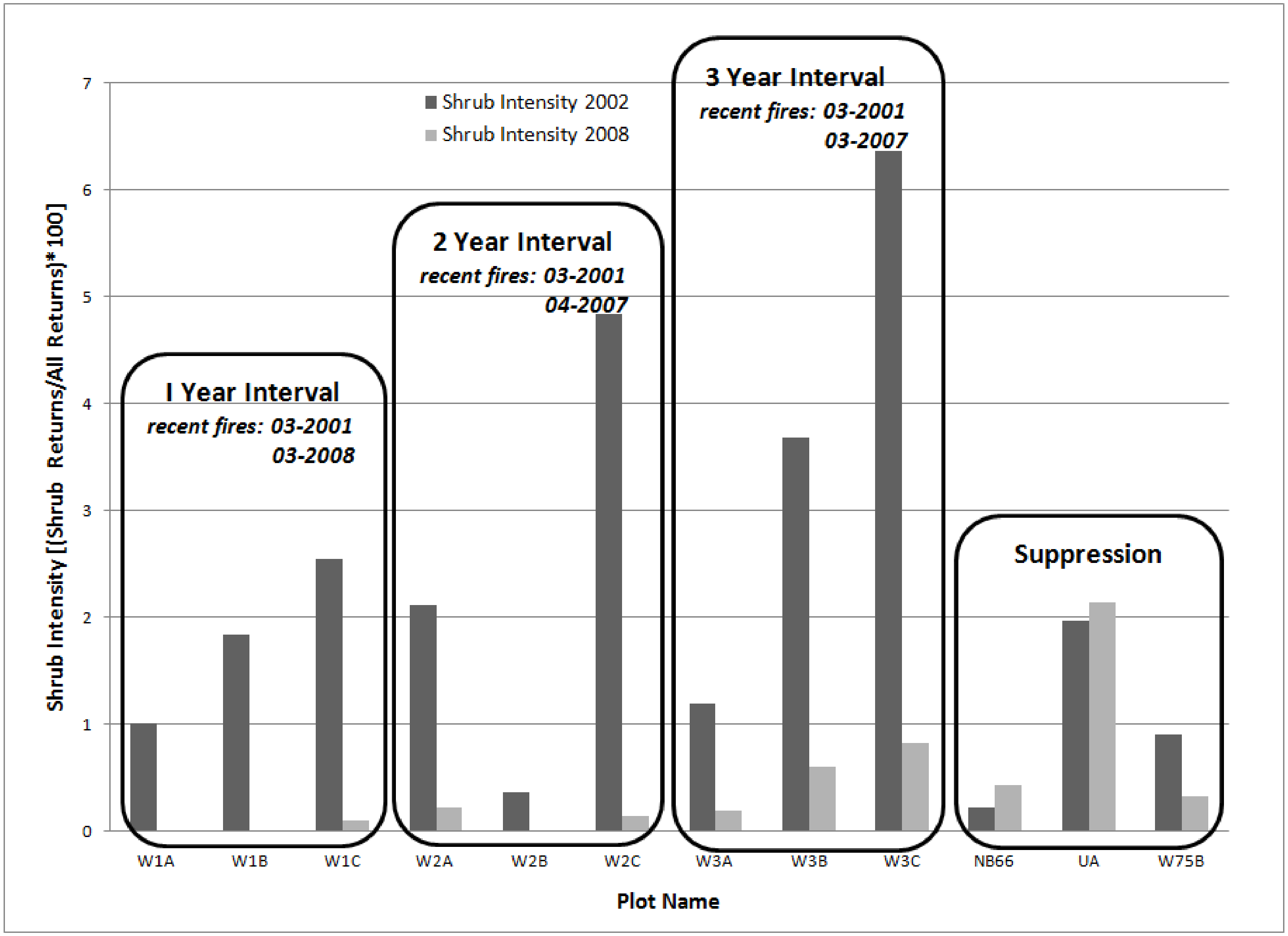

Figure 14. LiDAR-derived Shrub Intensity among Stoddard plots with multiple fire treatments and control plots

Relative shrub cover among the different fire treatments presented a subtle pattern for the 2002 dataset (2008 had several plots without cover values), especially when examining the “C” replicates (Figure 14). The 2002 mean relative shrub cover for the 1-, 2-, 3-, and 4- year fire return treated plots was 1.8% , 2.4%, 3.7%, and 4.5%, respectively. The variability among the replicates for each treatment group is very large, causing the standard deviations to range between 0.7 to 2.6%. An increase in shrub cover or dominance with a greater interval in the fire regime is in complete agreement with other studies which measure a statistically significant increase in number of hardwood stems with less frequent fire (Hermann 1995). However, fire suppressed control plots presented very low shrub cover (1% for both 2002 and 2008 datasets), when compared to a longer fire return interval plot. In these plots, the hardwood canopy mid story component is now dominating the canopy, effectively shifting over time, canopy constituents to a mesic hardwood-pine forest with dense canopy cover. The significantly reduced number of saplings (which composes most of the woody encroachment in the non-annual treatment plots) can be explained by a reduction in light availability after 50 years of canopy closure in these hardwood forested environments and possibly increased root competition.

Analyses of Variance of multiple LiDAR-derived metrics among the three treatments and one control group yielded consistent statistically significant differences in only the canopy cover (Table 8 and Figure 15) and height diversity variables. Canopy height variables (mean and maximum) and shrub variables (shrub mean height and cover) were either not found to be significant in either one or both years.

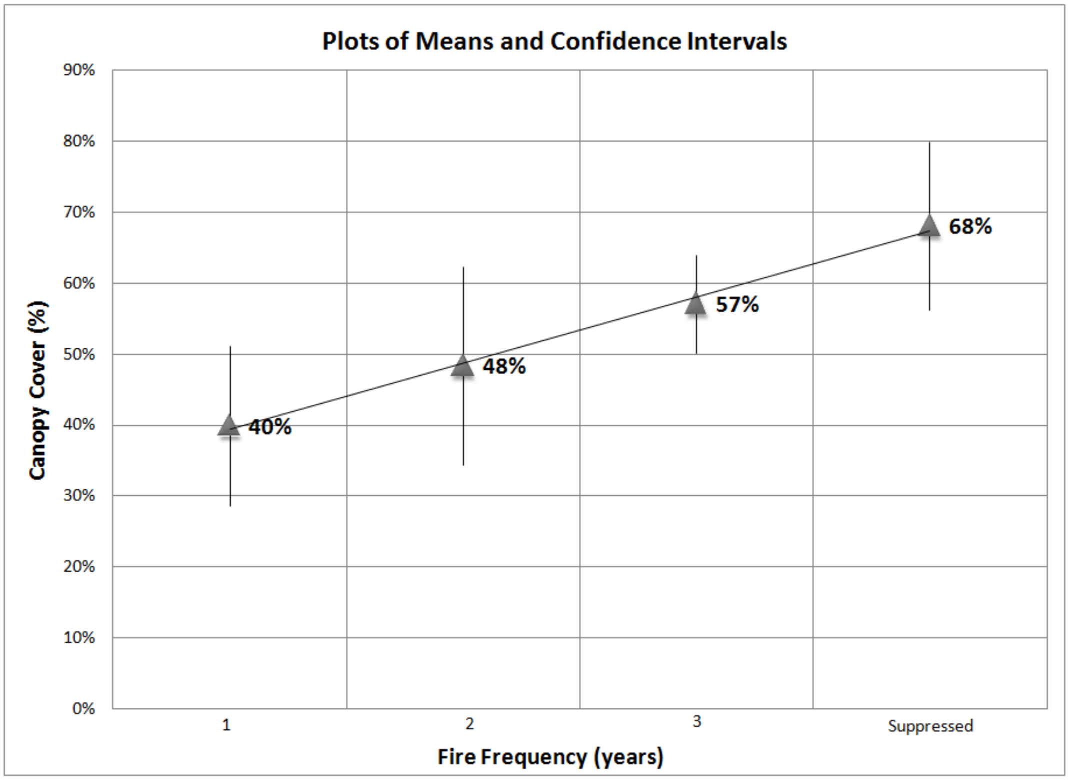

Figure 15. Means and Confidence Intervals of 2008 LiDAR Derived Canopy Cover among Treatment and Control Plots.

Further Post-Hoc Analyses – Fisher LSD and the Tukey's HSD tests- of the canopy cover variable determined that no significant differences were present between the one – and two-year fire return treatments for both 2002 and 2008 datasets (Table 9). Canopy cover means from 2002 and 2008 were significantly different using either post-hoc tests between one-year and 3 year- treatment plots,- and also between one or two-year treatments and control (fire suppression) plots. Canopy Cover differences between one or two-year treatment plots and three-year treatment plots were only significant using the more sensitive Fisher LSD test, for both 2002 and 2008 (Table 9). In most instances, there were no significant differences between canopy cover of the control plots and 3-year fire return treatment; the only exception to this was the 2008 dataset using the Fisher LSD analysis.

In general, the Post-Hoc Analyses agree with the assessment that there is a great disparity between canopy cover of high frequency burned plots (1 and 2-year frequencies) and low frequency or suppressed plots (3-year and control plots). Other studies have effectively demonstrated that 3-year interval is an “ecological threshold” for upland pine systems (Masters et al. 1993; Masters et al. 2005), with stands under 3-year fire frequencies being dominated by herbaceous understory, and stands at and over 3-year intervals dominated by woody vegetation. This implies fire management at 3-year interval – commonly thought as being within the “natural” fire regime for upland pine woodlands in the Southeast-, will allow a progressive increase in hardwood presence at least on old-field derived lands. The rate at which this shift from an open pine-grassland to a more mesic hardwood-pine type forest would occur is probably linked to soil and fuel moisture (Masters and Robertson 2007), and potentially other environmental variables.

Table 9. Post-Hoc Test (Fisher LSD/Tukey's HSD) Results for 2002 and 2008 Statistically Significant Structural Variables among Fire Treatments.

Canopy Cover

		2002						*2008*			
		1-Year	2-Year	3-Year	Suppression			1-Year	2-Year	3-Year	Suppression
2002	1-Year		0.25/0.62	**0.01/0.03**	**0.00/0.01**	***2008***	1-Year		0.05/0.2	**0.00/0.01**	**0.00/0.00**
	2-Year	0.25/0.62		**0.05**/0.17	**0.01**/0.05		2-Year	0.05/0.2		**0.05**/0.17	**0.00/0.00**
	3-Year	**0.01/0.03**	**0.05**/0.17		0.41/0.83		3-Year	**0.00/0.01**	**0.05**/0.17		**0.02**/0.07
	Suppression	**0.00/0.01**	**0.01**/0.05	0.41/0.83			Suppression	**0.00/0.00**	**0.02**/0.07	**0.02**/0.07	

Shannon Height Diversity Index (SHDI)

		2002						*2008*			
		1-Year	2-Year	3-Year	Suppression			1-Year	2-Year	3-Year	Suppression
2002	1-Year		0.35/0.76	**0.01/0.03**	**0.01/0.03**	***2008***	1-Year		0.15/0.43	**0.00/0.01**	**0.00/0.00**
	2-Year	0.35/0.76		**0.03**/0.12	**0.03**/0.11		2-Year	0.15/0.43		**0.02**/0.08	**0.00/0.00**
	3-Year	**0.01/0.03**	**0.03**/0.12		0.93/1.00		3-Year	**0.00/0.01**	**0.02**/0.08		**0.06**/0.19
	Suppression	**0.01/0.03**	**0.03**/0.11	0.93/1.00			Suppression	**0.00/0.00**	**0.00/0.00**	**0.06**/0.19	

Evenness Height Index (EHI)

		2002						*2008*			
		1-Year	2-Year	3-Year	Suppression			1-Year	2-Year	3-Year	Suppression
2002	1-Year		0.19/0.52	**0.00/0.02**	**0.00/0.01**	***2008***	1-Year		**0.03**/0.12	**0.00/0.01**	**0.00/0.00**
	2-Year	0.19/0.52		**0.03**/0.12	**0.03**/0.10		2-Year	**0.03**/0.12		**0.05**/0.17	**0.00/0.00**
	3-Year	**0.00/0.02**	**0.03**/0.12		0.90/0.10		3-Year	**0.00/0.01**	**0.05**/0.17		**0.02**/0.08
	Suppression	**0.00/0.01**	**0.03**/0.10	0.90/0.10			Suppression	**0.00/0.00**	**0.00/0.00**	**0.02**/0.08	

Bolded values are signficant at α=0.05; cells shaded in gray are significant for both the Fisher LSD and Tukey's HSD tests

Field Stoddard Plot Canopy Cover Data

Field Canopy Cover data for the Stoddard and Control Plots vary between treatments and across data collection events (Table 10). The 1-year fire return treatment plots have field canopy covers of 11 to 51% across all dates and replicates, with an overall average canopy cover of 33%. The 2-year Stoddard plots had higher canopy cover values than the 1-year plots, varying between 28 and 73% canopy covers, with an overall mean across dates of 52%. The 3-year fire return plots have even more dense canopy, with canopy cover values varying between 44 and 84%, and an overall mean of 67%. Since the 4-year fire return plots were rotated as 2-year fire return plots for the majority of the years presented, the canopy covers were expected, if indeed shaped by fire interval, to be similar to the 2-year fire treatment plots. In fact, the 4-year replicate Stoddard plots had canopy cover similar to the 2-year fire return plots, with cover between 40 and 65%, and the same average canopy cover average of 52%. Finally, the control plots with fire suppressed for at least 50 years, have the highest canopy cover values ranging between 78 and 99%, and with an across the years and replicates average of 87%, 20% higher than the 3-year Stoddard plots.

Table 10. Field Canopy Cover Data using a Sighting Griding Scope of the Stoddard Plots.

Plot Name	Fire Treatment	4/30/2004	3/15/2005	4/12/2005	3/21/2006	4/13/2010
W1A	1 year	17.44%	19.14%	21.45%	11.42%	17.90%
W1B	1 year	38.73%	43.06%	41.36%	35.49%	44.60%
W1C	1 year	36.88%	42.13%	44.91%	30.86%	51.39%
W2A	2 year	51.54%	65.43%	73.15%	51.70%	56.79%
W2B	2 year	36.73%	35.96%	34.72%	28.24%	31.64%
W2C	2 year	62.19%	64.81%	62.50%	61.42%	59.88%
W3A	3 year	76.85%	82.87%	83.80%	64.20%	68.98%
W3B	3 year	58.33%	60.03%	66.67%	44.44%	59.10%
W3C	3 year	72.07%	68.98%	73.77%	58.49%	66.36%
W4A	4 year*					50.62%
W4B	4 year*					40.12%
W4C	4 year*					65.12%
NB66	Suppressed	98.92%	88.12%	89.81%	85.65%	84.41%
UA	Suppressed	93.36%	84.88%	85.80%	86.11%	81.33%
W75B	Suppressed	94.91%	71.76%	97.22%	76.39%	88.73%

Preceding 12-month cumulative rainfall for the field data collection events are: 102 (4/30/2004 event), 170 (3/15/2005 event),192 (4/12/2005 event), and 159 cm (for 3/21/2006). Rainfall for 2010 event not available.

Across the different data collection events, canopy cover for individual Stoddard plots did vary (Table 10). For one-year Stoddard Plots the variation ranges between 9 and 21%, for individual replicates, 2-year treated plots ranged between 5 and 22%, 3-year plots between 15 and 22%, and fire suppressed plots between 12 and 26% (4-year Stoddard plots only had data collected in the 2010 event). Across all treatments, with the exception of the control plots only, canopy cover values tended to be lowest during the March 2006 data collection event and highest during the April 2005 event. This might likely be linked to rainfall differences between both years: while 2006 was an extreme below average rainfall year (99 cm), 2005 was an extremely wet year with rainfall well above historical average (174 cm) (Tall Timbers, unpublished data).

Comparison between April 2004 Field and February 2002 LiDAR canopy cover data yielded a correlation coefficient of 0.56 (Figure 16). The largest difference between the 2002 LiDAR and the 2004 field canopy cover data can be found in the W3B Stoddard plot. The 2004 field data indicates a canopy cover of 58%, almost 22% lower than the 2002 LiDAR-derived canopy of the same plot (Table 10). The fire intensity of the 2004 burns was very high and had dramatic influence on upper mid-story hardwood canopy cover. If this outlier were to be removed from the comparison, the regression coefficient would increase to 0.84, an indicator of a strong relationship between the two datasets. It is difficult to compare datasets over 2 years apart, especially when these were affected differently by recent fire treatments. Whereas prior to the LiDAR data collection, none of the Stoddard and control plots had been burned for at least 12 months, all plots with the exception of the 2-year fire return treatment plots, were burned just before the 2004 field data collection. The immediate reduction of canopy cover data in the 2004 field dataset could be a result of mid-story hardwood species being eliminated, and the W3B plot likely was affected by the higher intensity fire, making this reduction even more dramatic.

The comparison of April 2010 Field and March 2008 LiDAR canopy cover data yielded a strong relationship, with a 0.82 regression coefficient (Figure 16). The higher correlation between these two datasets could be related to a more similar season (both collected during the transitional season), newer technology LiDAR sensor (with a greater number of returns, capturing more mid canopy data), and a similar fire treatment history.

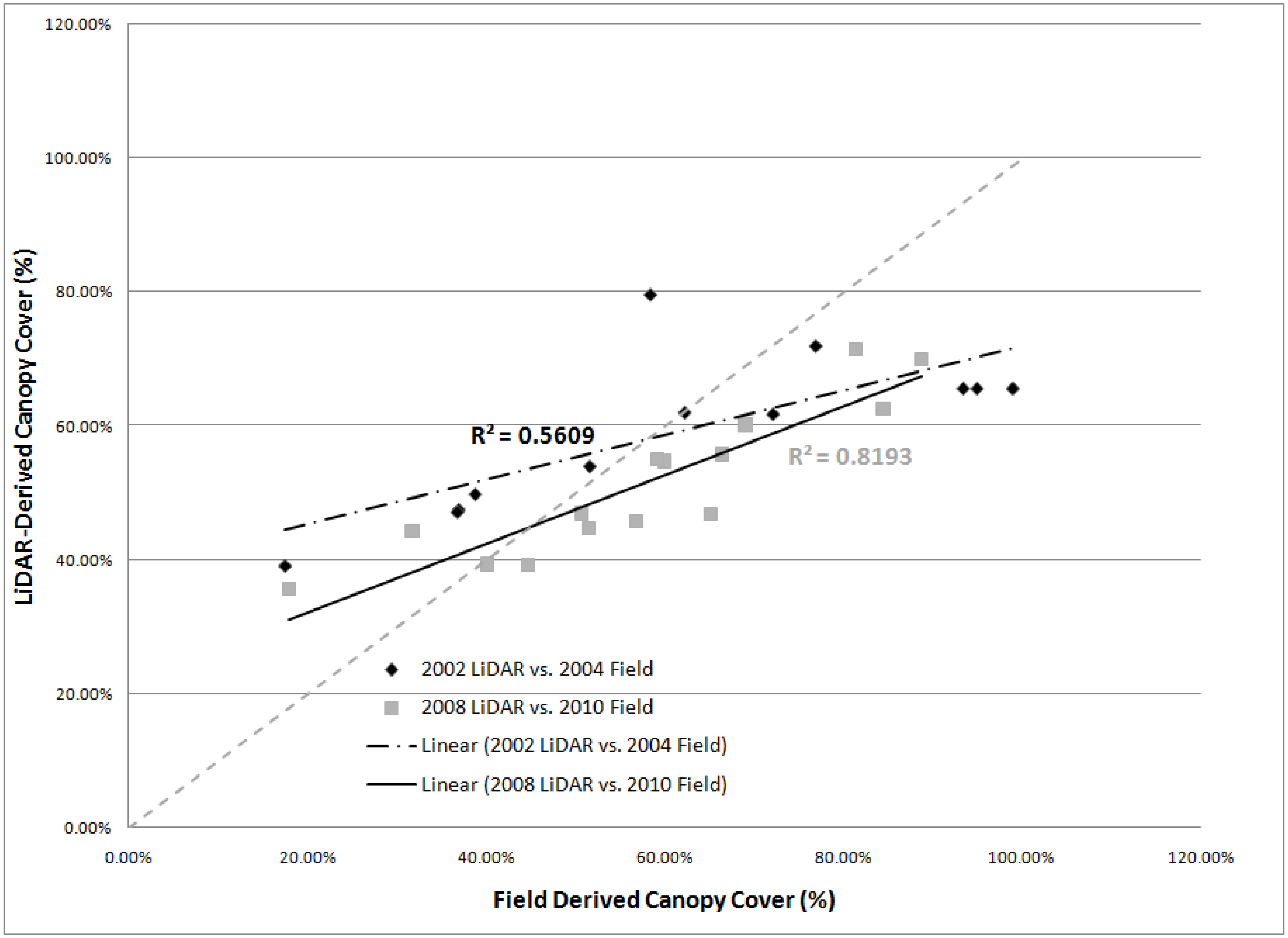

Figure 16. Correlation Results between Field and LiDAR Canopy Cover Data (2002 LiDAR versus 2004 Field and 2008 LiDAR versus 2010 Field measurements).

Height Diversity of Variable Fire Return Intervals

Beyond simple structural metrics, airborne LiDAR allows a better understanding of three-dimensional structural measurements (Leksfy et al. 2002; Kao et al. 2005), such as height distribution and diversity among plots. The percentage of LiDAR returns across heights is dramatically different among treatments (Figure 17-Figure 19). The amount of ground returns (<1m) is the most variable of all height categories, indicating the canopy cover differences among treatments: frequently burned plots have over 50% of the returns categorized as ground returns (64% for 1-year plots and 54% for 2-year plots), while less frequently burned plots (3-year fire return) and control plots have less than 40% of ground returns (39 and 30%, respectively).

Overall, in more frequently burned plots, the proportion of LiDAR returns is reduced in the lower height categories (<3 m), and this proportion increases with a decrease in fire frequency. In one-year fire return plots, the shrub height vegetation is absent or heavily reduced (>0.2% of the LiDAR returns), and the bulk of the LiDAR returns is concentrated around the midstory canopy level, between 5 to 12 m in height (Figure 17a and Figure 18a). In the 2-year fire plots, the shrub layer is still reduced, but more visible than in the 1 year treatments, and the vegetation is typically less focused in one height interval, and clustered around the mid to higher canopy heights, between 17 to 20 m in height (Figure 17b and Figure 18b). With a decrease in fire frequency, the 3-year fire plots present a structural distribution resembling a normalized curve, with no visible gaps in either lower or higher height categories (Figure 17c and Figure 18c).

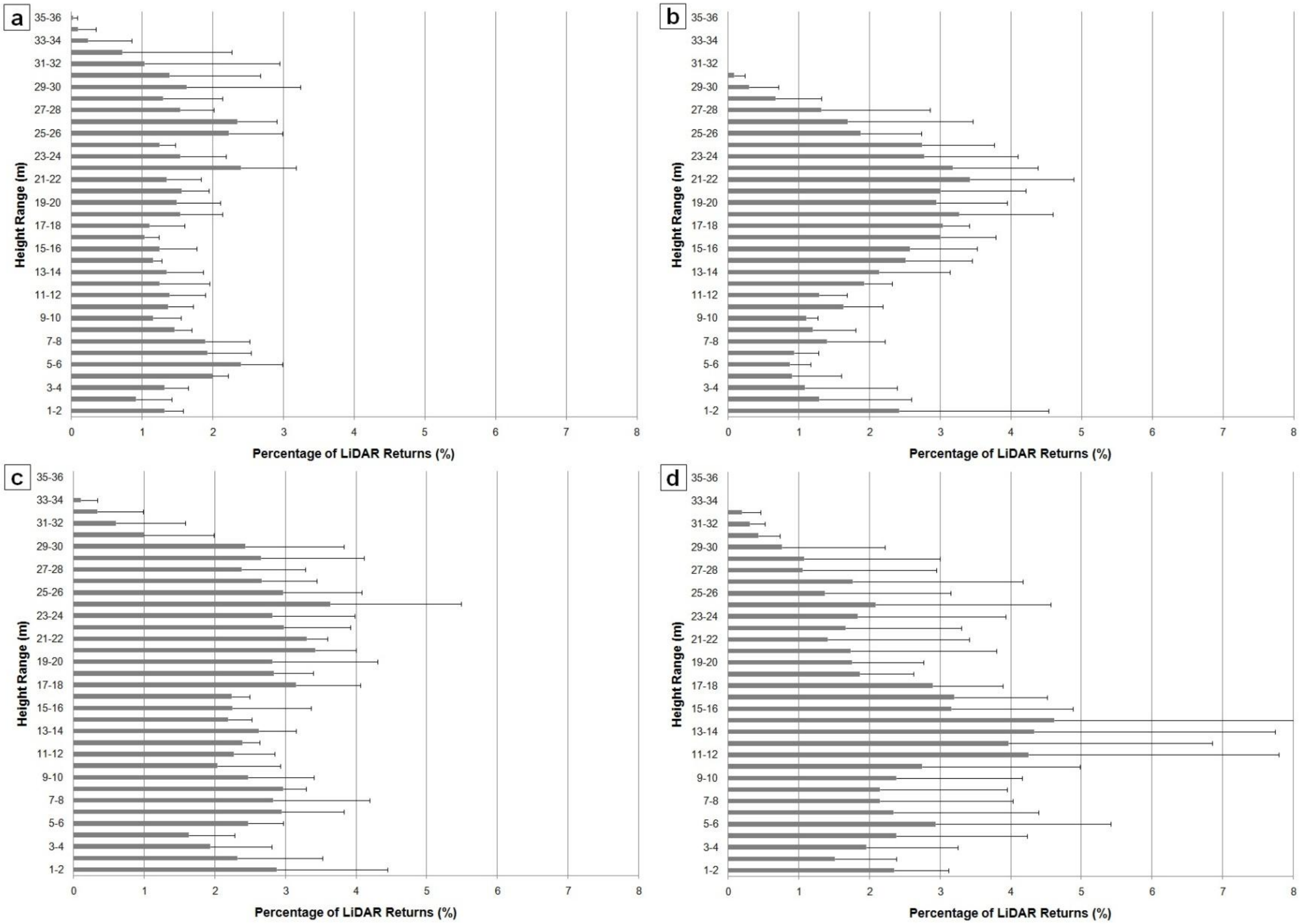

Figure 17. Mean Height Distribution of 2002 LiDAR Returns for differently treated Stoddard Fire Plots: a) 1-year b) 2-year c) 3-year d) 4-year fire return interval. Standard deviation across plot replicates of the same treatment (A, B, and C) represented as error bars.

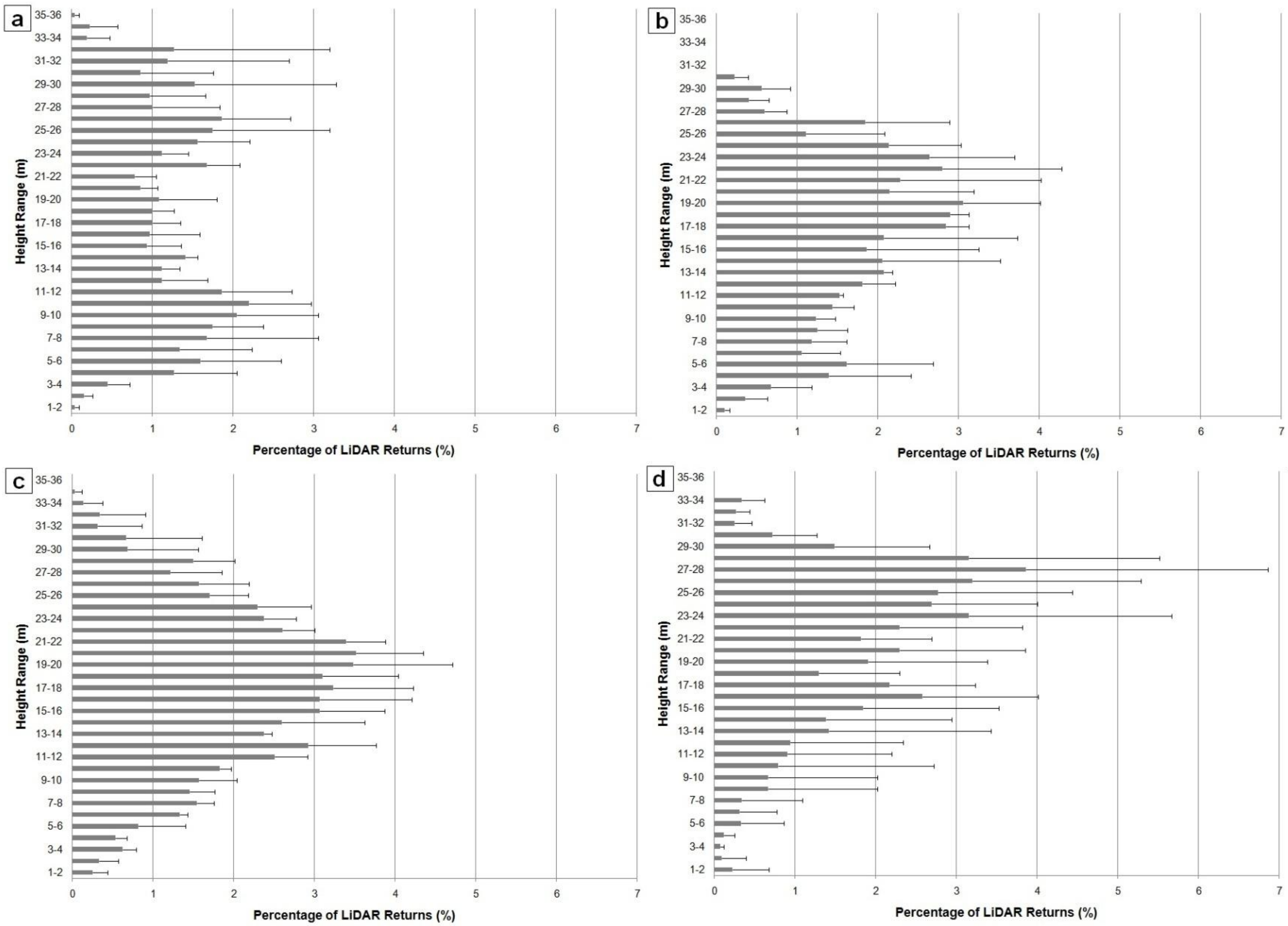

Figure 18. Mean Height Distribution of 2008 LiDAR Returns for differently treated Stoddard Fire Plots: a) 1-year b) 2-year c) 3-year d) 4-year fire return interval. Standard deviation across plot replicates of the same treatment (A, B, and C) represented as error bars.

The exception to the previously described pattern – increasing numbers of shrub-level returns – is found in the 4-year fire return interval treatment plots, which have been treated out of rotation, mimicking 2-year old fire return treatment for about a decade. These plots present a structure that is heavily weighted towards higher canopy and scarce in the shrub height categories, with most of the vegetation found between 22-28 m in height (Figure 17d and Figure 18d). The number of returns in the shrub layer (<5 m) is almost non-existent, and less than 0.5% of LiDAR returns are present in any of the height categories below 12m. In the control –fire suppressed- plots, the distribution of LiDAR returns is almost even across the entire height profile (Figure 19), which indicates the presence of dense vegetation across all height categories.

Differences between the vegetation distribution between the 2002 and 2008 LiDAR datasets are present in the less frequently burned plots, 3- and 4-year fire return intervals, and control plots. In the treatment plots, the 2002 profiles are more heavily weighed by shrub and lower mid story vegetation (1-10 m) than the 2008 profiles (Figure 17 and Figure 18). This is in agreement with the lower shrub intensity values observed in 2008 than in 2002, which could be explained by cumulative rainfall differences prior to data collection.

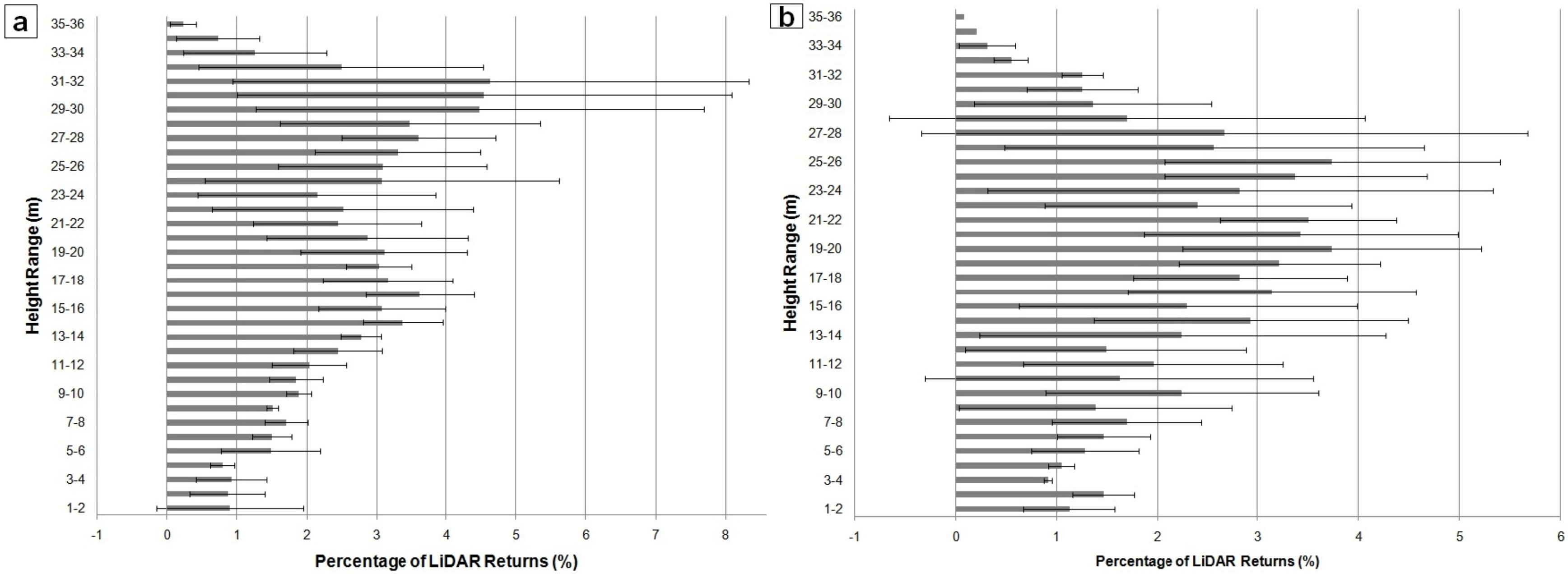

Figure 19. Mean Height Distribution of Fire Suppressed Stoddard Plot using two sets or Airborne LiDAR: 2002 dataset (a), and 2008 dataset (b).

The structural diversity – as measured by the Height Diversity Index (HDI) and Height Evenness Index (HEI) - is also highly variable among treatment and control plots. As the LiDAR returns become more evenly distributed and less densely focused on a height category, both indices will indicate higher values. An increase in both the HDI and HEI is visible with a decrease in fire frequency (Table 8, Figure 20, Figure 21). Stoddard treatment plots have 2002 HDI means of 2.58, 2.85, and 3.57 for one-, two-, and three-year fire return intervals, respectively, while control plots have a HDI mean of 3.6. The 2008 HDI pattern is identical with mean values increasing with less frequently treated plots: 2.21, 2.48, 2.97, and 3.35 for one-, two-, three-year treatments, and control plots, respectively. The 2002 HEI means are 0.62, 0.70, and 0.85 for 1-, 2-, and 3- year Stoddard treated plots, respectively, and slightly higher, 0.86, for control plots. For 2008 the values are slightly lower than 2002 values, but still consistent in pattern across treatments, with means of 0.54, 0.63, 0.71, and 0.81 for one-, two-, three-year treatments, and control plots, respectively. Four-year fire return interval plots, treated as 2-year fire return intervals for about a decade, presented values for both indices very similar to 2-year treated Stoddard plots: HDI means of 2.91 (2002), and 2.30 (2008), and HEI means of 0.71 (2002) and 0.57 (2008).

Both diversity indices indicate an increase in structural diversity with a decrease in fire frequency. Unlike in other ecosystems, southeastern pine, however, doesn't present an increase in species diversity with increases in structural diversity, since most of the floral diversity is in the groundcover layer. As structural diversity increases, shrub and mid canopy presence threatens this very unique floral richness.

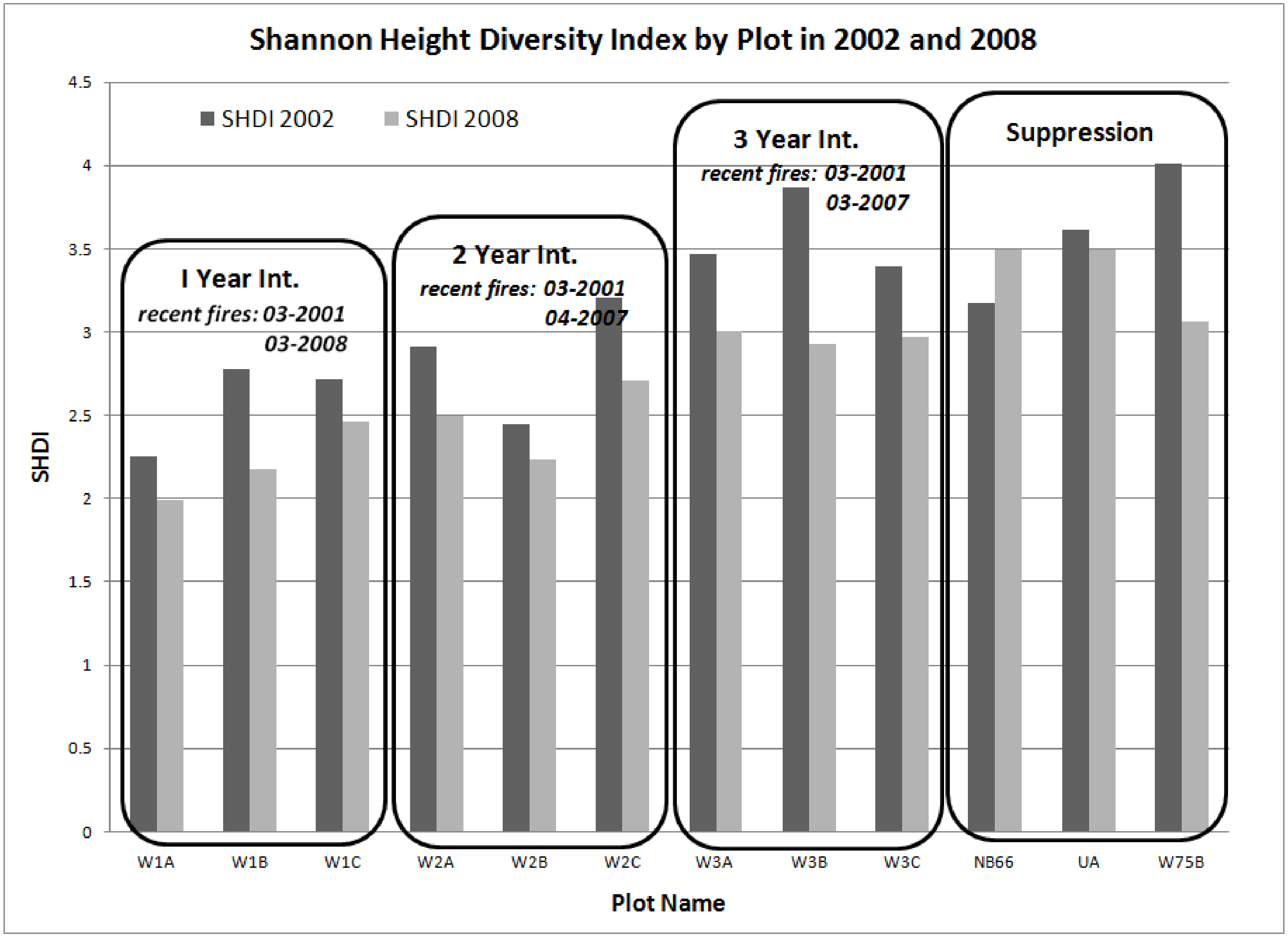

Figure 20. LiDAR-derived Height Diversity Index (HDI) values among Stoddard plots with multiple fire treatments and control plots.

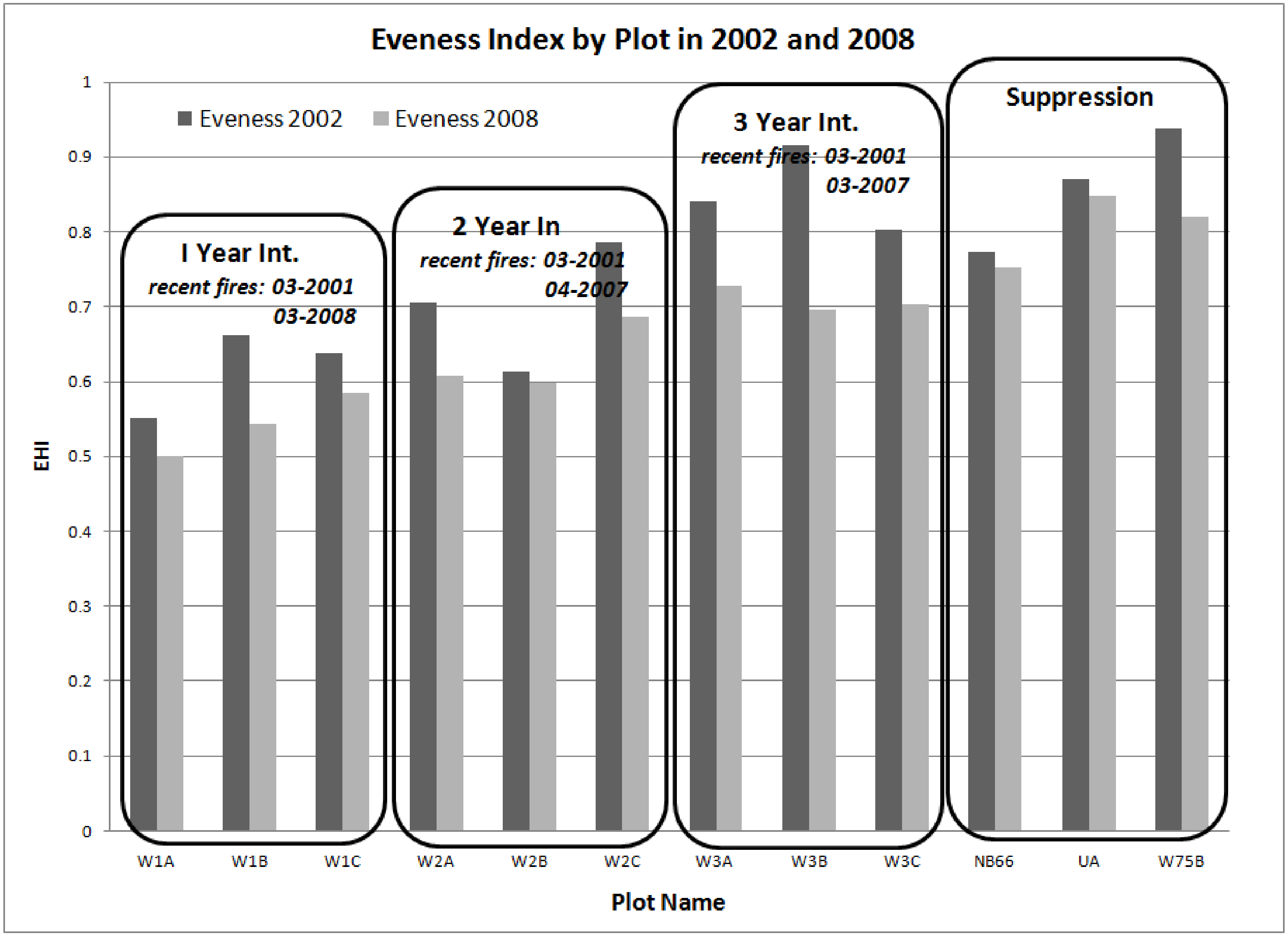

Figure 21. LiDAR-derived Evenness Height Index (EHI) values among Stoddard plots with multiple fire treatments and control plot.

Statistical comparison of structural indices means (or medians, when the data did not meet parametric assumptions) across treatment and control plots indicated that the visually apparent patterns (Figure 20 and Figure 21) are significant. The HDI is statistically higher in lower frequency and control plots both for 2002 and 2008 with p-values of 0.014 and 0.000, respectively. The HEI test of means across treatment and control plots for 2002 is also statistically significant, according to Analyses of Variance, with a p-value of 0.008. Medians of treatment and control groups are also significantly different, according to the non-parametric Kruskal-Wallis test, with a p-value of 0.000.

Further Post-Hoc Analyses – Fisher LSD and the Tukey's HSD tests- of the HDI variable determined that no significant differences were present between the 1- and 2--year fire return treatments for both 2002 and 2008 datasets (Table 9). The HDI means from 2002 and 2008 were determined to be significantly different using either of the post-hoc tests between the one-year and 3 year-return treatments, and also between one- year treatments and the control (fire suppression) plots. No statistically significant differences occurred in the Height Diversity means between one-year and two-year fire return treatment plots for either 2002 and 2008 datasets (Table 9). In most instances, the HDI mean of 2-year treatment is significantly different than the control plot mean; the only exception to this is visible for the 2002 dataset using the Tukey test. Whereas the Fisher test showed a larger number of significant differences between different treatment groups, especially in 2008 (Table 9), the Tukey post-hoc test, maintained the alpha level but also reduced the power of detection of significant differences, reducing the amount of significant interactions detected (Table 9).

The Height Evenness index (HEI), is highly correlated with the HDI, and the post-hoc results, were, in general, very similar. In addition to all the significant differences in means among treatment and controls described for the HDI, the 1- and 2-year treated plots showed significantly different means for only the 2008 dataset only using the Fisher LSD test.

Overall, the Post-Hoc analyses of the structural indices are consistent with the differences among treatment and control groups observed for canopy cover. Consistent significant differences between control plots and high frequency burned treatment are present in all variables of focus, and, in most cases, the increase of the 2- year fire burn interval to 3-years or greater caused significant changes in structural metrics. The 3-year interval appears to be the “ecological threshold” as described previously in this secondary upland pine ecosystem (Masters et al. 1993; Masters et al. 2005), with significant structural changes occurring at or above this interval. Interestingly, a similar pattern that highlighted the same ecological threshold was detected by Glitzenstein et al. (2008) using groundcover species diversity, where the majority of the floral diversity is contained in this systems, as a measure of species composition.

Soil and Past Land Use

The Stoddard Plots were selected over 50 years ago, using a stratified design with replicates randomly placed across the Tall Timbers upland land area. This design attempted to remove bias from other independent variables (such as soil, slope, exposure/direction, distance to road, among others), isolating the independent factor of interest (fire return interval). Different soil types (Table 11) encountered in the Red Hills upland area are represented within the Stoddard treatment and control plots (Table 6). The two main soil types represented in the Stoddard plots are Faceville (common in both A and C replicates across all treatment types) and Orangeburg (present mostly in all B replicate treatments and the NB66 control plot), with a few plots having soil identified as Fuquay (W3A) and Pelham (W3C).

Soil types are not consistent per treatment type with all treatment groups represented by different types of soils (e.g.: one-year fire return treatment plots have either the Faceville soil type –A and C replicates or Orangeburg soil type – B replicate). With different soil types represented across each treatment type, soil differences are not correlated with significant differences in structural metrics encountered between treatments. Soil type, at least across the range of conditions studied, can be eliminated as a factor explaining the differences in canopy cover and structural diversity among fire return treatments.

Past land use of the Tall Timbers area, as depicted in the 1930s aerial photography, consists of cleared areas for agriculture, fields, and roads, and secondary growth pine forest. The specific land use of the Stoddard plots represents this mixture, with a great variation in the dominance of past land use (Table 6). Whereas eight plots are dominated by forested area (either densely forested or open canopy), the remaining six plots were dominated by cleared areas. Only three Stoddard treatment or control plots, W2A, W75B, and W4A (87%, 78%, and 71% forested, respectively), were largely covered by secondary forest, whereas W2C and NB66 where dominated by cleared land (12% and 25% forested only). The past land use cover varies across all types of treatments with no consistent patterns, with some 2-year fire return treatment plots dominated by secondary forest (W2A with 87% forest), and others represented by cleared land (W2C with 88% non-forested cover).

The alteration ratio or the proportion of non-forested to forested cover is an indicator of past land use changes compared to present conditions: a high alteration ratio value, especially higher than 1, indicates that a major change in land use took place, with over 50% of the plot having been non-forested in the 1930’s. The Stoddard plots with significant alteration ratios are encountered across all treatment types (Table 6), ranging from 1-year fire treated plots (W1A with 1.29), 2-year fire return plots (W2C with 7.35), 3-year fire return plots (W3A with 1.17), and finally control plots (NB66 or 3.06). Furthermore, no significant linear correlations between past land use (as portrayed by the alteration ratio) and significant structural metrics were encountered in this study with r^2 coefficients all below 0.01. This indicates that past land use is not a good predictor of the significant changes in canopy cover, Height Diversity Index, and Height Evenness Index among different fire treatments at Tall Timbers. At the least, it suggests that the fire-frequency influences on woodland succession has an over-riding influence.

Conclusion

The structural characteristics of southeastern pine woodlands are molded and shaped by the fire behavior and history (Glitzenstein et al. 2008). There have been multiple studies focusing on the short- and long-term effects of different fire-return intervals on the species composition of pine woodlands (Sparks et al. 1998; Gliztenstein et al. 2003). Other studies have looked at specific structural variables, such as canopy cover or individual species tree and population growth (e.g. of *Pinus palustris*), in an attempt to understand the best management strategies for recruitment success (Ford et al. 2010). This study confirms many of the previously encountered impacts of different fire return treatments on structural metrics, using high density multiple return LiDAR, a breakthrough technology for forestry application throughout the last decade (Dubayah and Drake 2000). Furthermore, the clear detection of structural differences among the Stoddard plots with different fire regime histories which matched or even further magnified previous results, allows the advantages of the use of fine-scale LiDAR in the evaluation of three-dimensional structural differences to be highlighted.

One of the clear advantages of using LiDAR remote sensing is the ability to detect fine nuances in the mid-structure levels in a woodland, allowing an easier detection of succession changes easily overlooked otherwise. In contrast, obtaining statistically sound data in a field setting for height distribution is, in many cases, time- and cost-prohibitively. Canopy height profiles can be easily constructed from point cloud data, and even further indices or canopy cover for different height categories determined. In the Stoddard Fire Plots, it was clear that the three-dimensional structure of the forest is heavily altered by the frequency of fire. With an increase in fire interval, an increase in shrub presence is noticeable, and a more normalized vertical distribution of vegetation across all heights takes place. Height diversity indices (both the Height Diversity Index and the Height Evenness Index) show similar increases in value with a decrease in fire frequency. Fire suppressed plots have much higher structural diversity, with vegetation evenly occupying all height strata. Annual fires prevent shrub encroachment, both from woody and pine species in this secondary pine forest, which, consequently prevent pine recruitment and "degrade forest resources" (Hermann 1995). Masters et al. (2005) observed that recruitment of loblolly pine will not take place with a fire rotation of ≤ 3 years, while short-leaf pine will be able to survive and recruit with shorter interval burns. Managing secondary old field upland pine forests with a combination of different fire tolerant pine species is complex, and perhaps requires a variable fire frequency regime (Hermann 1995).

Another advantage of using LiDAR data is the ability to detect changes quickly after a new management regime is established; this allows for the appropriate feedback to be promptly incorporated in a responsive management strategy. Additionally, scalability is a significant advantage is using airborne LiDAR for the determination of structural differences. Since LiDAR data are usually collected for large areas (which proves to be much more cost-effective), study areas are not limited to a few plot samples or a specific scale. This is an important advantage, allowing for remotely sensed data to be collected simultaneously and at one cost for a variety of studies and applications, making this dataset even more valuable and cost-effective.

LiDAR-derived data can also be used to provide variables that are commonly collected in the field, such as canopy cover, further reducing the amount of fieldwork required to manage or restore an area. LiDAR- derived canopy cover and diversity structure measurements yielded significant differences among different fire return interval treatments. Canopy cover percentages are significantly greater, especially when the fire interval is increased beyond two years, with canopy means rising from 48-54% to 57-71% in three year fire return interval treatments. Fire suppression or control plot did present the highest canopy covers, but these did not consistently differ significantly from the 3 year fire return plots. To keep the canopy closure at no more than 40%, fire must be frequent in the landscape and occur every 1 to 2 years. Increasing fire intervals to three years will allow the structure to undergo significant alterations, even if the new regime is temporary in nature. Results from this study confirm the 3-year interval, previously highlighted using field-derived data, as the ecological threshold in maintaining the typical open canopy, herbaceous dominated understory of secondary upland pine forest (Masters et al. 1993; Masters et al. 2005).

Both past land use and soil types were examined as potential independent factors that could have coincidently also explained the significant differences in the structural metrics and diversity among plots. The past land use alteration ratio had very poor correlation with the significant structural variables and the dominant soil types were spread throughout all replicates of the same treatment. Fire frequency was the only factor that seemed to clearly explain the structural changes recorded in the Tall Timbers area woodlands.

This study reaffirms the use of LiDAR in the evaluation of different resource management prescriptions (Zimble et al. 2003). The use of active remote sensing tools in forestry management, especially with the potential of identifying small differences in shrub and mid-structure levels at varying spatial scales, can greatly decrease field assessment efforts and allow timely management decisions.

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CHAPTER THREE - PORTABLE SMALL FOOTPRINT LIDAR: VALIDATION AND APPLICATIONS FOR FOREST CANOPY STRUCTURE ESTIMATION

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Abstract

This study uses an affordable ground-based portable LiDAR system to provide an understanding of structural differences between old-growth and secondary-growth Southeastern pine. It provides insight into the strengths and weaknesses in structural determination of portable systems in contrast to airborne LiDAR systems. Portable LiDAR height profiles and derived metrics and indices (e.g. canopy cover, canopy height) are compared among plots with different fire frequency and fire season treatments within secondary forest and old growth plots. The treatments consisted of transitional season fire with four different return intervals: 1-year, 2-year, 3-year fire return interval, and fire suppressed plots. The remaining secondary plots were treated using a 2-year late dormant season fire cycle. The old growth plots were treated using a 2-year growing season fire cycle. Airborne and portable LiDAR derived canopy cover are consistent throughout the plots, with significantly higher canopy cover values found in 3-year and fire suppressed plots. Portable LiDAR height profile and metrics present a

higher sensitivity in capturing subcanopy elements than the airborne system, particularly in dense canopy plots. The 3-dimensional structures of the secondary plots with varying fire return intervals were dramatically different than old-growth plots, where a normal distribution with clear recruitment was visible.

Introduction

Light detection and ranging (LiDAR), irrespective of the type of platform (terrestrial, airborne, or spaceborne), has allowed the quantification of the 3D structure of forest canopies in a cost-effective, rapid, and accurate manner (Van der Zande et al., 2008). Applications of these remotely sensed data range between forest inventory, ecosystem functions - i.e. carbon and water cycling, microclimate regulation- (Roth et al., 2007), and habitat suitability studies (Parker, 1995;Bradbury et al., 1999). Some of the initial challenges and limitations in the use of LiDAR for forest inventory applications have centered on the specialized expertise needed for data processing, the reliability of extracted canopy structural metrics, and the initial hardware cost (Nelson et al., 2003). As more off-the-shelf software products have become available and a large range of validation studies have demonstrated the correspondence of extracted canopy metrics to field data (Lim et al., 2003;Lovell et al., 2003;Clark et al., 2004;Coops et al., 2007), the use of LiDAR, especially the airborne platform systems, has entered the commercial arena.

The variety of available sensors, particularly airborne ones, have made the use of this new technology attractive, but sometimes difficult to understand by users in the forestry community. The type of platform used for these airborne laser sensors is an important factor to take into account, when selecting the most appropriate remote sensing technique for a study. The combination of footprint, return type (discrete versus waveform), and scale of interest (from individual tree to stand level, small to large landscape scale) should all be carefully considered when selecting the appropriate sensor and platform.

Airborne LiDAR sensors are the most commonly available ones today, and discrete return sensors are usually used for forest inventory studies (van Leeuwen and Nieuwenhuis, 2010), particularly when taking the cost-effectiveness at the plot to landscape level scale into account. Full waveform airborne sensors, initially only developed for research purposes by NASA, i.e. the SLICER (Blair et al., 1994;Harding et al., 1994) and LVIS (Blair et al., 1999), are now commercially available for forestry applications as well (Hug et al., 2004;Kirchhof et al., 2008). Well known limitations of airborne LiDAR include the systematic underestimation of the canopy height at both the plot and stand scales (Gaveau and Hill, 2003;Coops et al., 2007), due to the low likelihood that the beam hits the tree tops. Additionally, validating LiDAR tree height with field data can be challenging due to temporal and spatial scale differences of acquisition (Popescu et al., 2002;Zhao et al., 2009;van Leeuwen and Nieuwenhuis, 2010). Finally, the cost of many of the units is another limitation that, in recent years, is slowly disappearing: while the powerful research laser scanners (SLICER and LVIS) have remained at or above the million dollar range, and commercial units, designed for accurate Digital Elevation Model (DEM) creation with costs around still hundreds of thousands of dollars, new cost-effective portable airborne sensors have been in development and testing phases for almost a decade (Nelson et al., 2003).

Another platform of sensors, spaceborne LiDAR, is much more limited, especially for forestry applications. The ICESat satellite has the geoscience laser altimeter system (GLAS) mounted, and this sensor, up to 2009, when turned off, could provide very large-footprint (>60 m) long-term dataset as a full waveform (Nelson, 2008). The limitation of this platform was the large footprint of the current available sensor does not allow detailed forest structure to be extracted, and it even proved to be challenging to estimate accurate tree heights (van Leeuwen and Nieuwenhuis, 2010).

Most of the available terrestrial based laser sensors fit within the terrestrial laser scanning (TLS) category, instruments that emit high spatial density of light beams from a stationary location, rotating or moving around its axis, in order to provide a detailed 3D point cloud dataset (Takeda et al., 2008). The application of TLS systems has focused on the reconstruction of the detailed forest architecture at a small plot or even individual tree scale: providing accurate tree volume or leaf area estimates (Lefsky and McHale, 2008;Strahler et al., 2008), defining plant area density profiles for agricultural and natural lands (Takeda et al., 2008;Van der Zande et al., 2008;Hosoi and Omasa, 2009;Jupp et al., 2009), and evaluating stem and branch morphology (Teobaldelli et al., 2008). The benefits of TLS include the high level detail capacity to map 3D surfaces in a reproducible and unequivocal manner (Lefsky and McHale, 2008;van Leeuwen and Nieuwenhuis, 2010), avoiding the destructive and cost- and time-intensive field methods (Henning and Radtke, 2006). Repeated measures of TLS allow growth and other structural changes to be easily detected (i.e. canopy gaps, shrub encroachment, fuel loading, and disturbance events), which are crucial applications in forestry management.

Compared to airborne sensors, terrestrial laser scanning is limited by the short functional range (van Leeuwen and Nieuwenhuis, 2010), the high cost of the acquisition and processing (Wulder et al., 2008), and the lack of characterization of the upper canopy layers (Hilker et al., 2010;Hosoi et al., 2010). Strengths of any bottom-up sensors, such as TLS or the one presented in this study, a portable ground-based system (Parker et al., 2004), are in the sensitivity to lower canopy levels, usually missed by airborne systems (Hilker et al., 2010;Hosoi et al., 2010;Ni-Meister et al., 2010).

This study further explores the use of an affordable system, first presented by Parker et al. (2004), and modified further for portability and consistency in difficult terrain (forested areas with significant shrub encroachment) in a managed forest setting. The high-speed, commercially purchased laser rangefinder allows the capture of a high sample size, previously a limitation when estimating canopy structure and leaf area densities (Sumida et al., 2009) from ground-based methods. Other strengths of this system are in the retrieval of a higher level detail assessment of lower canopy structure (Hilker et al., 2010), and rapid assessment of forest structure (Parker et al., 2004).

The objective of this study is twofold: 1) to provide a better understanding of the canopy structure metrics and profiles of the portable LiDAR system and how these relate to discrete return airborne LiDAR data and 2) to apply the use of the portable LiDAR system to detecting differences in the 3D canopy structure of different fire managed forest plots.

Materials and Methods

Study Area

This study focuses on the Red Hills area of the northwestern Florida and southwestern Georgia (Figure 22). This region occupies approximately 300,000 ha between Thomasville, Georgia and Tallahassee, Florida and is home to over 230 rare types of plants and animals and over 27 federally listed threatened and endangered species (Masters et al., 2007). The Red Hills area is comprised of a mixture of young and old growth longleaf pine forests, natural and planted loblolly (*Pinus taeda*) and shortleaf (*Pinus echinata*) pine forests primarily in an old field context, mixed hardwood and pine forests, forested and herbaceous wetlands, agricultural fields, and residential/urban land cover types .

Three sites within the Red Hills area were selected for this study, the Tall Timbers Research Station (TTRS), the Pebble Hill Plantation (PB) and Wade Tract at Arcadia

Plantation (WT). The first objective of the study, the comparison of the portable and airborne LiDAR structural results, took place at TTRS, a research forest located on the historic Beadel plantation in north Florida. The second objective, the application of portable LiDAR metrics and profiles to understand the effects of fire management strategies on forest canopy structure, added six additional plots located at the Pebble Hill and Arcadia Plantations, located in Georgia.

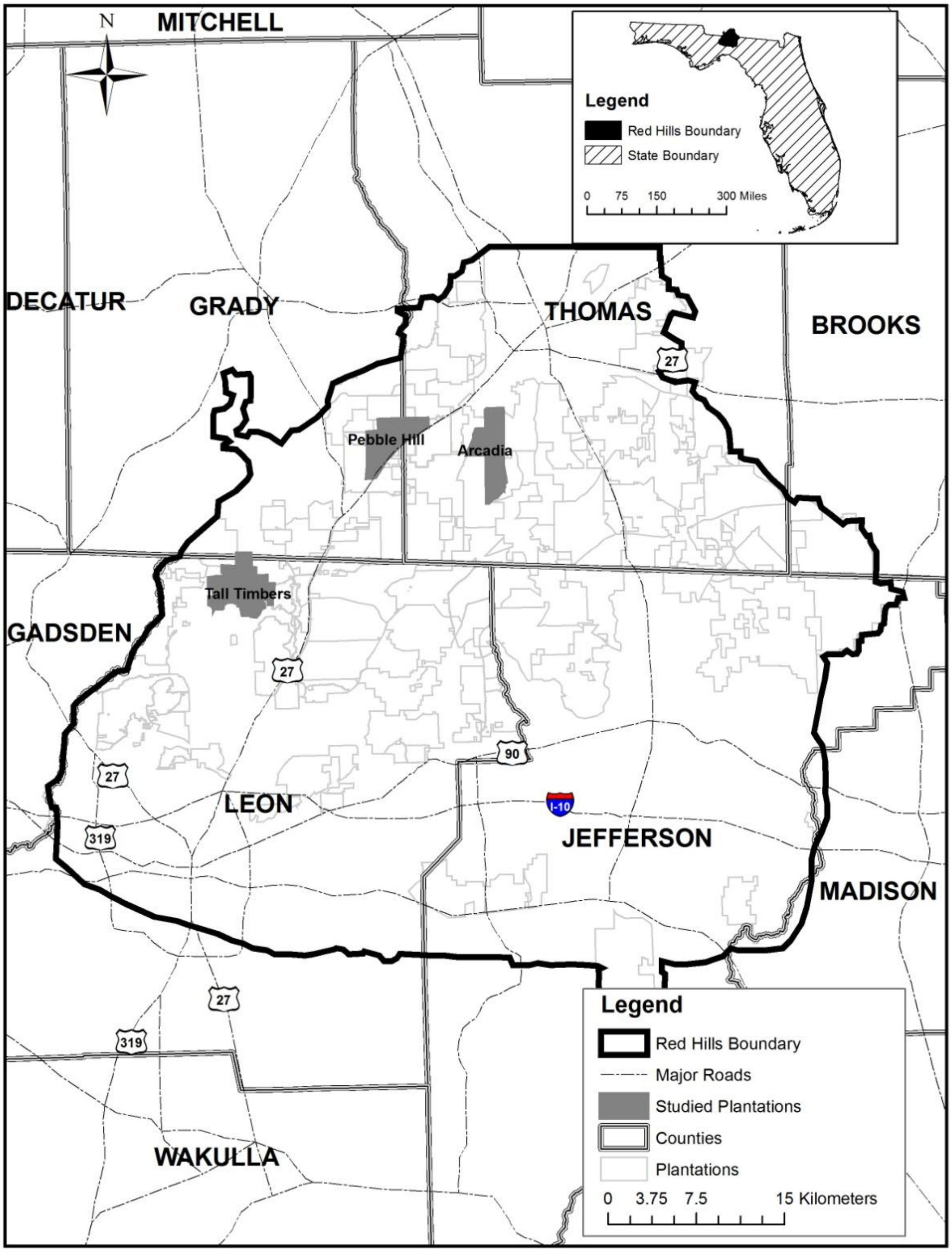

Figure 22. Location of Tall Timbers Research Station within the Red Hills area.

The Tall Timbers Research Station (TTRS) covers 1600 ha within the Red Hills area, and is located just north of Tallahassee, FL. The upland pine ecosystems at TTRS, which, up to 1895 were dominated by pristine longleaf pine savanna uplands, have been highly disturbed by agriculture, and are dominated by a mixed canopy of loblolly pine (*Pinus taeda*), shortleaf (*Pinus echinata*) and longleaf (*Pinus palustris*) (Masters et al., 2005). The groundcover at the study site is dominated by many legumes and composite family members and interspersed with grasses (broomsedge bluestem, *Andropogon virginicus*, primarily), but lacking the wiregrass typical of pristine longleaf pine savanna ecosystems (Hermann, 1995).

The first objective of this study specifically targeted the Stoddard Fire plots located throughout the central upland areas of TTRS (Figure 23). These plots were initially setup in 1959 by Herbert Stoddard, a prominent conservationist in the southeastern US ecosystem (Hermann, 1995). The 12 Stoddard fire plots and an additional three control plots are each 20 by 20 m (0.3 ha) and were strategically placed to represent a variety of soil types (Figure 23). There are replicates (designated A, B, and C) for each of the four fire returns applied: W1, W2, W3, and W4 correspond to the 1-, 2-, 3-, and 4-year fire return interval treatments. The control plots (UA, NB66, and W75B) have been fire suppressed since 1959 except for NB66 which has been fire suppressed since 1967.

All the treated plots were burned using low intensity fires during the transitional season (between the dormant and growing season or March-April) at their dedicated fire rotation for 50 consecutive years. The only treated plots out of rotation for a period of time were the 4-year fire return Stoddard plots (W4 A, B, and C). These latter plots were treated as 2-year fire return interval plots during the 1999-2007 period. Due to the alteration of the treatment rotation of the 4-year fire return plots, these were excluded from the portable LiDAR data collection. A total of 9 Stoddard treatment plots and 3 additional control plots had data collected using both airborne and portable LiDAR sensors.

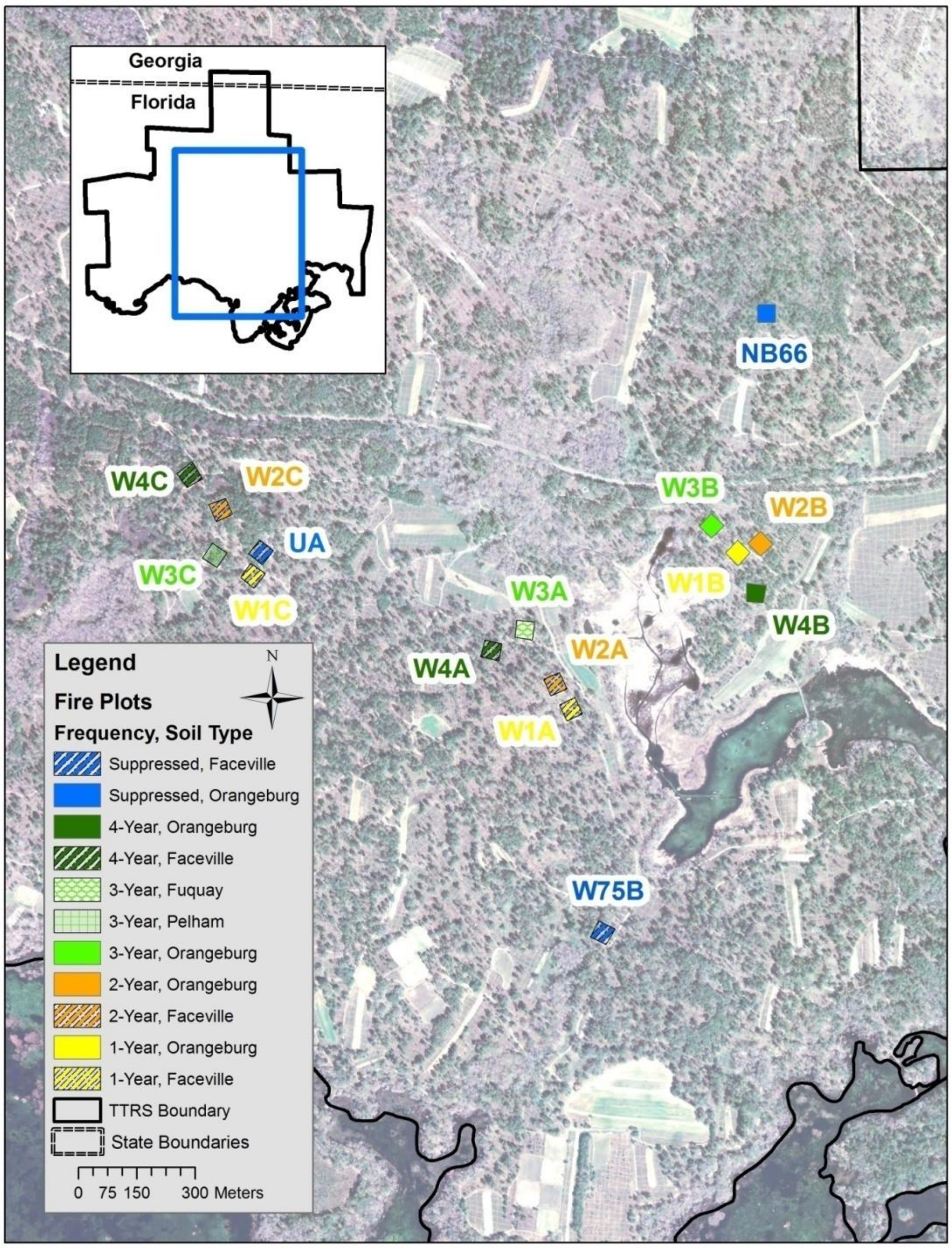

Figure 23. Location of the Stoddard Fire Plots, their Fire Frequency, and Soil Type in TTRS.

For the second objective of the study, six plots similar in size (0.3 ha) to the Stoddard fire plots, were randomly placed throughout Pebble Hill and Wade Tract in Arcadia Plantation (Figure 24). Pebble Hill consists of 1200 ha of secondary growth mixed upland forest located in Thomasville, Georgia. Prior to the Civil War, Pebble Hill was a cotton plantation, and was converted back to Coastal Plain upland forest cover, with patches of plantation, in the early 1900's. Currently, portions of Pebble Hill are opened to the public with an on-site museum, and the upland pine systems are maintained using a 2-year late dormant season fire cycle.

The Wade Tract Preserve is an 85 ha research plot located within the private hunting Arcadia Plantation estate (1260 ha) in Thomasville, Georgia (Figure 24). The Wade Tract is one of the few remaining old-growth longleaf pine stands in southeastern Coastal Plain, and is now managed under a conservation easement by TTRS using a 2-year growing season fire cycle.

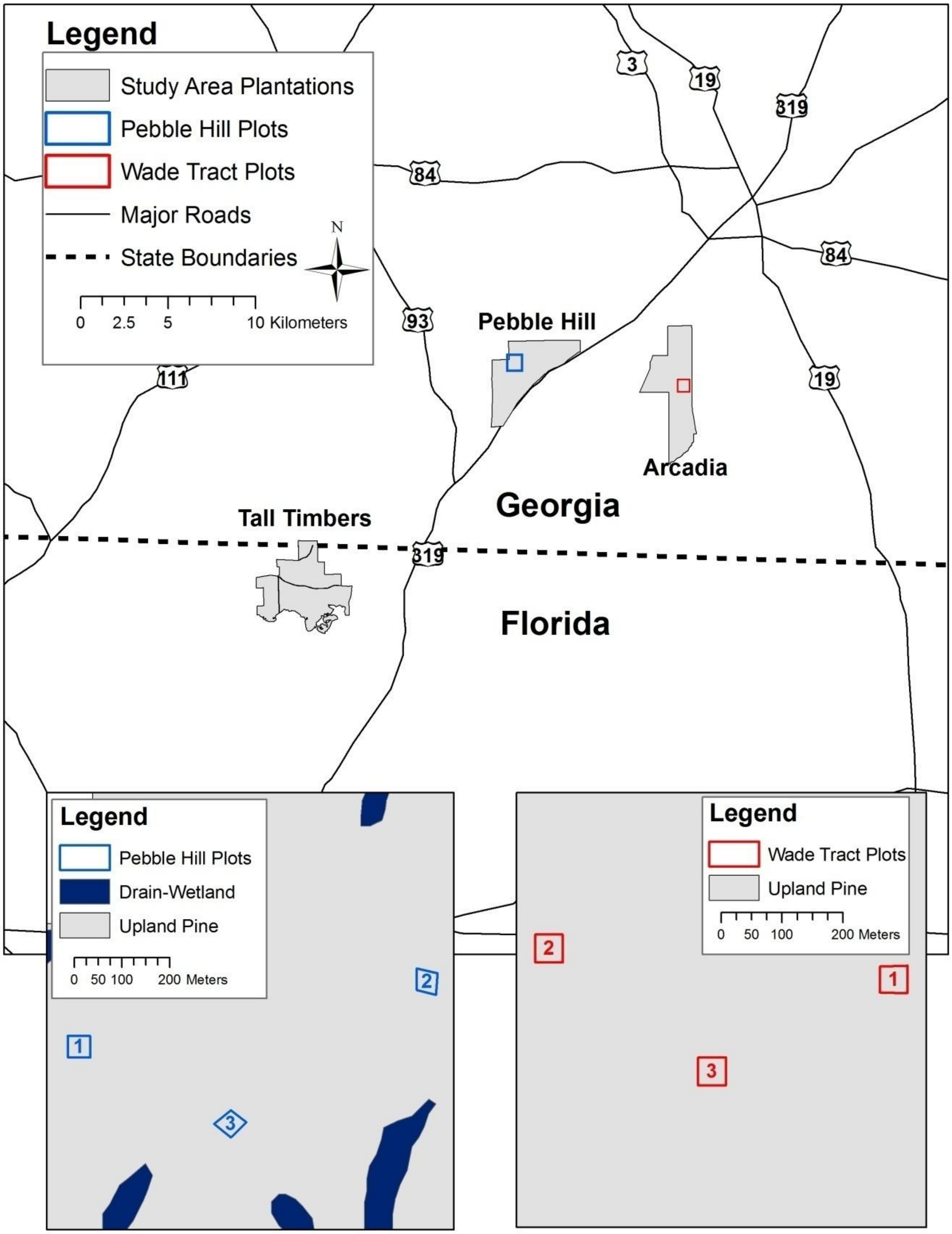

Figure 24. Location of the 2-year Fire Return Plots at Pebble Hill and Wade Tract, Arcadia (GA).

Airborne LiDAR Data

A small footprint multiple return LiDAR (Light Imaging and Ranging) dataset, collected by Merrick & Co using a Leica ALS50 Geosystem was obtained from the Tallahassee-Leon County Geographic Information Systems (TLGIS) Department. This dataset included raw 1.1 format LAS files and was flown in the 2008 transitional season (March 2008) with the goal of creating countywide detailed floodplain mapping. The mean and minimum point spacing of this LiDAR data were 1.55 and 1.19 m, respectively. This dataset covered approximately one third of the Red Hills area (105,000 ha), but excluded the Arcadia and Pebble Hill Plantations.

The obtained point cloud included specified multiple return numbers and class types in accordance with the 1.1 LAS format specifications. The 2008 airborne LiDAR dataset selected for this research study was collected by TLGIS 2 years after the portable LiDAR data collection, and it is the closest available dataset to the portable LiDAR data.

The point cloud data were converted to multipoint files (all, ground points only, and canopy points only), and then interpolated in the 3D Analyst GIS environment to a Digital Elevation Model (DEM) and a Digital Surface Model (DSM) (Zimble et al., 2003). For the DEM, an Inverse Distance Weighted (IDW) Interpolation of ground points only were used, whereas for the DSM all first returns were interpolated in the same manner. After the construction of the DEM using an IDW second degree interpolation of ground returns, the Digital Canopy Height model was extracted from the difference between the

DSM and the DEM. All IDW interpolations performed were second power interpolations with a variable search of up to 12 neighbors and a 1 meter grid output size (instead of a much smaller 0.2 m grid used by (Zimble et al., 2003). Post processing of all the raster products took place to fill most, if not all, empty cells, with nearby interpolated values. The DEM heights were assigned to all point cloud data, allowing the computation of height above ground for every data point.

A personal ESRI ArcGIS geodatabase was created to manage and streamline all the spatial data layers relating to the Stoddard fire treatment plots in one location. The boundaries of the Stoddard field plots were collected using a sub-meter GPS, and a 5 meter buffer surrounding these was applied for airborne LiDAR point cloud data extraction. This buffer provided greater certainty that none of the field data collection was outside of the analyzed LiDAR data.

Portable LiDAR Data

Portable LiDAR data were collected in March-April 2006 for all 18 plots (12 at TTRS, 3 each at PB and WT) using a Riegl LD90-3100 HS eye-safe (laser safety class I) first-return type rangefinder operating at 890 nm and 1 kHz, connected to a lightweight Toughbook and placed in a lightweight backpack homebuilt frame. This is a very similar setup to the one used by Parker et al. (2004), with frame modifications for greater portability (Figure 25). This Riegl rangefinder averages a minimum of five ranges together to give one measurement, and presents “sky hits” (open canopy) as an error, allowing for easy accounting of open canopy returns.

Figure 25. Portable LiDAR unit in the backpack frame.

Since the portable LiDAR system does not collect x and y positional information, evenly spaced transects across all the field plots were predetermined in ArcGIS, and a Trimble GeoXT (submeter) unit was used in conjunction with the portable unit for LiDAR data collection. The data are recorded in a ASCII text file format using a serial data connection, and appropriately labeled for each plot. Since the assumption of constant walking speed is important to be able to assign positional accuracy, the portable LiDAR system was redesigned from the one used by Parker et al. (2004) to include a on/off switch. This allows the data collection to be paused temporarily and resumed when there are difficult field conditions, such as heavy understory cover and impassible ditches.

Field Data Collection of Stoddard Plots

Canopy cover and an annual basal area was collected for all 12 Stoddard fire plots starting in 2004. These plots were sampled on April, August, October, and December 2004, all months of 2005, January-March 2006, and April 2010. For the canopy cover assessment, 8 permanent point locations within each fire plot were established. These permanent plots were located at 10 m intervals on two randomly located lines perpendicular to the fire plot boundary. To avoid bias caused by influences from adjacent treatment units, no sampling took place within 10-m of any edge. Overstory canopy cover was determined using a 9-point grid in a sighting tube with vertical and horizontal levels. Cover was determined at each plot center and the four cardinal points at 2-m and 4-m from each permanent plot location. The yearly basal area assessment was determined by the variable radius plot method. Basal areas of trees/stems with ≥ 5 cm in DBH were quantified with a 10-factor wedge prism at each of the 8 permanent plot locations that were used for collecting canopy cover.

For comparison with the portable LiDAR data, the 2006 collected data were used, since these are synchronous (within 2 months) to the portable LiDAR data collection.

Data Analyses

Airborne LiDAR Data Analysis

For appropriate validation and comparison with portable LiDAR data, x,y,z data points from the airborne LiDAR dataset with height above ground were clipped to the Stoddard fire plots. The variables of interest included canopy cover, canopy height (maximum, minimum, mean, and standard deviation), and two structural diversity indices, the Height Diversity Index(HDI), and the Height Evenness Index (HEI). Both diversity indexes use a modification of the Shannon Diversity Index (H') to calculate Foliage Height Diversity or Structural Diversity (MacArthur and MacArthur, 1961). Definitions and details of how these were calculated from the LiDAR point cloud datasets are included in Table 11. Canopy height and cover indices were extracted using similar methodology described by (Lim et al., 2003) for discrete return LiDAR, with slight modification from the 20X20m window used by Lovell et al (2003) and Coops et al. (2007). For the canopy heights, instead of using a 20X20 m window to obtain the highest canopy point as the maximum height, the entire Stoddard plots, which are only about 40X40m in dimension, were used. Maximum mean height corresponded to the highest LiDAR canopy classified return within the entire plot, and mean canopy height used an average of all canopy returns over 2m, and is expected to underestimate the average field tree heights (Lim et al., 2003). Canopy cover was measured by redefining closed canopy returns as only the ones over 2 m and dividing the total number of these returns in each plot by all discrete returns in the same plot (Table 11). The proportion of canopy returns is a standard canopy cover index (Lim et al., 2003), which, for this study, has been slightly modified to exclude the herbaceous and lower shrub layers.

Table 11. Definitions of LiDAR-Derived Structural Information

Name	**Acronym**	**Units**	**Description**
Canopy Cover	CANCOV	%	(Count of Canopy Returns >2m/Count of All Returns) * 100
Mean Canopy Height	CANAVGHT	m	Average Height of all Canopy Returns (>2m in height)
Maximum Canopy	CANMAXHT	m	Maximum Height of all Canopy Returns (>2m in
Shrub Mean Height	SHAVGHT	m	Average Height of all Shrub Returns, which are defined as Canopy Returns > 0.34m and <2m in height
Shrub Dominance Index	SHINT	N/A	Total Shrub Returns/All Returns
Height Diversity Index	HDI	N/A	The Shannon Diversity Index (H') modified to calculate Foliage Height Diversity or Structural Diversity (MacArthur & MacArthur 1961).
Height Evenness Index or Equitability Height Index	HEI	N/A	Another measure of diversity that takes the total number of height classes into account (MacArthur & MacArthur 1961).

In order to examine the Stoddard plots three-dimensional structure, histograms of the proportion of LiDAR returns per 1 m height interval were constructed. Additionally, the Height Diversity Index (HDI) and corresponding Height Evenness Index (HEI) were calculated (Table 11) using a finer scale interval of 0.5 m intervals. The Height Diversity Index (HDI) was calculated using the standard *Shannon-Height Diversity Index formula*

(H'): $H' = -\sum_{i=1}^{S}(\mathrm{p_i} \ln p_i)$. The Height Evenness Index (HEI) was calculated by using the following formula: $HEI = \frac{HDI}{\ln S}$, where S is the total number of foliage layers.

Portable LiDAR Data Analyses

The portable LiDAR data collected in ASCI text file formats were merged by Stoddard plot into database tables. Pre-processing of these data including assigning open/closed canopy indicators for all returns and adding 1.3 m (the height above ground of the portable LiDAR data collector) to all canopy return heights.

Similar metrics were calculated for the portable LiDAR Stoddard data: canopy cover, canopy height (maximum, minimum, mean, and standard deviation), and two structural diversity indices, HDI and HEI. The canopy cover for the portable LiDAR, included all captured canopy returns (>1.3 m) divided by the total returns (open and canopy returns).The structural indices were calculated using the proportion of returns within every 0.5 m intervals. Histograms, mimicking the ones created with the airborne LiDAR data, were constructed for the portable LIDAR height classes of 1 m, providing a graphical 3-dimensional structural representative of the Stoddard fire plots.

Comparisons and Statistics

To meet the first objective of this study, paired t-tests (or non-parametric alternatives, i.e. Wilcoxon signed rank test) of the extracted metrics using the two methods were implemented. The within-subjects design compares the airborne with portable LiDAR method per Stoddard plot in extracting canopy cover, mean and maximum canopy height, and the diversity indices.

Further analyses to provide an understanding of the correspondence between the airborne and portable LiDAR data collection methods, include the comparison of the return distributions across heights of each plot. Return histograms, pictures, and boxplots representing means and interquartile distributions of heights for both data collection methods were also studied.

The second objective used one-way ANOVAs to highlight the sensitivity of the portable LiDAR in detecting structural differences among secondary and old-growth forest managed plots. The dependent variables examined were canopy cover, mean and maximum canopy heights, height and evenness diversity indices (HDI and EDI). The independent variable or grouping was based on the fire return interval and seasonality: transitional season fire with 1-, 2-, 3- return intervals (Stoddard plots), dormant season 2-year return intervals (Pebble Hill), and 2-year growing season return intervals (Wade Tract). With the exception of the plots at Wade Tract, which are in a remnant of old-growth longleaf pine forest, all other 15 plots are located in secondary old field pine forest ecosystem. Three replicates per treatment type (represented by location of block number A, B, and C at Tall Timbers) were included in the analyses of variance. Post-hoc tests, Tukey Honestly Significantly Different (HSD) tests were performed to determine pairwise significant differences among means of treatment.

In addition to the statistical analyses discerning the impact of a variety of fire treatments on several structural metrics, visual representations (i.e. bar graphs and histograms) were constructed for all metrics of interest with 5 treatment types.

Results

Comparison of Airborne and Portable LiDAR

Canopy cover estimates from the portable LiDAR sensor were 7-23% lower than airborne LiDAR canopy cover estimates in all fire treated Stoddard plots (1-3 year fire return) (Table 11). For the hardwood dominated plots, where fire had been excluded for over 4 decades, portable LiDAR canopy cover estimates were 7 to 18% higher than the corresponding airborne LiDAR results. The mean canopy cover differences between the portable and airborne canopy cover estimates for all the TTRS study plots were not statistically significant using a paired t-test ($p = 0.153$). Portable LiDAR derived canopy cover measurements mimic field collected canopy cover (average of 8 permanent plot locations) more closely than airborne portable LiDAR canopy cover estimates: 8 of the 12 forestry plots have portable LiDAR estimates within 8% of field canopy cover measurements, and none of the plots' estimates are over 20% of the measured field values.

Canopy mean height estimates for the sensor types are statistically different ($p<0.001$) with an overall negative bias for the portable LiDAR when comparing to the airborne LiDAR (Table 12, Figure 26). The mean portable LiDAR return height for all treatment and control plots at TTRS ranges between 0.8 and 6.8 m lower than the airborne LiDAR mean returns. The only treatment plot with higher portable LiDAR mean return height - by 0.6 m- than airborne mean height is W2A, a 2 year fire return interval treatment plot. The average underestimation of portable LiDAR mean returns, in comparison with the airborne sensor, is 3.12 m (Figure 26). The difference between sensors is most visible in plots with canopy covers greater than 60%, the suppressed or control plots, where portable mean heights were 5-6 m lower than the airborne counterparts (Table 12).

In contrast with the average canopy height, the maximum return height per plot (Table 11) yielded higher values, when using the portable LiDAR sensor (Table 12, Figure 27). The overall statistically significant higher maximum plot heights using portable LiDAR ($p=0.0024$), would be negligible (<1.5 m average difference) if the outlier treatment plot W3B would be removed. This 3 year fire return treatment plot presented a portable maximum LiDAR height of 45.1 m, 11.2 m higher than the airborne derived maximum canopy height (33.9 m). The differentials of all other plots between both sensors were within 0.2 to 3.1 m range, with consistently higher values detected by the portable method.

Table 12. Portable and Airborne LiDAR Metrics for the Stoddard Fire Plots at Tall Timbers Research Station.

Plot Name	Fire Frequency	Portable Cover (%)	Airborne Cover (%)	Δ Cover (Port-Air)	Portable Mean Ht (m)	Airborne Mean Ht (m)	Δ Mean Ht (Port-Air)	Portable Max Ht (m)	Airborne Max Ht (m)	Δ Max Ht (Port-Air)	Portable HDI	Airborne HDI	Δ HDI (Port-Air)
W1A[1]	**1**	**17.99**	**35.73**	**-17.74**	**11.91**	**12.73**	**-0.83**	**29.77**	**29.25**	**0.52**	**3.85**	**1.99**	**1.86**
W1B[1]	**1**	**16.20**	**39.23**	**-23.03**	**13.21**	**15.79**	**-2.58**	**32.12**	**31.96**	**0.16**	**3.90**	**2.18**	**1.73**
W1C[1]	**1**	**29.53**	**44.73**	**-15.20**	**17.67**	**19.22**	**-1.55**	**36.87**	**35.07**	**1.80**	**4.09**	**2.46**	**1.63**
W2A	2	32.06	45.87	-13.81	13.51	12.93	0.58	33.37	30.75	2.62	3.97	2.50	1.47
W2B	2	36.54	44.34	-7.80	13.98	16.92	-2.95	27.94	27.70	0.24	3.62	2.24	1.38
W2C	2	44.25	54.76	-10.51	14.35	18.63	-4.28	29.41	29.84	-0.43	3.80	2.71	1.09
W3A	3	61.74	60.22	1.52	13.74	14.51	-0.77	35.15	32.03	3.12	3.85	3.01	0.84
W3B	3	42.73	55.08	-12.35	14.43	17.66	-3.23	45.14	33.95	11.18	4.06	2.93	1.13
W3C	3	47.47	55.85	-8.38	13.27	18.00	-4.74	36.13	34.21	1.92	3.97	2.97	1.01
NB66	Suppressed	80.98	62.63	18.35	12.03	18.80	-6.77	34.12	30.99	3.12	3.82	3.49	0.33
UA	Suppressed	78.09	71.48	6.61	12.36	17.56	-5.20	32.54	31.68	0.86	3.90	3.50	0.40
W75B	Suppressed	83.64	70.02	13.62	13.71	18.90	-5.20	38.14	35.58	2.56	4.05	3.07	0.98
Plot Mean		**47.60**	**53.33**	**-5.73**	**13.68**	**16.80**	**-3.12**	**34.22**	**31.92**	**2.31**	**3.91**	**2.75**	**1.15**

[1] Plots were burned 10 days prior to portable LiDAR data collection.

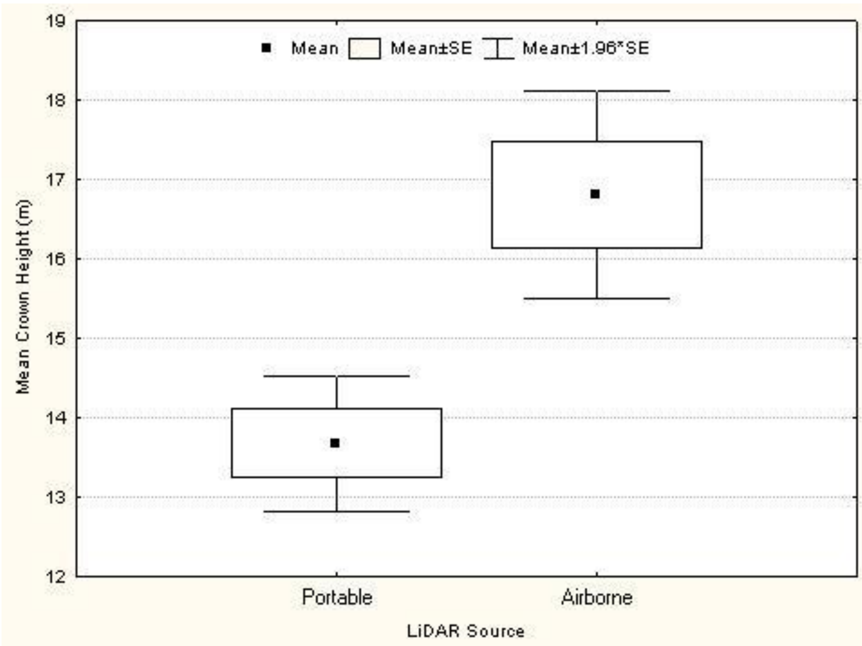

Figure 26. Mean Canopy Height of the Stoddard Fire Plots using Portable and Airborne LiDAR (TTRS, FL).

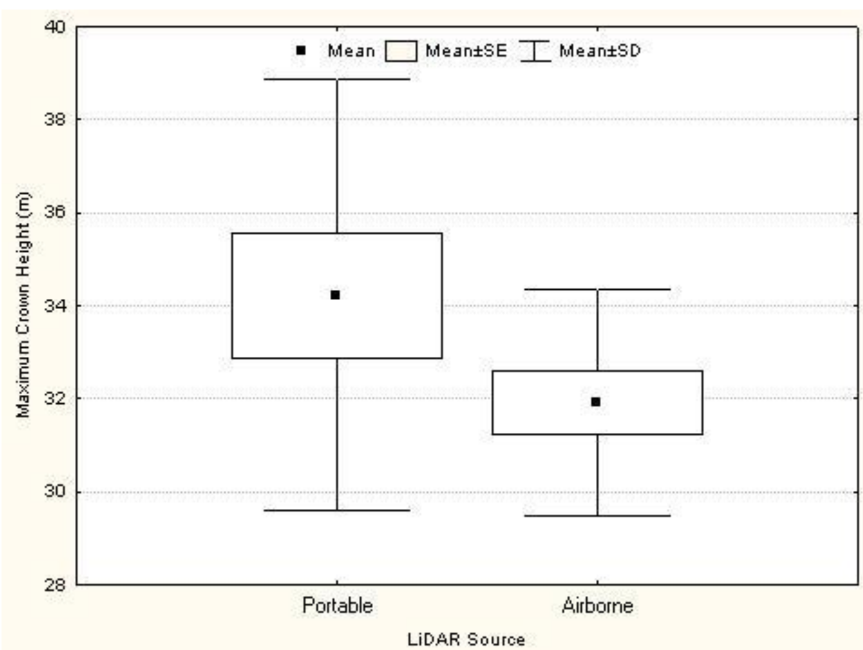

Figure 27. Maximum Canopy Height of the Stoddard Fire Plots using Portable and Airborne LiDAR (TTRS, FL).

Structural diversity measures (HDI and HEI) are consistently higher using the portable system (Table 11), with statistically significant (p<0.001) higher mean HDI (3.91) than with the airborne (2.75) (Figure 28). The mean HDI was 1.15 higher, when derived from portable LiDAR returns than when stemming from airborne LiDAR returns, with differences ranging between 0.3 and 1.9 (Table 12). Structural diversity differences between both sensors are more obvious in higher fire return interval plots (with canopy covers below 50%) than in denser canopy plots.

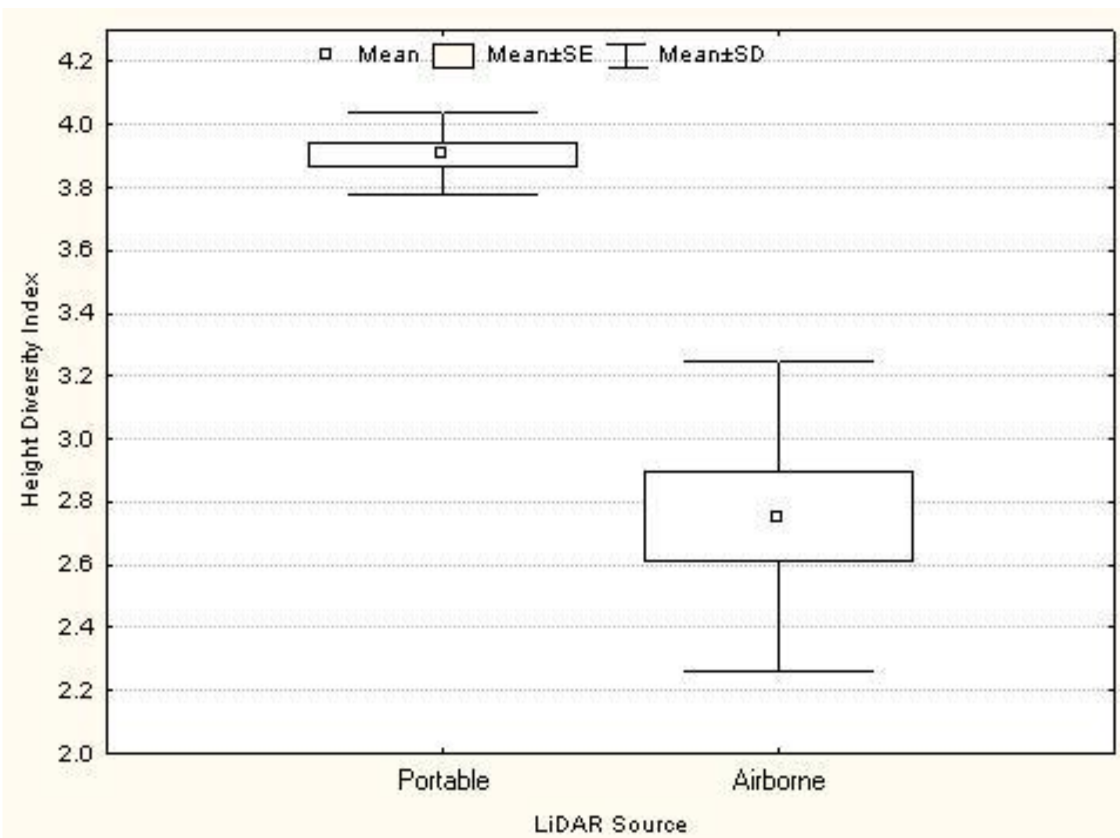

Figure 28. Height Diversity Index (HDI) of the Stoddard Fire Plots using Portable and Airborne LiDAR (TTRS, FL).

Extraction of structural metrics using LiDAR sensors is only a small part of the strength of active remote sensing tools for forestry applications. Understanding the impact of the use of airborne and portable LiDAR sensors in capturing the three dimensional forest structure is even more important for future applications of these sensors. Comparisons of the LiDAR vertical profiles, the proportional distribution of LiDAR returns by height class, between both sensors yielded some consistent differences. Portable LiDAR profiles, independent of treatment type, provided a higher proportion of high shrub/lower subcanopy vegetation (3-7 m) representation than airborne LiDAR profiles (Figure 29 to Figure 32). Conversely, the airborne LiDAR profiles provided, in most cases, a more detailed and substantial representation of the highest canopy layers (>27 m) (Figure 29 to Figure 32).

Portable and airborne LiDAR profiles from the most frequently burned Stoddard plots (1-year fire return intervals) have a similar bimodal type distribution: both histograms present two peak areas of percentage returns, one in the high shrub/small tree height and the other at the mid canopy height (Figure 29). However, both peaks appear at slightly lower heights using the portable LiDAR (3-7 m and 19-26 m; Figure 29a) in comparison to the airborne LiDAR profile (5-12 m and 23-27 m; Figure 29b).

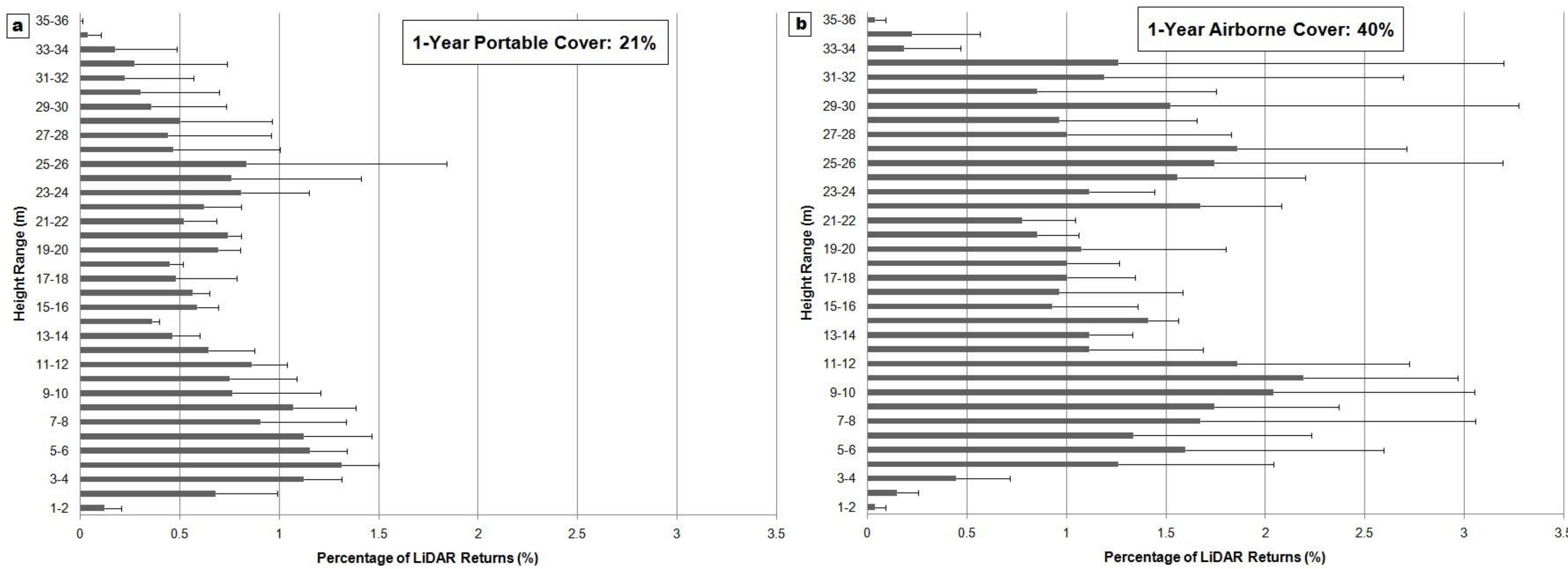

Figure 29. Vertical Distribution of Portable (a) and Airborne (b) LiDAR returns for the One-Year Fire Return Treatment Stoddard Plots (TTRS, FL).

The profiles of the two-year return treatment plots have a distinctly unimodal distribution of LiDAR returns for both the portable and airborne sensors (Figure 30). Once again, while the peak of the returns is lower for the portable LiDAR data (9-18 m) (Figure 30a), the distribution appears skewed to a higher vegetation layer in the airborne LiDAR profile (16-25 m) (Figure 30b).

With higher canopy cover plots, either the least frequently burned treatments (3-year fire return intervals) or the control plots, the overall profile of the LiDAR returns starts becoming distinct between the two sensors. For the 3-year fire return treatments, the portable LiDAR profile indicates the highest presence of vegetation between 4-11 m and 14-21 m (Figure 31a), whereas the airborne LiDAR profile mimics a normal curve with peak vegetation between 11-24 m (Figure 31b). The most obvious differences between the three-dimensional forest structure captured by both sensors are detected in the fire suppressed plots: while the portable LiDAR presents an extreme bottom-heavy distribution with most canopy returns between 2-20 m in height (Figure 32a), the airborne LiDAR profile present a closer to a normal distribution, where most returns are in the 13-29 m range (Figure 32b).

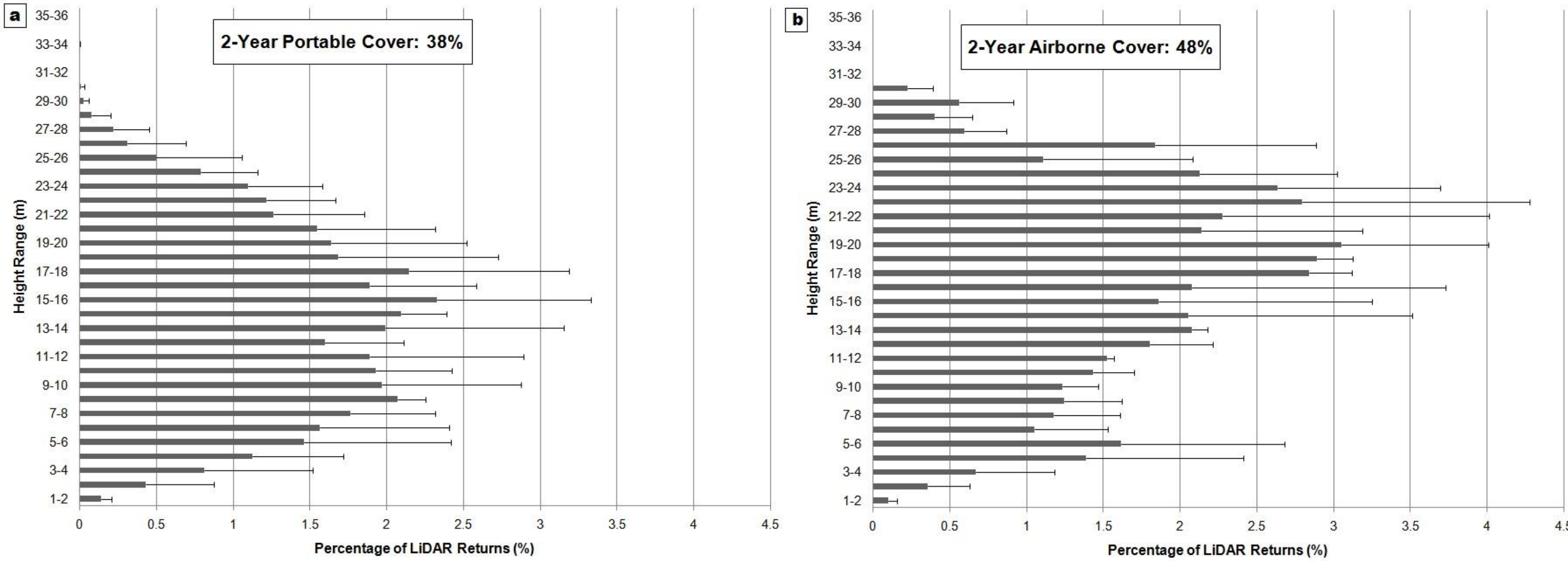

Figure 30. Vertical Distribution of Portable (a) and Airborne (b) LiDAR returns for the Two-Year Fire Return Treatment Stoddard Plots (TTRS, FL).

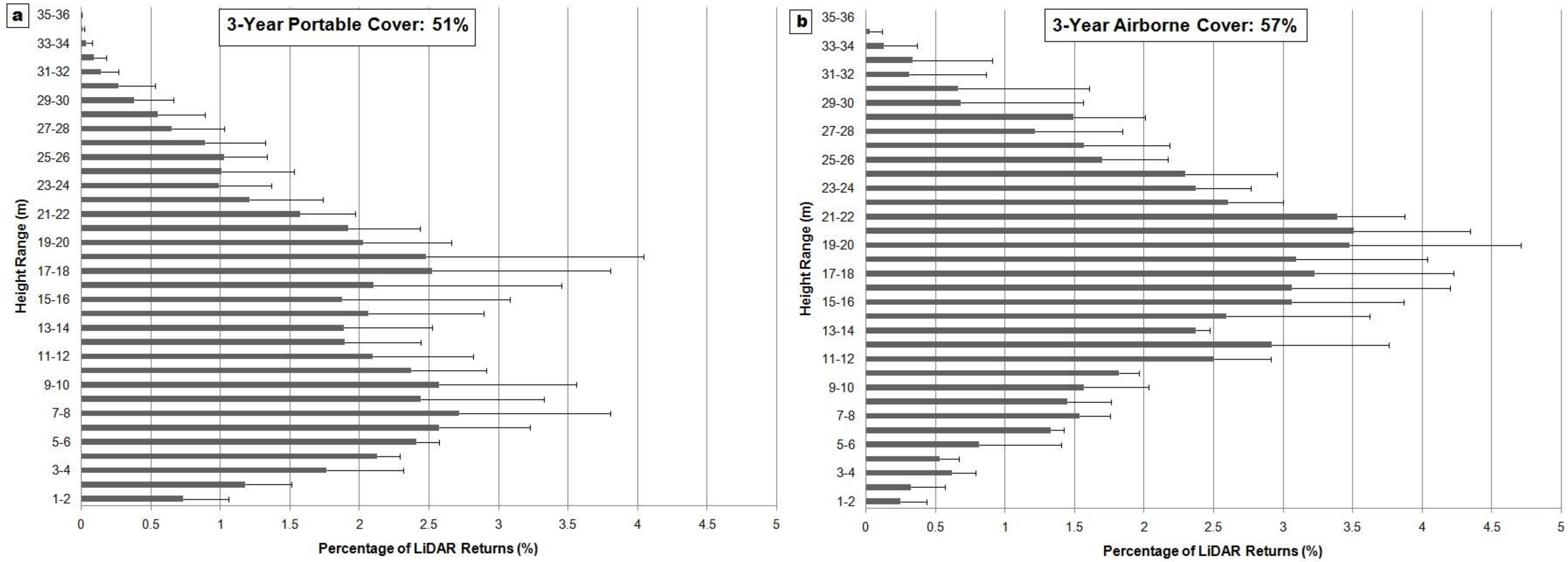

Figure 31. Vertical Distribution of Portable (a) and Airborne (b) LiDAR returns for the Three-Year Fire Return Treatment Stoddard Plots (TTRS, FL).

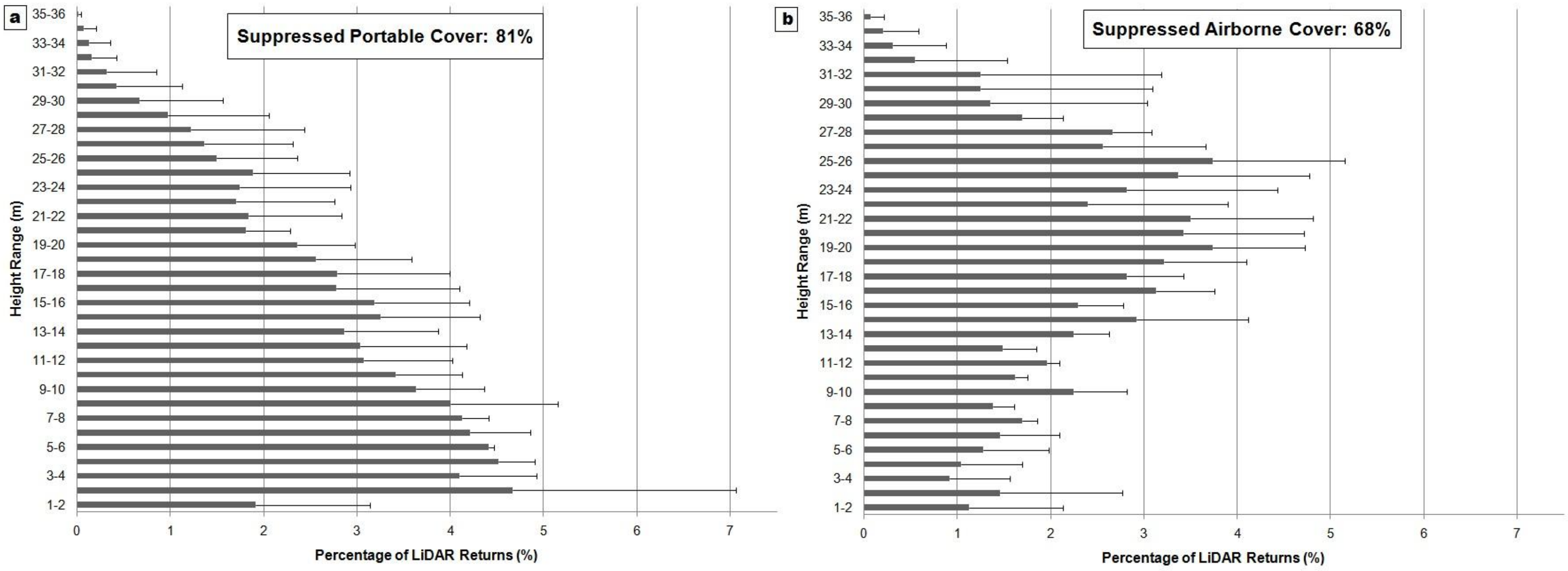

Figure 32. Vertical Distribution of Portable (a) and Airborne (b) LiDAR returns for the Suppressed Fire Treatment Plots (TTRS, FL).

Portable LiDAR and Fire Management

The assembled portable LiDAR sensor was able to detect statistically significant differences (ANOVA p-value < 0.001) in canopy cover across differently managed forest plots within the Red Hills area (Table 13 and Figure 33).

Other extracted canopy height variables (mean, median, maximum canopy heights) did vary across the fire management regimes and forest types (secondary versus old-growth), but these were not statistically significant across treatments (Table 13).

Table 13. Portable LiDAR Metrics for the Stoddard Fire Plots (TTRS), Wade Tract (Arcadia) and Pebble Hill Plantation managed plots.

Plot Name	Area	Fire Frequency	Forest Type	Fire Season	Canopy Cover (%)	Mean Height (m)	Standard Dev. (m)	Median Height (m)	Max Height (m)	HDI	HEI
W1A	Tall Timbers	1	Secondary	Transition	17.99	11.91	7.17	10.66	29.77	3.85	0.95
W1B	Tall Timbers	1	Secondary	Transition	16.20	13.21	8.14	11.52	32.12	3.90	0.95
W1C	Tall Timbers	1	Secondary	Transition	29.53	17.67	9.37	18.06	36.87	4.09	0.96
W2A	Tall Timbers	2	Secondary	Transition	32.06	13.51	7.20	12.70	33.37	3.97	0.96
W2B	Tall Timbers	2	Secondary	Transition	36.54	13.98	4.80	13.58	27.94	3.62	0.91
W2C	Tall Timbers	2	Secondary	Transition	44.25	14.35	6.16	15.54	29.41	3.80	0.94
W3A	Tall Timbers	3	Secondary	Transition	61.74	13.74	6.11	14.07	35.15	3.85	0.92
W3B	Tall Timbers	3	Secondary	Transition	42.73	14.43	8.22	13.93	45.14	4.06	0.94
W3C	Tall Timbers	3	Secondary	Transition	47.47	13.27	7.58	11.50	36.13	3.97	0.92
NB66	Tall Timbers	Suppress	Secondary	Transition	80.98	12.03	6.03	11.51	34.12	3.82	0.91
UA	Tall Timbers	Suppress	Secondary	Transition	78.09	12.36	8.13	10.36	32.54	3.90	0.94
W75B	Tall Timbers	Suppress	Secondary	Transition	83.64	13.71	8.68	12.21	38.14	4.05	0.94
ARC1	Wade Tract	2	Old-growth	Growing	19.50	17.31	7.91	18.88	32.63	3.94	0.95
ARC2	Wade Tract	2	Old-growth	Growing	22.59	17.17	4.37	17.83	29.14	3.53	0.89
ARC3	Wade Tract	2	Old-growth	Growing	24.08	21.20	5.68	21.29	33.00	3.78	0.92
PEBHL1	Pebble Hill	2	Secondary	Dormant	19.19	18.69	4.72	19.43	28.47	3.49	0.91
PEBHL2	Pebble Hill	2	Secondary	Dormant	14.73	8.20	2.13	8.23	15.46	2.80	0.84
PEBHL3	Pebble Hill	2	Secondary	Dormant	22.54	19.06	4.52	19.74	30.20	3.53	0.89

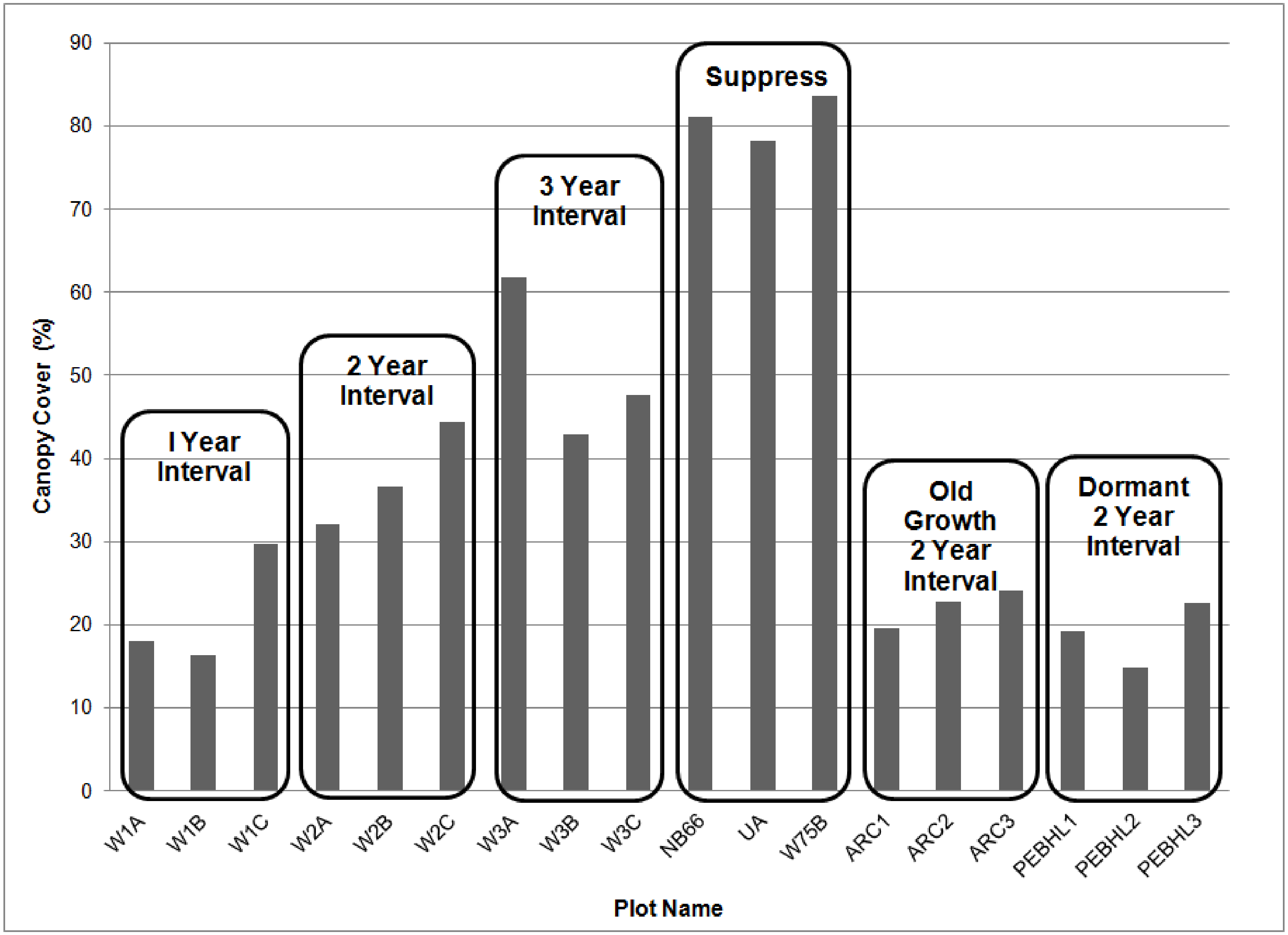

Figure 33. Portable LiDAR Derived Canopy Cover for all forest plots: 12 secondary forest with transitional varying fire return intervals (W1A-W75B), three old-growth forest plots with 2-yr fire regime (ARC1-ARC3), and three secondary forest with a dormant 2-yr fire regime (PEBHL1-3).

Plot canopy cover increases significantly with an increase in fire return interval at the secondary forest locations (TTRS). The mean canopy cover detected by the portable system is as low as 21% for one-year fire return treatment, but increases quickly to 38% and 51% for 2- and 3-year fire return treatments, respectively (Figure 33). Cover differences between 1- and 2-year treatments are not statistically significant, but differences between these two treatments and the 3-year fire return treatment are significantly lower (Table 14). Secondary forest suppressed plots have canopy cover as high as 84% (W75B), with an average control canopy cover of 81%, according to the portable LiDAR data. Fire suppressed plots have statistically significant higher canopy cover than any of the other treated plots (Table 14). The canopy cover means of both the old-growth longleaf pine (*Pinus palustris*) plots and the secondary dormant season treated forest plots, are as low as the mean from the most frequently burned plots at Tall Timbers (22% and 19% for the Arcadia and Pebble Hill plots, respectively). Even though the 2-year Stoddard plots (TTRS) have the same fire return interval as the other two site locations, the resulting plot canopy cover values are almost twice (38%) as high as the ones measured at Arcadia and Pebble Hill (Figure 33). These differences, however, due to the large variability between individual plot covers, are not statistically significant (Table 14). Potential reasons for the observed differences in canopy cover could be linked to historical land use differences, and seasonality of the fire treatment at all three locations.

Mean canopy height, as defined by the use of the portable LiDAR (Table 11), was consistent across most secondary forest treatments, both at Tall Timbers and Pebble

Hill (Table 13): mean return heights varied between 13.9 and 15.3 m, with Pebble Hill demonstrating the greatest variation between same treatment plots (8.2 to 19.1 m heights). The old-growth plots, however, did present much higher mean canopy heights (18.6 m) than all remaining treatments, with plots ranging from 17.2 to 21 m in height (Table 13).

No statistical significant difference among treatments was detected in any of the statistical analyses performed for mean canopy heights. Maximum canopy heights did present some variations between treatment types, yet, the within treatment variation of these heights was higher. Maximum canopy heights were lower in the most frequently burned plots, independently of the type of forest of seasonality, with heights in the 30.2 to 32.9 m range (Table 13). The secondary forest plots with 3-year or suppressed fire regime presented the highest canopy height values, with 38.8 and 34.9 m, respectively. One of the 3-year Stoddard fire plot, W3B, did present one exceptionally high tree (>45 m), which did skew the average of the 3-year fire return treatment from 35.6 to 38.8 m. This skewed maximum canopy height average was captured by the Tukey test as a statistically significant difference when compared to the slightly lower maximum heights at dormant 2-year fire return interval plots (Table 14). The maximum canopy height at one of the three Pebble Hill plots, PEBHL2, was negatively skewed due to the large planted pine to enhance recruitment in that specific area.

Table 14. Post-hoc Tukey HSD results for the structural variables derived from the portable LiDAR dataset among fire treatments.

Treatment Type Location	*Canopy Cover*						*Mean Canopy Height*					
	1-Year	2-Year	3-Year	Suppression	2-Year Old-growth	2-Year Dormant	1-Year	2-Year	3-Year	Suppression	2-Year Old-growth	2-Year Dormant
1-Year		0.052	**0.001**	**0.000**	1.000	0.996		1.000	1.000	0.986	0.522	0.998
2-Year	0.052		0.157	**0.000**	0.068	**0.023**	1.000		1.000	0.995	0.453	0.992
3-Year	**0.001**	0.157		**0.001**	**0.001**	**0.000**	1.000	1.000		0.997	0.424	0.988
Suppression	**0.000**	**0.000**	**0.001**		**0.000**	**0.000**	0.986	0.995	0.997		0.231	0.883
2-Year Old-growth	1.000	0.068	**0.001**	**0.000**		0.983	0.522	0.453	0.424	0.231		0.766
2-Year Dormant	0.996	**0.023**	**0.000**	**0.000**	0.983		0.998	0.992	0.988	0.883	0.766	

Treatment Type Location	*Maximum Canopy Height*						*Height Diversity Index (HDI)*					
	1-Year	2-Year	3-Year	Suppression	2-Year Old-growth	2-Year Dormant	1-Year	2-Year	3-Year	Suppression	2-Year Old-growth	2-Year Dormant
1-Year TTRS		0.977	0.640	0.994	0.999	0.318		0.949	1.000	1.000	0.860	**0.023**
2-Year TTRS	0.977		0.280	0.810	0.999	0.693	0.949		0.931	0.975	1.000	0.097
3-Year TTRS	0.640	0.280		0.902	0.443	**0.027**	1.000	0.931		1.000	0.828	**0.020**
Suppression TTRS	0.994	0.810	0.902		0.943	0.146	1.000	0.975	1.000		0.911	**0.029**
2-Year Old-growth	0.999	0.999	0.443	0.943		0.491	0.860	1.000	0.828	0.911		0.149
2-Year Dormant	0.318	0.693	**0.027**	0.146	0.491		**0.023**	0.097	**0.020**	**0.029**	0.149	

Treatment Type Location	*Evenness Height Index (EHI)*					
	1-Year	2-Year	3-Year	Suppression	2-Year Old-growth	2-Year Dormant
1-Year		0.976	0.703	0.884	0.562	**0.019**
2-Year	0.976		0.975	0.999	0.918	0.064
3-Year	0.703	0.975		0.999	1.000	0.204
Suppression	0.884	0.999	0.999		0.987	0.115
2-Year Old-growth	0.562	0.918	1.000	0.987		0.291
2-Year Dormant	**0.019**	0.064	0.204	0.115	0.291	

Bolded values and shaded cells in gray are signficant at α=0.05

Finally, both diversity indices - the HDI and HEI - are very consistent across all treatment types, and no overall statistically significant difference was detected for either of these. The Height Diversity Index (HDI) ranged between 3.60 and 3.96, with the secondary forest plots at Tall Timbers having a slightly higher values (greater diversity) than the Arcadia and Pebble Hill plots (Table 13). The relatively even-aged PEBHL2 plot, caused the below average height diversity values at the dormant 2-year fire return treatments to be detected as statistically significant from most other treatments (Table 14). The Height Evenness Index, which accounts for the total number of height classes used in the calculation of the HDI, presented even less variation across all treatment and forest types (0.91 to 0.95).

The portable LiDAR distribution of returns clearly shows dramatic differences in the overall structure of the forest plots treated with varying fire return intervals and/or fire seasonality. Both of the most frequently burned Stoddard treatments located at Tall Timbers (1- and 2-year fire return interval treatments), a secondary forest, have a dramatically different vegetation distribution than the Pebble Hill and Arcadia forest plots, both burned with the same or similar frequency (Figure 34). The Tall Timbers plots burned annually during the transition season present a bimodal distribution of returns, with a peak located in the high shrub/small tree height (3-11 m), and the other in the top canopy height (20-26 m) (Figure 34a). The 2-year fire treatment at Tall Timbers no longer presents this distribution, but is closer to a normal distribution, with the majority of the vegetation returns located in the 7-21 m bulk canopy height (Figure 34b). In contrast to the plots at TTRS, the Pebble Hill (secondary forest with dormant season 2-year fires) and Wade Tract (old-growth forest with growing 2-year fires) have very similar distributions. Both of these (Figure 34c-d), present a skewed normal distribution, with larger proportion of returns in the higher canopy heights (12-29 m), but also a visible contribution of new recruitment with heights between 2 and 8 m.

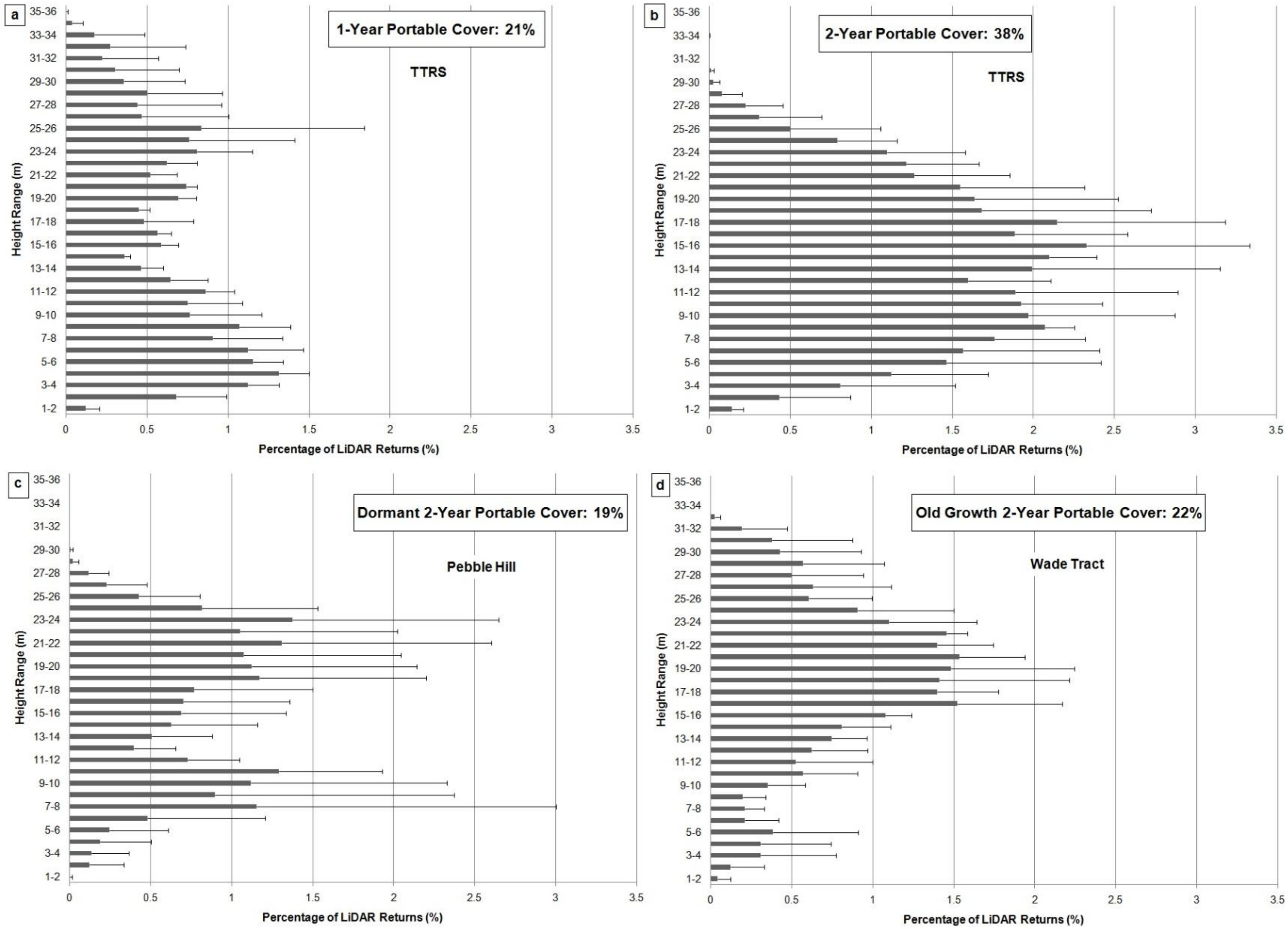

Figure 34. Vertical Distribution of Portable LiDAR returns for Treatment Plots in the Red Hills Area: a) secondary forest burned in the transitional season with 1 year fire return interval and b) two year fire return interval c) secondary forest burned in the dormant season with a 2-year fire return interval d) old growth plot burned in growing season.

Discussion

Strengths and Limitations of Airborne and Portable Sensors

Structural plot metrics obtained from airborne and portable LiDAR systems presented some similarities (i.e. canopy cover), but distinct differences appeared when measuring canopy heights (maximum and mean heights) using these different methods. Both the top-down (airborne) and bottom-up (ground) systems were able to provide gap detection and canopy cover estimation at the plot level. The portable system, when compared to the airborne LiDAR sensor, provides an underestimation of canopy cover in open forest systems (<50% canopy cover), but is more sensitive in detection of cover in hardwood woodland plots (>60% canopy cover). The strength of the bottom-up system, with higher sensitivity in detecting lower canopy levels (Welles and Cohen, 1996;Parker et al., 2004;Strahler et al., 2008;Van der Zande et al., 2008;Hilker et al., 2010), which are missed by the airborne systems, explained the trend in the canopy cover data. The hardwood dominated plots contained dense subcanopy and shrub elements, underrepresented in the airborne LiDAR return data.

Plot mean height was significantly lower (by a mean of 3.12 m) when using the ground-based LiDAR, since this system included more lower canopy returns, which is considered to be a blind region for the airborne systems (Hosoi et al., 2010). Maximum heights were statistically higher when captured using the portable system; however, the differences between both methods would have been minimal if one plot outlier (W3B) had been removed from the dataset. The impact of missing a tree apex by the airborne

LiDAR highlights a common weakness in these systems (Gaveau and Hill, 2003;Coops et al., 2007), especially with airborne data point-spacing of 1 m or greater. The fine-grained data collection of the portable LiDAR system (thousands of returns per meter) would eliminate, in large part, missing a tree apex.

Both sensors provided a detailed plot-level 3D structure of the forest, with differences in these profiles being minimal in open canopy setting. The sensitivity of the portable LiDAR in capturing lower subcanopy layers, while becoming blind to upper canopy elements (Hilker et al., 2010;Hosoi et al., 2010) becomes obvious in denser conditions (>60% cover). Portable LiDAR, even though unable to detect data below the collection height (1.3 m, in this case), is still a powerful tool in detecting establishment of hardwood shrub or small tree species in open pine forests.

The ecological implication of being unable to detect shrub level data (<1.3 m) with this portable system is especially relevant in habitat suitability modeling of species of management and conservation concern. Many pine-grassland obligate species, such as Prairie Warbler (*Dendroica discolor*), Indigo Bunting (*Passerina cyanea*), Red-headed Woodpecker (*Melanerpes erythrocephalus*), and Bachman's Sparrow (*Aimophila aestivalis*), are negatively associated with midstory canopy and positively associated with dense understory (Masters et al., 2002). In fact, for many wildlife species, being able to describe the understory structure is an important factor in predicting habitat suitability (Müller et al., 2009). Specific species of management concern in the southeastern U.S., i.e. Northern Bobwhite (*Colinus virginianus*), is currently managed by the maintenance of permanent woody cover < 2 m in height (Cram et al., 2002;Masters et al., 2006). Without access to this understory canopy layer, suitability models for many species would be incomplete, and monitoring or implementation of management plans could not be guided.

However, for species directly impacted by canopy cover, the portable LiDAR system would be able to provide clear guidance: canopy cover differences could be clearly detected among fire treatments and forest types. Furthermore, it provided vegetation height profiles that indicate the impact of both fire return and season in the canopy structure. Plots managed with fire returns of 2-years had significantly different profiles, depending on the seasonality of the fire treatment (dormant, transition or growing season) and/or the historical context of the forest (i.e. secondary versus old-growth forest). A distinct advantage of using portable LiDAR was the clear detection of recruitment, which provides invaluable information for land managers. Another important application of LiDAR would be in the detection and monitoring of structural complexity (above 1.3 m) and canopy closure, which impact the small mammal community, in particular habitat specialists such as the harvest mouse (*Reithrodontomys nutalli*) and hispid cotton rat (*Sigmodon hispidus*) (Masters et al., 2002).

Recommendations and Future Applications

The evaluation of a portable ground-based system is an expansion of the Parker et al. (2004) study and provides further insight into the value of an affordable and rapid assessment system for forestry applications. The strengths of this portable unit are in its cost, ease of use in the field and analysis, and high sensitivity to lower canopy elements. Canopy cover metrics are consistent with airborne LiDAR metrics, with higher detection of canopy closure in heavily hardwood-dominated plots. This system provides a repeatable method for structural change detection through time, without expending significant additional costs, unlike airborne LiDAR data acquisition.

Some elements of this system could be further refined to reduce its limitations. One of the most important components that would increase the usability of the system would be the addition of a GPS tagging throughout the data collection. This would allow a 3D data collection to occur, and point cloud datasets to be constructed. Geotagging could occur at certain time intervals, and be provided by an external submeter GPS data collector. Having geotagged height information would reduce the data preparation time of creating transects and allow detailed profiling of subplot elements to occur.

Another weakness of the ground-based system was the exclusion of the herbaceous and lower shrub-level structure, which, in some habitat suitability modeling and monitoring, are of high interest. Shrub encroachment and initial recruitment are two elements that land managers would like to have immediate feedback on without extensive fieldwork. It would be interesting to explore combining a bottom-up with a top-down approach of this same system; this could only be properly combined with appropriate geotagging. Furthermore, airborne LiDAR systems have limitations in detecting lower canopy structure which could be minimized by the fusion of data derived from bottom-up sensors, especially if these were inexpensive. The idea of fusing airborne and portable ground-based LiDAR systems to reduce blind spots has been just recently independently suggested by Hosoi et al. (2010).

Future work should focus of providing synchronous airborne and portable LiDAR data collection to eliminate any other potential factors in canopy structure changes detected between both sensors. Repeated analyses of the same plot through time, maintaining seasonality and treatment, would allow an understanding of the consistency and repeatability of this system in structural determination. Finally, the future of active remote sensing techniques for natural resource management hinges on data fusion, specifically bottom-up and top-down sensors, to eliminate weaknesses and biases of either approaches. A focus on the methodology of LiDAR fusion and its application to a variety of ecosystems is warranted.

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CHAPTER FOUR - - AN APPLICATION OF FINE-SCALE LIDAR TO MODEL SONGBIRD OCCURRENCE IN SOUTHEASTERN U.S. WOODLANDS

Abstract

Adopting appropriate conservation strategies for individual species of wildlife or wildlife assemblages requires a fine-grained understanding of habitat-animal relationships. This study applies airborne LiDAR (Light Detecting and Ranging) data to create habitat suitability models for species of management and conservation concern. Structural habitat metrics, such as canopy cover at various height strata, height information, and a measure of vegetation distribution (clumped versus dispersed), were derived from LiDAR datasets and used to model habitat relationships for 10 songbirds of conservation interest in southeastern U.S. woodlands.

LiDAR structural habitat data, at both fine and coarse spatial scales, explained up to 54% of the variance in bird species abundance. Non-parametric multiplicative regression (NPMR) modeling using remotely derived structural predictors yielded cross-validation R^2 relationships between 0.39 and 0.69 for each of the selected avian species. These results provide insight into the powerful use of airborne LiDAR to provide specific management guidance to enhance the suitable habitat for songbird woodland species of conservation concern.

Introduction

The importance of habitat structure in determining overall wildlife species biodiversity, particularly avian diversity, has been studied for decades (MacArthur and MacArthur, 1961;MacArthur, 1964;Karr and Roth, 1971). Ecological concepts, such as "Niche-Gestalt" (James, 1971;James et al., 1996) suggest habitat structure plays a dominant role in species distributions, and a number of studies has focused on predicting bird assemblages using structural variables (Pain et al., 1997;Chapman et al., 2004b;Chapman et al., 2004a;Masters, 2007). A challenge in constructing ecological predictors has been the lack of three-dimensional structural data, particularly at spatial scales that are ecologically relevant (Russell et al., 2007;Venier and Pearce, 2007;Martinuzzi et al., 2009).

The rapid development of airborne LiDAR has been a breakthrough in measuring 3-D structure at broad spatial scales (Lefsky et al., 2002b;Newton et al., 2009), and advantages of using LiDAR in understanding the functional role of structure in avian species occurrence are clear. The cost and time effort is greatly reduced from conventional efforts for vertical structure data collection, particularly in complex environments such as forested or savanna-woodland ecotones (Michel et al., 2008;Goetz et al., 2010). Airborne LiDAR accounts for small structural elements, such as vines, and minor branches and leaves (Michel et al., 2008), providing insight into the microhabitat variables important for nesting or reproductive success. Providing this type of fine-grained structural information in any broad spatial extent would be impossible without the advent of active remote sensing.

With the advent of high density datasets, the applications of LiDAR in the ecological world have been extended to assessing habitat features for wildlife assemblages (Hinsley et al., 2009;Müller et al., 2009;Goetz et al., 2010) and individual species (Bradbury et al., 2005;Seavy et al., 2009). These studies have concluded that LiDAR is a powerful tool in providing habitat associations for individual or groups of species (Goetz et al., 2007;Clawges et al., 2008;Müller et al., 2009).

This study assesses the use of LiDAR-derived structural indicators in predicting individual songbird species in southeastern U.S. woodlands. It further expands on the importance of spatial scale, just recently addressed in a multi-scale approach for riparian bird associations (Seavy et al., 2009), and spatial heterogeneity in habitat suitability predictions.

Additionally, this study assesses habitat suitability models for 10 species that include common inhabitants of mature southeastern pine forests as well as three species of conservation and management concern: Bachman's Sparrow (*Aimophila aestivalis*), Northern Bobwhite (*Colinus virginianus*), and Red-headed Woodpecker (*Melanerpes erythrocephalus*)(Cox and Widener, 2008). The relationship between habitat quality and species occurrence has been examined for a few of the selected species, such as for the Northern Bobwhite (Cram et al., 2002;Masters et al., 2006), and some pine-grassland indicators (Masters et al., 2002;Masters, 2007). The individual models presented in this study exclusively use airborne LiDAR predictors and take both horizontal and vertical spatial heterogeneity into account, providing quantitative predictors that can be implemented in land management approaches.

Results from this study provide further evidence of the validity of LiDAR derived structural data in examining very detailed wildlife species-habitat relationships in a broad spatial scale (Vierling et al., 2008). The future of species conservation rests on the creation of specific quantitative habitat suitability models to guide management of vegetation structure and monitoring. Airborne LiDAR can assist in providing information to help in the effort of predicting habitat suitability at broad scales, important for determining conservation priorities.

Methods

Study Area

The study site location is Tall Timbers Research Station (TTRS), located in the Red Hills area of the northwestern Florida and southwestern Georgia (Figure 35). This region occupies approximately 300,000 ha between Thomasville, Georgia and Tallahassee, Florida and is home to over 230 rare types of plants and animals and over 27 federally listed threatened and endangered species (Masters et al., 2007). The Red Hills area comprises a mixture of young. mature, and old-growth longleaf pine forests

(*Pinus palustris*), natural and planted loblolly (*Pinus taeda*) and shortleaf (*Pinus echinata*) pine forests primarily in an old field context, mixed hardwood and pine forests, forested and herbaceous wetlands, agricultural fields, and residential/urban land cover types .

The TTRS covers 1600 ha within the Red Hills area, and is located just north of Tallahassee, FL. Upland pine ecosystems on TTRS were likely dominated by open longleaf pine forests until late 1800's when agriculture moved into the area. Follow the cessation of agriculture, second-growth forests dominated by loblolly and short-leaf pine have recolonized abandoned agricultural lands (Masters et al., 2005). The groundcover at the study site lacks the wiregrass (*Aristida*) and many other plants that occur in pristine longleaf pine sites (Hermann, 1995), but it is dominated by many legumes and composite family members and interspersed with grasses (broomsedge bluestem, *Andropogon virginianus*, primarily).

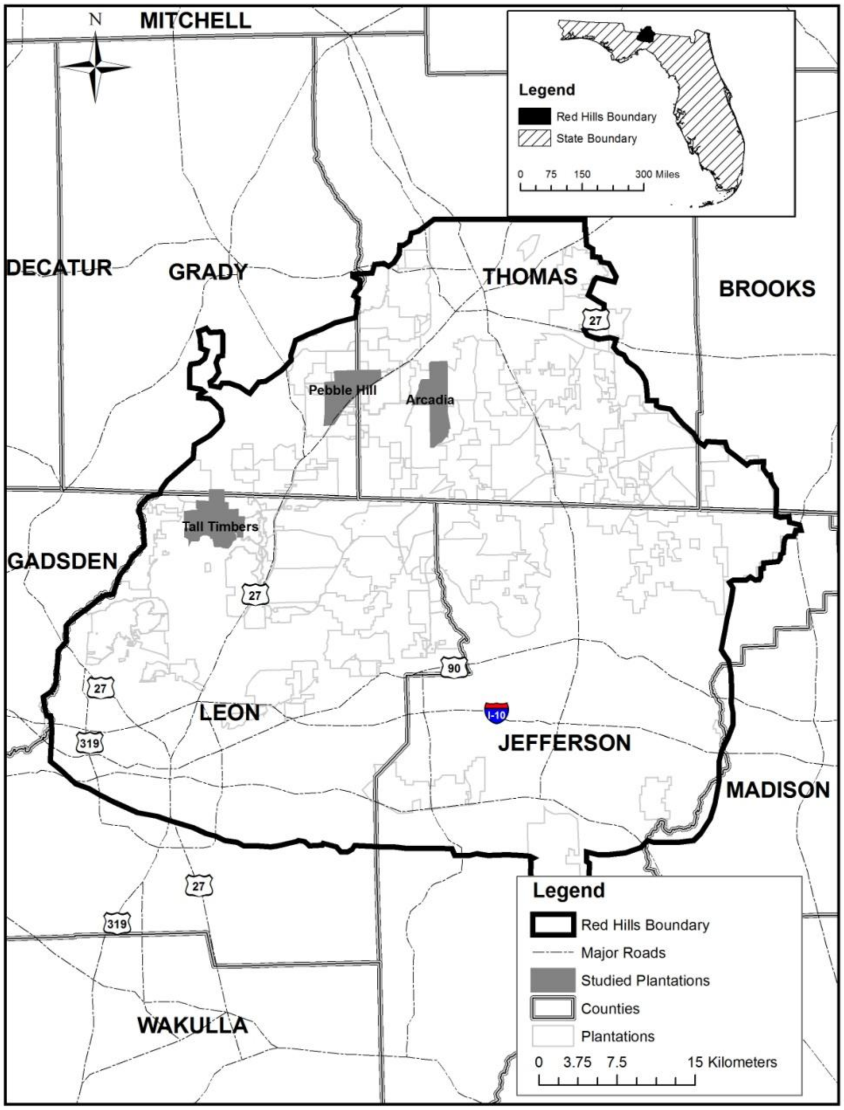

Figure 35. Location of the Study Area, Tall Timbers Research Station located within the Red Hills area.

Tall Timbers has been actively managing its secondary upland pine forest using prescription fire of low intensity transitional season treatments with a return interval of 1-2 years (applied in a heterogeneous pattern using small-scale areas). Most of the survey locations are located within this old field ecosystem type, with a few representing wetland and hammock conditions (Figure 36).

Avian Point Counts

Two sets of avian point-count surveys were located historically throughout Tall Timbers (Figure 36). The initial set was established in 1997 and consisted of 17 plots (N1-N8 and S1-S9) located in the central and eastern upland areas of the property. Data at these survey locations were originally collected to compare the effects of hardwood removal conducted in upland pine woodlands with pre- and post-treatment sampling events (1997 and 1999). The second set of point-count survey locations consisted of 20 survey points randomly located throughout TTRS. These sample areas were used to monitor breeding populations of birds on Tall Timbers, and the counts were initiated in 2005, with additional annual sampling between 2008-2010.

Counting stations were located > 300 m apart (Figure 36) for both avian surveys. In all instances, counts were conducted during the height of breeding season between May and 28 June using standardized point-count methods (Ralph et al., 1993). For each year, a minimum of three was made to each station, separated by a week. Observations at each station consisted of all birds seen or heard within 200 m of the station (segregated by <50, 50-100, >100 m counts) for 10-min in non-rainy and low wind conditions.

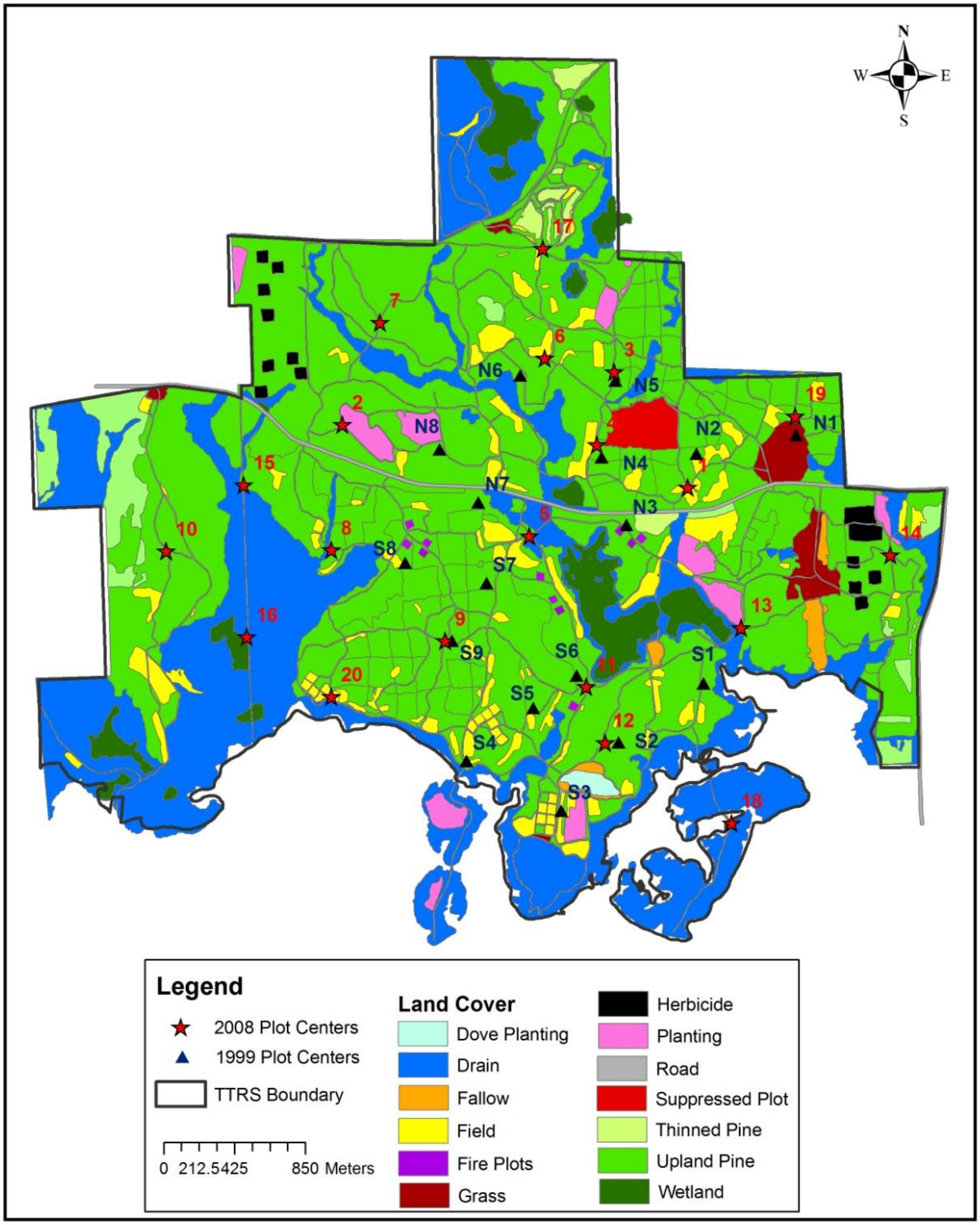

Figure 36. Location of the Historic (1997-1999) and Current (2008-present) avian point-count survey locations at TTRS (FL).

For the analysis, only counts of species of management and conservation concern with enough variability in their frequency among plots were selected (Table 15). For the habitat suitability model development, only 2008 counts (total counts of the three events within that spring) were used, while 1999 data were selected for independent model evaluation. The selection of these particular years is related to the availability of LiDAR datasets for 2002 (closest to the 1999 bird count data) and 2008 (within 3 months of avian bird count collection).

Table 15. Selected bird species for habitat suitability modeling and their respective nesting preferences and conservation status.

Acronym	Common Name	Latin Name	Nest Type/Habitat	IUCN Conservation Status	Count Plot Presence	
					1999	2008
BACS	Bachman's Sparrow	*Aimophila aestivalis*	Ground-Nesting Pine-Grassland	Near Threatened	17	12
BLGR	Blue Grosbeak	*Passerina caerulea*	Low-Shrub Pine-Grassland	Least Concern	18	12
CARW	Carolina Wren	*Thryothorus ludovicianus*	Tree Cavity, Midstory Thickets	Least Concern	18	18
EAWP	Eastern Wood-Pewee	*Contopus virens*	Mature Hardwood Trees	Least Concern	18	12
INBU	Indigo Bunting	*Passerina cyanea*	Low-Shrub Pine-Grassland	Least Concern	18	18
NOBO	Northern Bobwhite	*Colinus virginianus*	Ground-Nesting Pine-Grassland	Near Threatened, Game Spp.	18	14
PIWA	Pine Warbler	*Dendroica pinus*	Mature Pine Trees	Least Concern	18	13
RHWO	Red-headed Woodpecker	*Melanerpes erythrocephalus*	Tree Cavity, Hardwood Trees	Near Threatened	14	13
WEVI	White-eyed Vireo	*Vireo griseus*	Mid-Story Thickets	Least Concern	15	9
YBCH	Yellow-breasted Chat	*Icteria virens*	Mid-Story Thickets	Least Concern	12	14

LiDAR Data and Vegetation Metrics

Two datasets of small footprint multiple return LiDAR (Light Detecting and Ranging) were obtained from the Tallahassee-Leon County Geographic Information Systems (GIS) Department. These datasets included raw LAS files for the entire Leon County in both 2002 and 2008 transitional seasons (February and March, respectively) with the goal of creating countywide detailed floodplain mapping. The first set (2002) was collected using the ALS40 (Leica Geosystems) scanner by Merrick & Co. in February 2002. The 2008 dataset was collected using Leica ALS50 Geosystem in March 2008.

Point cloud data were converted to multipoint files and then interpolated using second power Inverse Distance Weighted interpolation in the 3D Analyst GIS environment (ESRI 2008) to a Digital Elevation Model (DEM) and a Digital Canopy Height Model (DCHM) (Zimble et al. 2003). Post processing of all the raster products took place to fill most, if not all, empty cells, with nearby interpolated values. The DEM heights were assigned to all point cloud data, allowing the computation of height above ground for every data point.

LiDAR measurements of canopy height, canopy cover, strata cover, and vegetation distribution were extracted to describe structural information around 100 and 200 m for each point location (Figure 37). The variables extracted from the LiDAR datasets included maximum and average heights, standard deviation and coefficient of variation of canopy heights (Seavy et al., 2009), canopy cover, cover and spatial distribution of vegetation at four height strata (Table 16). The different height strata used for data analyses were as follows: S1 represented ground vegetation between 0 - 0.6 m, S2 low shrubs between 0.6 - 1.5 m in height, S3 midstory between 1.5 - 6.1 m in height, and canopy heights above 6.1 m. These strata were selected to represent potential preferences of nesting or feeding habitat levels for bird species of interest, similarly to previous structure-avian diversity studies (Karr and Roth, 1971).

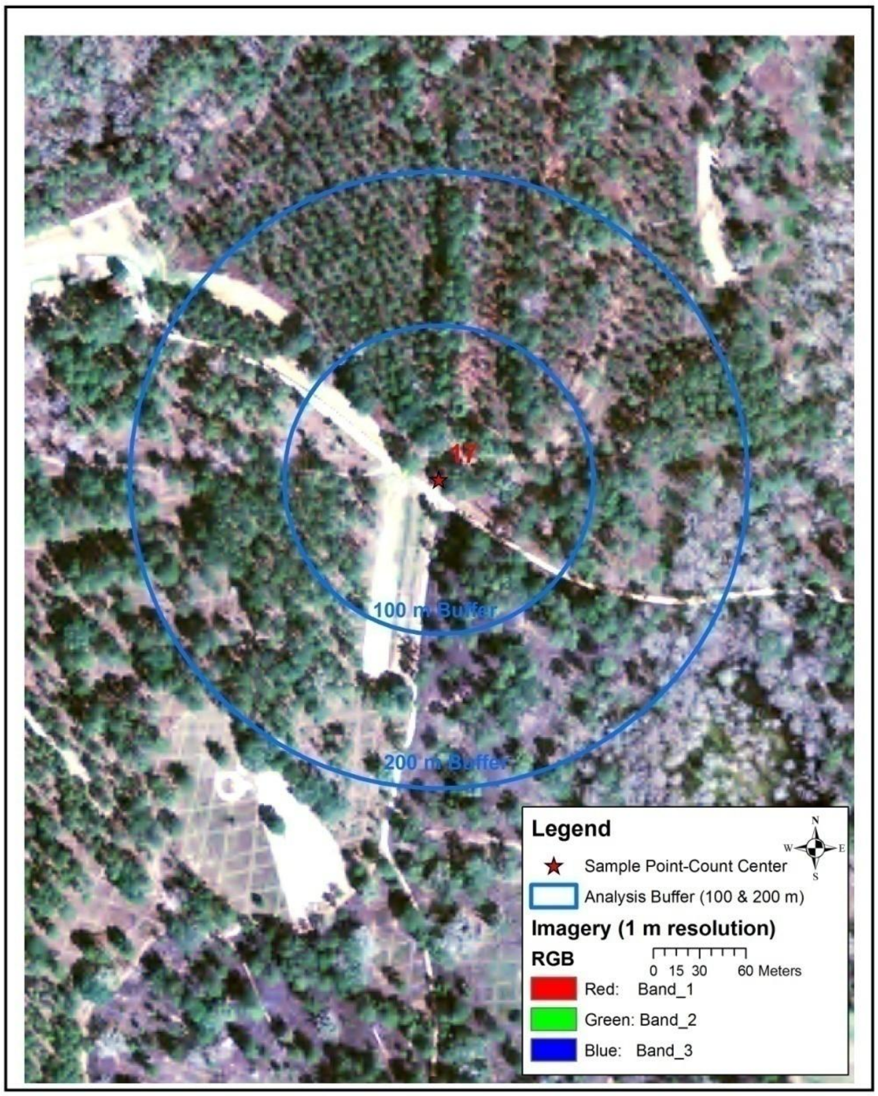

Figure 37. Sample point-count location with buffered radii (100 and 200 m) used for extraction of LiDAR structural data for habitat suitability modeling.

Table 16. Structural Metrics Derived from the 2002 and 2008 LiDAR Metrics for the Survey plot Locations.

Acronym[1]	Name	Unit	Description
CanCov	Canopy Cover	%	(Count of Canopy Returns >2m/Count of All Returns) * 100
AvgHT	Average Height	m	Average Height of all Canopy Returns (>0m in height)
MaxHT	Maximum Height	m	Maximum Height of all Canopy Returns (>0m in height)
Coef_Var	Coefficient of Variance of Height		(Standard Deviation Height/Mean Canopy Height)*100
S1Cov	Stratum 1 Cover	%	(Total returns within 0 - 0.6 m in height/Total Canopy Returns >0)*100
S2Cov	Stratum 2 Cover	%	(Total returns within 0.6 - 1.5 m in height/Total Canopy Returns >0)*100
S23Cov	Strata 2+3 Cover	%	(Total returns within 0.6 - 6.1 m in height/Total Canopy Returns >0)*100
S3Cov	Stratum 3 Cover	%	(Total returns within 1.5 - 6.1 m in height/Total Canopy Returns >0)*100
S4Cov	Stratum 4 Cover	%	(Total returns greater than 6.1 m in height/Total Canopy Returns >0)*100
S1_Z	Stratum 1 Z-value		Average Nearest Neighbor z statistic (clustered to dispersed) for Stratum 1 vegetation
S2_Z	Stratum 2 Z-value		Average Nearest Neighbor z statistic (clustered to dispersed) for Stratum 2 vegetation
S23_Z	Strata 2+3 Z average value		Average Nearest Neighbor z statistic (clustered to dispersed) for Strata 2 and 3 vegetation
S3_Z	Stratum 3 Z-value		Average Nearest Neighbor z statistic (clustered to dispersed) for Stratum 3 vegetation
S4_Z	Stratum 4 Z-value		Average Nearest Neighbor z statistic (clustered to dispersed) for Stratum 4 vegetation

1N and F after any of these acronyms indicates these correspond to the "Narrow" (100 m) or "Farther" (200 m) buffer (fine or coarse spatial scales) around the survey point count.

The structural variables were derived for the hardwood removal plots using the temporally nearest available LiDAR dataset (2002), while the structural habitat predictors for the 2008 survey point locations were derived from the 2008 LiDAR dataset. For both sets of survey locations, data were extracted for the narrower (referred as N or fine scale) and farther (hereafter F or coarse scale) buffer areas of 100 and 200 m, respectively.

The distribution of vegetation at the four specific height strata was approximated by the use of a spatial statistic, the average nearest neighbor z-value, obtained using ArcGIS 9.3 (ESRI 2008). The Z-value is a measure of statistical significance when compared to a null model (ESRI 2009) based on random distribution of points. Z-values are a measure of standard deviation of a normal distribution: a very high or low value would be located in the tails of the normal distribution, with very low likelihood of being randomly distributed. Dispersal or "clumpiness" of the LiDAR returns of the 4 strata levels were also calculated for both spatial scales (i.e. 100 and 200 m) around each point survey center.

Habitat Suitability Modeling

The objective of this study was to assess the potential of LiDAR data in describing the forest structure sought by woodland songbird species. The first step was to understand what response dataset, bird count data, should be selected for modeling, including if aggregation of several years of data was appropriate. Scatterplots and standard deviations of the selected bird species across 2008-2010 were examined and survey points were ordinated by Principal Components Analysis (PCA) and Non-metric Multidimensional Scaling (NMS) (PC-Ord, 2011) using bird count datasets.

Exploratory multivariate analyses were also conducted with the LiDAR derived structural metrics (Table 16) at both spatial scales (100 and 200 m), discerning the importance of these as predictors in the habitat modeling. Structural variables were used to ordinate the point centers by the use of Principal and Detrended Components Analyses. Additionally, Canonical Correspondence Analyses (CCA) (PC-Ord, 2011) with corresponding structural and species variables were conducted as a precursor to suitability modeling. These preliminary analyses were used to identify the structural predictors with greater weight in the distribution of the 10 selected woodland bird species. It also enabled grouping of the avian species by habitat preferences, effectively delineating guilds.

Subsets of 2008 LiDAR-derived variables (predictors) and exclusively 2008 bird count data (response variables) were used for individual species habitat suitability modeling with non-parametric multiplicative regressions (NPMR) and cross-validation (HyperNiche 2, 2009). NPMR has as advantage allowing predictors to have multiplicative interactive effects, incorporating built-in overfitting controls, and being independent from any requirement to provide an *apriori* model form (McCune, 2006). This type of modeling incorporates the ecological concept of species responses to variations in multidimensional habitat space, assuming that habitat factors interact in a multiplicative and not an additive fashion.

A Gaussian weighting function with a local mean estimator was used in a forward stepwise regression of species abundance values against the structural predictors. For each of the species, thousands of models were tested and the best fit, using leave one-out cross validated statistic, the cross R^2 was assessed and reported. The cross R^2 corresponds to proportion of the residential sum of squares (RSS) to the total sum of squares (TSS), and it can range from a negative to a positive value, with the former valued being indicators of weaker models (McCune, 2006). Only the best models, according to the cross validated R^2 and parsimonious number of predictors (LiDAR variables) were reported and further fitted to a 3D projection response surface. Furthermore, validation of the best models using independent dataset of both predictors and response variables was conducted. For this, the 1999 bird count data and 2002 LiDAR derived structural predictors for the hardwood removal survey point locations were used. Cross-validated R^2 were also calculated to provide a comparison between predicted and observed bird counts, based on the NPMR models.

Results

Bird Occurrences

Four broad guilds of bird species were represented by the 10 selected bird species (Table 15), and their occurrence across the point survey locations varied broadly (Appendix D, Table 20). Ground-nesting pine grassland nesting species, such as the Bachman's Sparrow (*Aimophila aestivalis*, BACS) and Northern Bobwhite (*Colinus virginianus*, NOBO) were better represented in points 2, 7, and 12 (2008 survey points), being clearly absent in points 16 and 18. Blue Grosbeak (*Passerina caerulea*, BLGR) and Indigo Bunting (*Passerina cyanea*, INBU), low-shrub pine-grassland nesters, were found in much higher abundance in points 7 and 12 than in the remaining points, and absent from the same points (16 and 18) as the grassland species. Bird species that prefer midstory thickets, such as Carolina Wren (*Thryothorus ludovicianus*, CARW), White-eyed Vireo (*Vireo griseus*, WEVI), and Yellow-breasted Chat (*Icteria virens*, YBCH), favored points 5 and 7, while occupying points 2 and 17 in low numbers. The Eastern Wood-Pewee (*Contopus virens*, EAWP), Pine Warbler (*Dendroica pinus*, PIWA), and Red-headed Woodpecker (*Melanerpes erythrocephalus*, RHWO), species which prefer to nest in mature trees, were more abundant in points 8 and 10, and almost absent in points 14 and 20.

Besides the spatial variability of bird occurrence discussed above, temporal variability, more specifically, annual variability, was very high, even if seasonality was accounted for by maintaining the data collection events within 6 weeks. For example, for

Bachman's sparrow, count numbers for the same point center (e.g. point 2) could vary from 2 to 9 occurrences between 2008 and 2010 (Figure 38). Changes of bird abundance numbers between 2008 and 2009 for the same point survey locations were large and unpredictable (Figure 39). When taking three consecutive years into account (2008-2010), standard deviations for the selected bird species were, in cases, close to or as high as the mean abundance for the three years (Table 21). The high fluctuation indicated that it was not appropriate to aggregate multiple years of bird abundance data for the model building effort.

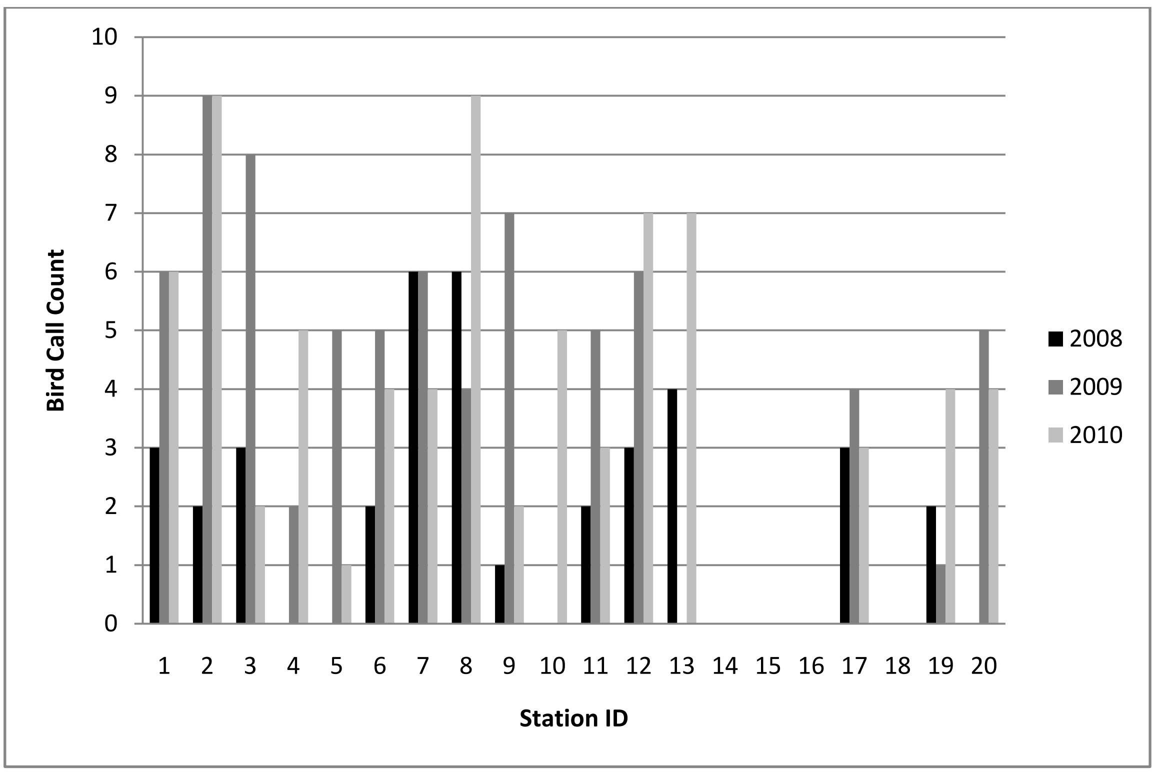

Figure 38. Annual variability of bird count data for the BACS (Bachman's Sparrow) at TTRS point centers from 2008-2010.

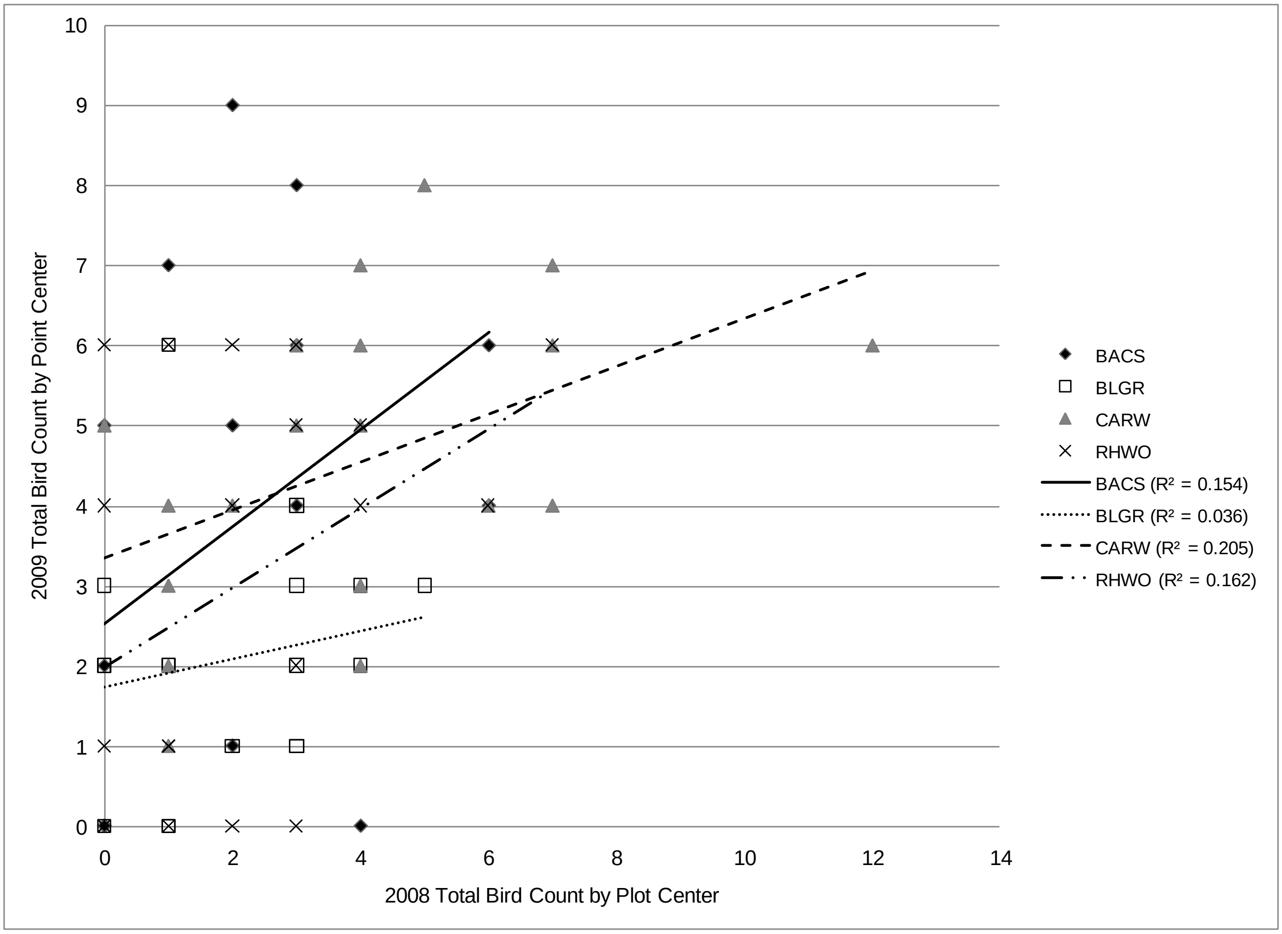

Figure 39. Scatterplot of the 2008 and 2009 point-based total sampled abundance for 4 representative species of their guilds: BACS, BLGR, CARW, and RHWO.

Bird abundance data was able to separate most of the 20 survey point locations with 66% of the variance explained in the first three axes of a PCA (Figure 40, Table 17). With community bird data, it is difficult to assume that relationships among variables are linear or monotonic, an assumption of the PCA. However, no arch effect was visible and the first few axes did seem to effectively summarize the trend in species composition along the gradient. Other ordination techniques with no linearity assumption (Non-metric Multidimensional Scaling or NMS) did present similar patterns (Figure 41), but are not as easy, without Eigenvectors to interpret.

Table 17. Eigenvalues for PCA Analyses of Bird Species and Structural Habitat Variables.

Ordination Type	Axis	Eigenvalue	% Variance	Cum.% of Var.
PCA Bird Species	1	3.231	32.306	32.306
PCA Bird Species	2	1.627	16.273	48.579
PCA Bird Species	3	1.444	14.442	63.02
PCA Structure Fine-scale	1	2.893	48.222	48.222
PCA Structure Fine-scale	2	1.811	30.182	78.403
PCA Structure Fine-scale	3	0.843	14.058	92.461
PCA Structure Multiple Scale	1	8.446	60.331	60.331
PCA Structure Multiple Scale	2	2.399	17.137	77.468
PCA Structure Multiple Scale	3	1.438	10.273	87.741

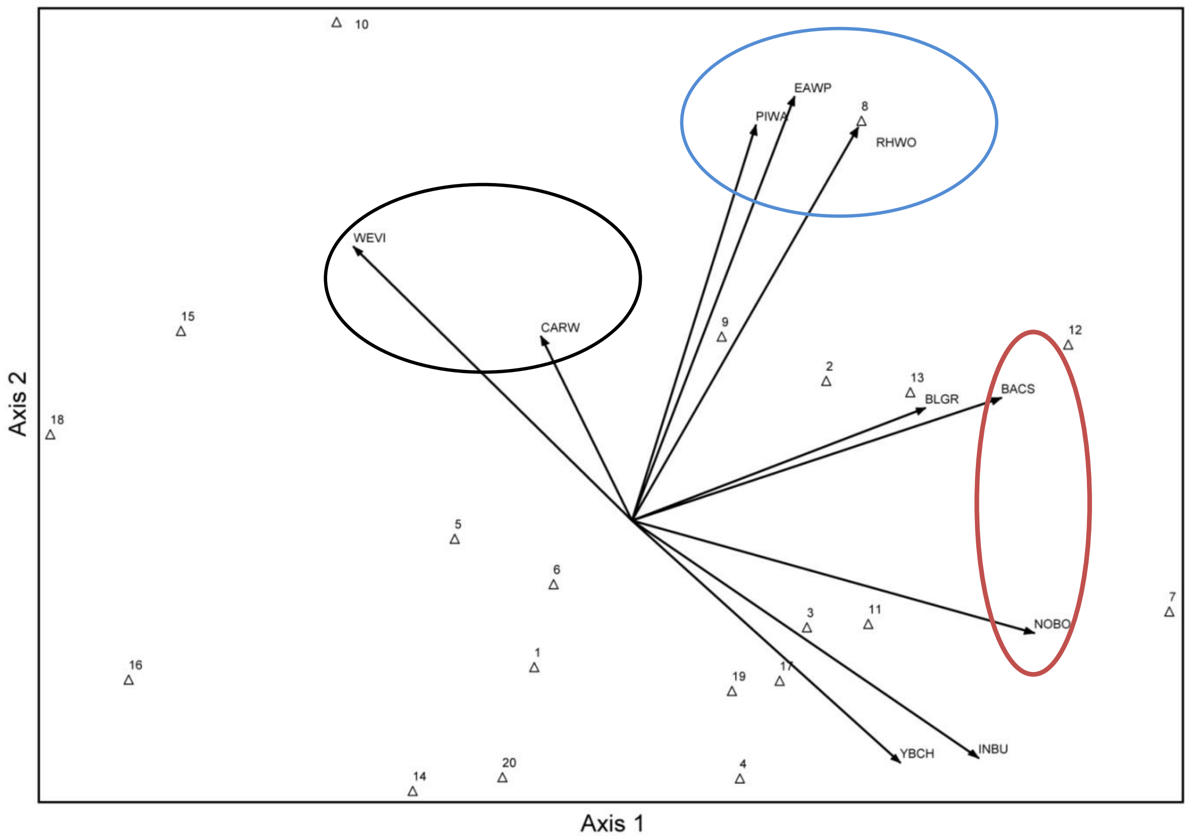

Figure 40. Principal Components Analysis results for 2008 Bird Abundance Ordination (Axes 1 and 2). The point centers are represented by the triangles and species as Eigenvectors. Black ellipse represent mid-story thicket nesters, blue ellipse tree nesters in pine-grasslands, and red ellipse ground-nesters in pine-grasslands.

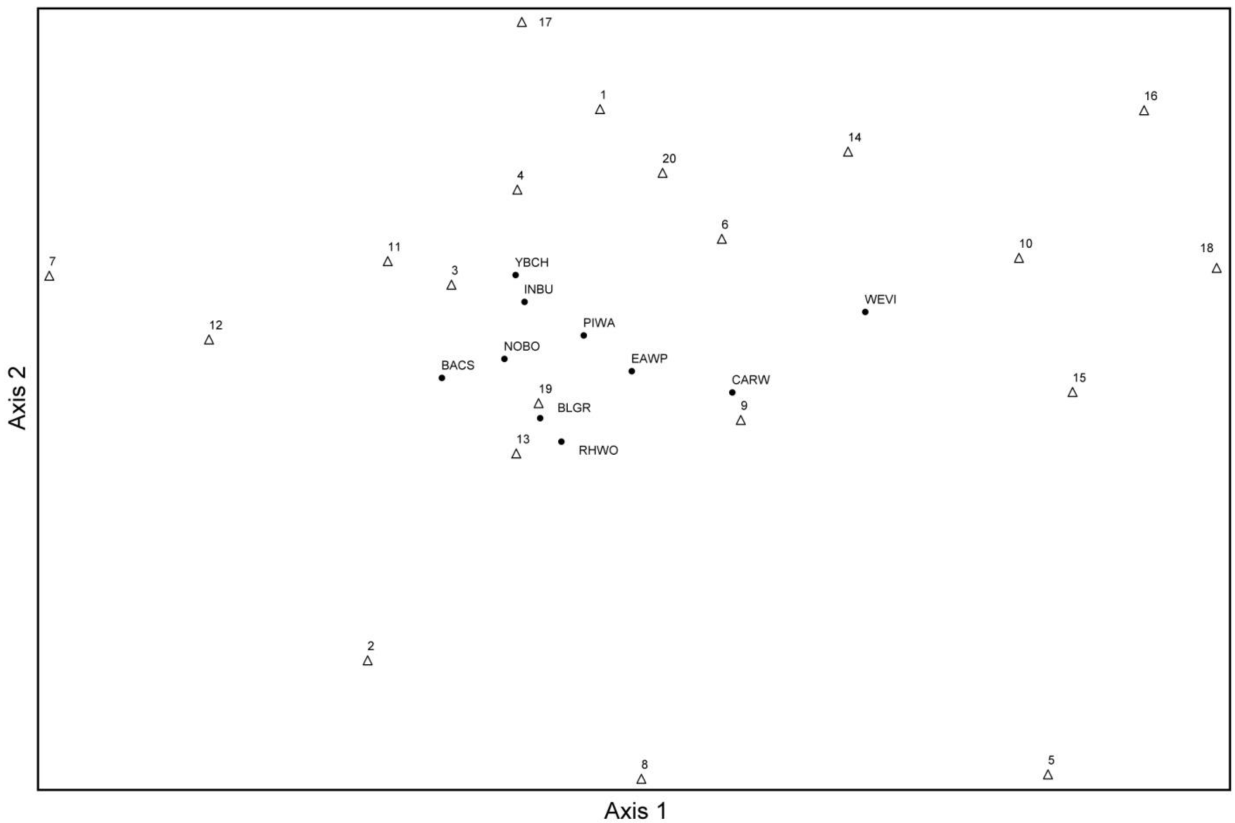

Figure 41. Non-metric Multidimensional Scaling results for 2008 Bird Abundance Ordination (Axes 1 and 2). The point centers are represented by the triangles and species as black point locations.

Ground nesting species, i.e. Bachman's Sparrow and Northern Bobwhite, were associated with the strongest Eigenvalues for Axis 1: stations 7, 12, and 13 have the highest frequency of ground-nesting bird species and these stations were closely associated with positive Axis 1 values. All three mature pine/hardwood nesters, Pine Warbler, Eastern Wood-pewee, and Red-headed Woodpecker had similar strong positive Eigenvalues for Axis 2, while Indigo Bunting (a low shrub nester) and Yellow-breasted Chat (midstory thickets nester) had the most negative Eigenvalues associated with Axis 3.

Detrended Correspondence Analysis (DCA) yielded similar results to the PCA, with Indigo bunting and Northern bobwhite having the strongest associations with Axis 1 (r= 0.65 and r=0.72, respectively), and Red-headed Woodpecker with the strongest association with Axis 2 (r=0.791, Figure 42). The cluster of points formed in the ordination analyses were dominated by species within the same guild, particularly visible for the ground nester (Bachman's Sparrow and Northern Bobwhite), and mature tree nesters (Pine Warbler, Eastern-wood Pewee, and Redheaded Woodpecker) (Figure 40). More interestingly, directionality of the ordination, especially in Axes 1 and 3 (Appendix D, Figure 103), indicated that the high abundance of midstory thicket species (White-eyed Vireo and Carolina Wren) was in direct opposition to some low shrub and mature species (Blue Grosbeak and Red-headed Woodpecker, respectively).

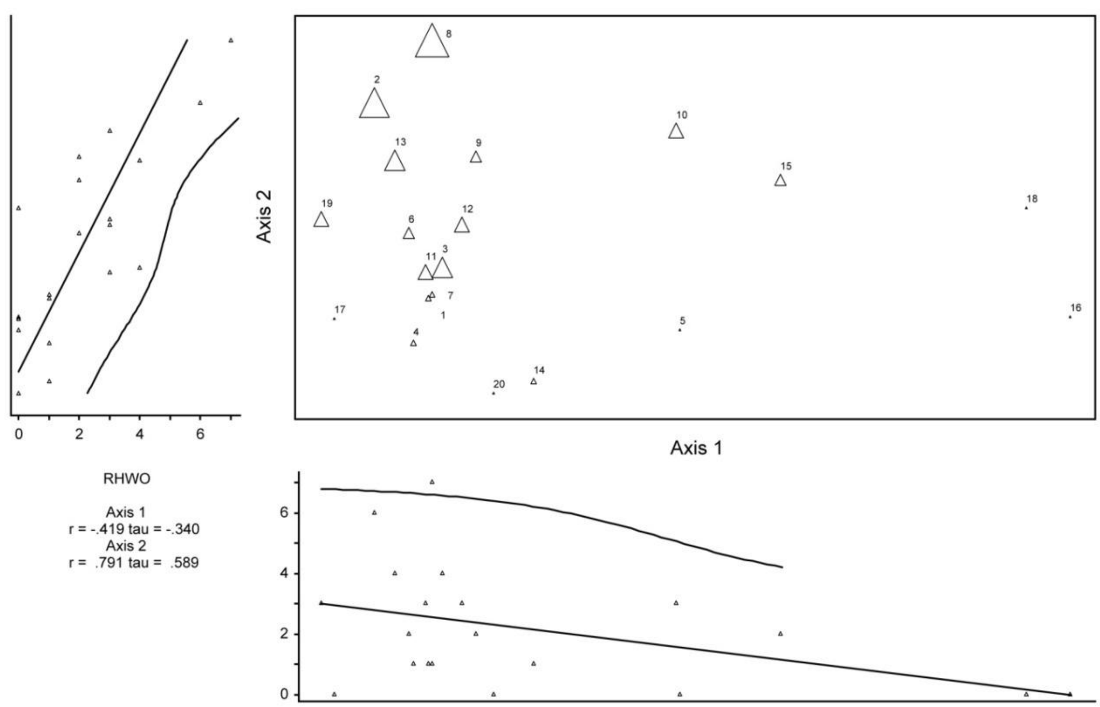

Figure 42. Detrended Correspondence Analysis and r-value results for the red-headed woodpecker across Axes 1 and 2.

Habitat Structure

Multiple LiDAR derived structural variables at two spatial scales, 100 and 200 m buffers around point centers, were examined in relation to the ordination of the 2008 point samples. A PCA of the six structural variables for the finer spatial scale of 100 m- canopy cover, S1-S2 covers, and average height explained 92.4% of the points distribution in the first 3 dimensions (Figure 43, Table 17). It became clear that overall canopy cover became less important in understanding differences in habitat structure, when specific strata covers were also incorporated. The strongest Eigenvalues for Axis 1 included the S1 cover (positive relationship) and, almost in direct opposition, S4 cover (negative relationship). In general, an increase in groundcover vegetation (<0.6 m) was accompanied by reduced canopy cover (>6.1 m in height), a trend described by the first axis of the ordination. The second axis of the PCA used the midstory canopy cover (S2 and S3 cover) to ordinate most of the points. In general, points with extremely high cover between 0.6 and 6.1 m were ordinated closer to 0 for Axis 2 (e.g. 14), while points with an almost absent midstory canopy (e.g. 9, 12) were near the highest Axes 2 values. Axis 3 corresponded to the overall canopy cover (positive relationship), and explained only 14% of the variance in the ordination.

Non-metric Multidimensional Scaling (NMS) of structural variables - height and cover variables - yielded similar results for both the finer (100 m) or coarser (200 m) scale with the most stable ordinations only using two dimensions. The most relevant variables in the NMS ordination were the S1 cover (r=0.980, Figure 44), Average Height and S4

Cover (r=0.816 and r=0.968, respectively) for Axis 1, and Canopy Cover for Axis 2 (r=0.885). In contrast to the PCA, the midstory cover variables (S2 and S3 cover) did not appear to be the most important structural variables in predicting species abundance in the NMS ordination.

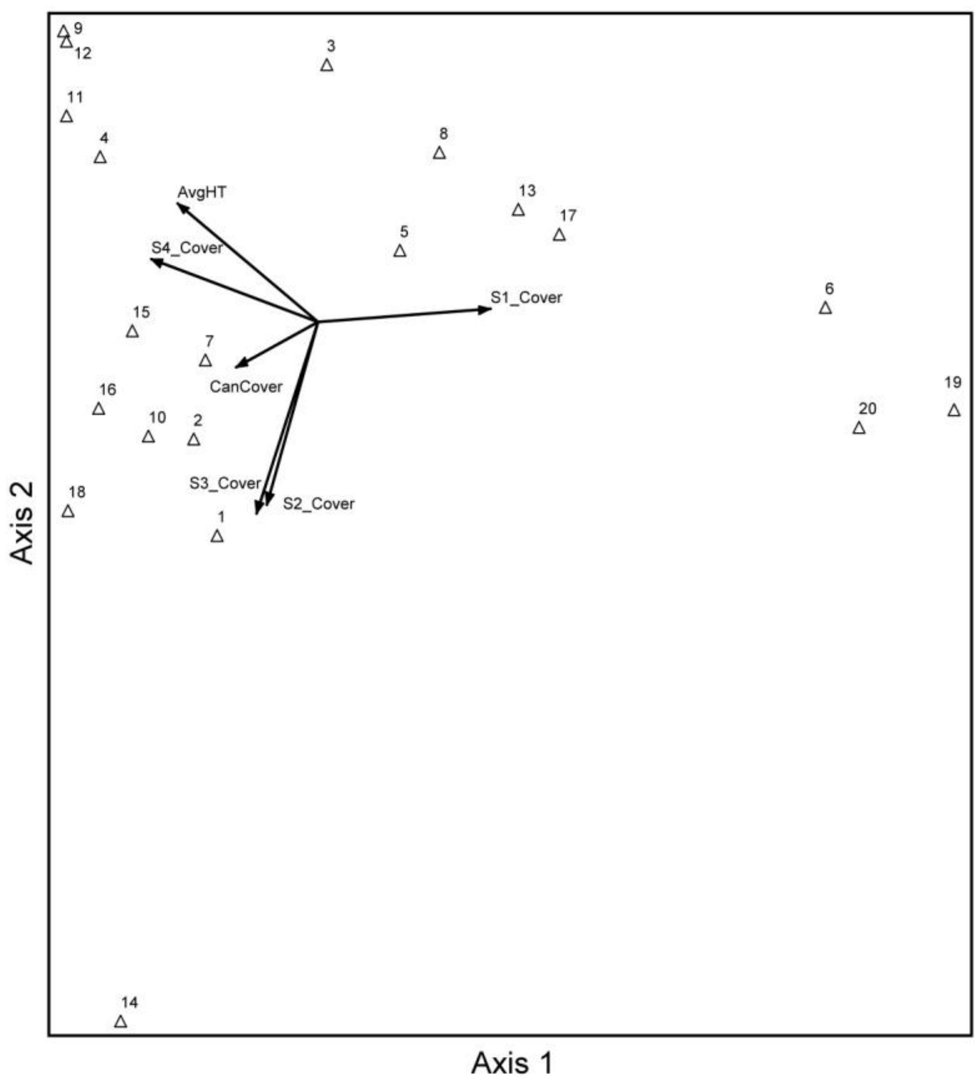

Figure 43. Principal Components Analysis results for 2008 LiDAR-derived Structural Variables for the 100 m buffer around point survey locations (Axes 1 and 2). The point centers are represented by the triangles and structural variables as Eigenvectors.

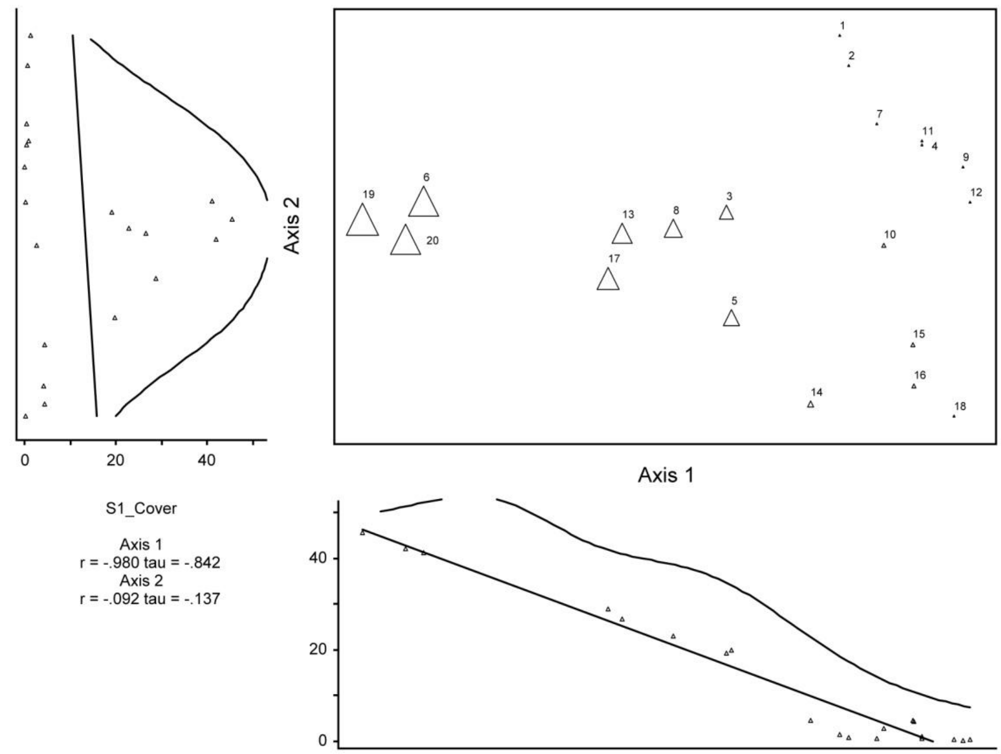

Figure 44. Non-metric Multidimensional Scaling and r-value results for the S1 (0-0.6 m) Cover across Axes 1 and 2.

The two habitat scales studied have very similar impact and directionality in ordination point survey locations (See Appendix D; Figure 107). PCA of the combination of cover, height and dispersal (Z-value) variables of both scales (N-fine scale and F-coarser scale) present overlapping Eigenvectors, with the exception of small differences in both the S23 and S4 distribution patterns. Even with the use of a large amount of environmental variables, almost 87% of the variation of the points could be explained by the first 3 axes (Table 17). The majority of the points were ordinated by the amount of groundcover (S1) and evenness of this same stratum (negative Z-value representing clumped vegetation) on Axis 1. On Axis 2, as similar to the previous ordinations, the mid-story (S2 and S3) cover had the strongest impact in the ordination.

Habitat Suitability Models

Selected bird species abundance varied across the gradients in structural habitat variables, with cover type variables explaining 54% of the variance (Figure 45, Table 18). The Canonical Correspondence Analysis (CCA) was able to distinctly separate all 10 studied woodland bird species using the first 3 axes of the ordination, providing an understanding that habitat suitability is species-specific.

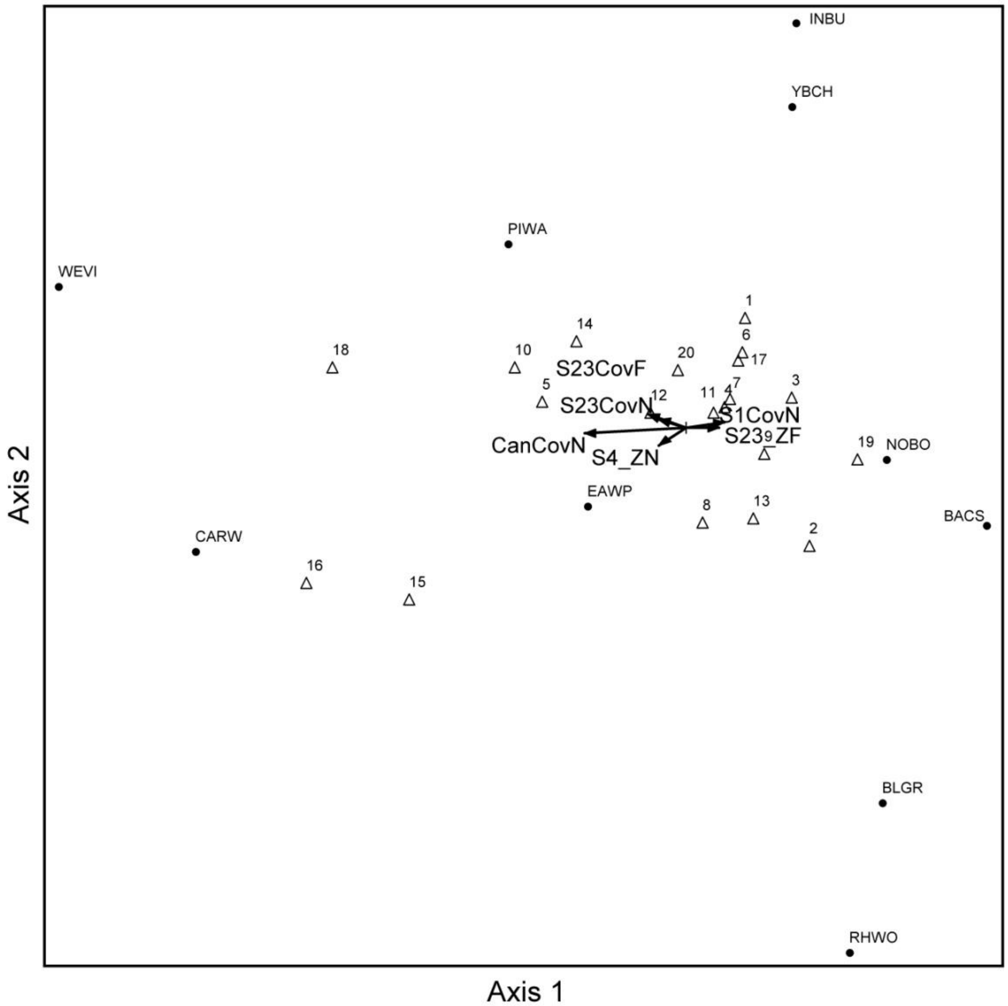

Figure 45. Canonical Correspondence Analysis Biplot for species and LiDAR-derived structural habitat attributes for 2008 survey point location data (Axes 1 and 2).

Table 18.Canonical Correspondence Analysis Eigenvalues and Pearson Correlation values for bird species abundance and structural variables.

Axis	Eigenvalue	% Variance	Cum.% of Var.	Pearson Corr.[1]	Kendall Corr.
1	0.181	33	33	0.945	0.684
2	0.064	11.6	44.7	0.873	0.579
3	0.05	9.2	53.8	0.819	0.716

Nevertheless, a few species did have similar habitat preferences. Northern Bobwhite (NOBO) and Bachman's Sparrow (BACS) were generally grouped together by points with low overall canopy cover and high groundcover 0-0.6 m (S1COV). In addition, these ground-nesters preferred a coarse-scale dispersed distribution of mid-story vegetation (0.6-6.1 m in height).

Indigo Bunting (INBU) and Yellow-breasted Chat (YBCH) were typically encountered in similar conditions, demonstrating these two species have a selective preference for relatively open, spatially cluster canopy cover (low S4 or >6.1 m z-level). The Indigo-Bunting, however, prefers higher groundcover, in comparison to both the Yellow-breasted Chat and the Blue Grosbeak (BLGR). The Blue Grosbeak, a low-shrub nester, as the Indigo Bunting, seems to have distinct habitat preferences from the latter. The Blue Grosbeak presents an aversion to a high percentage of midlevel canopy cover (S23Cov) at both fine and coarse spatial scales. In this regard, it is very similar to the Red-headed Woodpecker (RHWO), with the later preferring a more open groundcover as well.

From all the woodland songbird species, both the White-eyed Vireo (WEVI) and Carolina Wren (CARW) have the greatest association with high canopy cover and low amounts of groundcover. However, these two species have distinct habitat preferences: the vireo prefers a dispersed canopy (>6.1 m), whereas the wren selects for more clustered type of vegetation, particularly in the mid-canopy levels. Other mature tree nesters, such as the Pine Warbler (PIWA) and Eastern Wood-pewee (EAWP) prefer slightly more open canopy cover and the presence of some groundcover, with the warbler selecting for habitat with higher cover in the mid-story level (0.6 - 6.1 m) than the wood-pewee.

The individual habitat preference of each of the ten bird species was taken into account when modeling their habitat suitability. A large array of habitat predictors, extracted from both the fine (100 m) and coarse (200 m) scales, were used in multiplicative non-parametric modeling. Cross-validation xR^2 varied between 0.39 for the Carolina Wren to 0.69 for the Bachman's Sparrow, with parsimonious use of no more than 3 predictors or structural variables (Table 19). Validation of these models using an independent data set, the 1999 bird count data from hardwood removal survey points, yielded relatively weak results with negative xR^2, with the exception of the Carolina Wren and White-eyed Vireo habitat suitability models.

Table 19. Best Performing NPMR Models for the Ten Woodland Bird Species using LiDAR structural variables.

Response Variable	Form	Eval xR²	Ave Size	Pred Count	Variable 1	Tolerance	Variable 2	Tolerance	Variable 3	Tolerance	Spatial Scale	Independent Validation (1999/2002) xR²	Naive Est.	RSS	TSS
BACS	LM	0.69	1.48	3	AvgHT	4.07	S2_Z	1.73	S3_Z	3.21	Fine scale (100 m)	-0.053	1.85	678.54	644.08
BLGR	LM	0.55	2.17	3	MaxHt	4.07	S4_Cover	4.38	S2_Z	6.76	Coarse scale (200 m)	-0.389	1.8	718.74	517.28
CARW	LM	0.39	2.98	2	S3_Cover	5.32	S3_Z	3.21			Fine scale (100 m)	0.243	4	1313	1735
EAWP	LM	0.53	1.04	3	CanCovN	6.69	AvgHTN	4.07	S23CovN	1.10	Mixed scales	-0.24	1.5	570.77	460.25
INBU	LM	0.48	2.31	2	CanCover	4.46	S3_Cover	2.28			Fine scale (100 m)	-0.925	4.2	1532.1	795.88
NOBO	LM	0.67	1.03	3	CanCover	4.23	S1_Cover	4.40	S2_Z	5.80	Coarse scale (200 m)	-1.432	4.55	1369.2	563.04
PIWA	LM	0.55	1.06	3	S3_Cover	4.14	S1_Z	40.90	S4_Z	9.15	Coarse scale (200 m)	-0.139	1.2	1121.4	984.28
RHWO	LM	0.55	1.23	3	CanCovN	8.92	S23_ZN	4.21	S1CovF	4.40	Mixed scales	-0.317	2.15	146.99	111.58
WEVI	LM	0.51	1.02	3	S1_ZN	4.63	S23_ZN	2.11	S23CovF	10.62	Mixed scales	0.39	0.85	84.946	139.28
YBCH	LM	0.43	1.42	3	AvgHT	2.22	S3_Cover	1.38	S3_Z	19.97	Coarse scale (200 m)	-0.112	2.15	135.67	121.98

Response Variable are the avian species of interest, predictors are the LiDAR derived structural variables. Predictor Count indicated the total number of structural predictors used in the model (2 or 3). Tolerance is one standard deviation of the Gaussian smoothing function.

The ten species evaluated using the NPMR models can be divided into two broad groups: forest edge species (Blue Grosbeak, Carolina Wren, White-eyed Vireo, and Yellow-breasted Chat), and pine-grassland species (Bachman's Sparrow, Eastern Wood- pewee, Indigo Bunting, Northern Bobwhite, Pine Warbler, and Red-headed Woodpecker). Within these groups, bird species can be further subdivided into niches, by nesting preference (Table 15).

Pine-grassland species

The best NPMR model for the Bachman's Sparrow indicated that the most suitable habitat could be identified by the lowest average canopy height and dispersed distribution of Stratum 2 with low shrub heights between 0.6 and 1.5 m. For the other ground-nesting species, the Northern Bobwhite, the predictors with highest impact in their habitat selection were the low overall canopy cover (20-25%) and relatively high groundcover percentages (20-30%) (Figure 46).

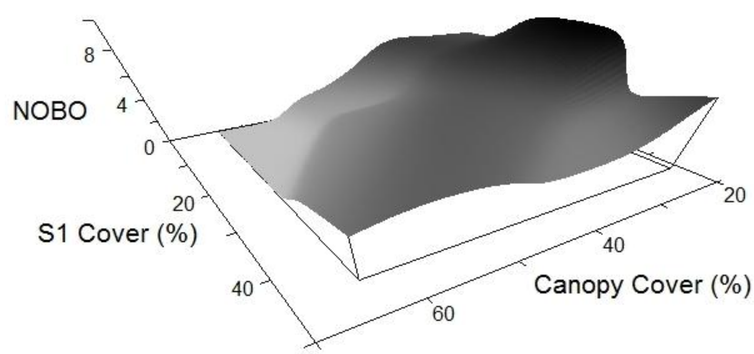

Figure 46. 3D Response Variable for the NOBO as the predictor and the two strongest predictors: coarse scale (200 m buffer) canopy cover and S1 Cover.

The Indigo bunting, the only pine-grassland species with nesting preference in low-shrub areas, could be best predicted by canopy cover between 30-40% and high vegetation cover in the 1.5-6.1 m height range.

For species nesting in mature pine or hardwood trees (including some cavity-dwelling bird species), habitat preferences were drastically distinct. The Eastern Wood-pewee suitable habitat is characterized by mid canopy cover values (40-50%) and high overall canopy heights. Pine Warblers have a distinct preference for high shrub covers (1.5-6.1 m) and dispersed spatial pattern of groundcover vegetation. Red-headed Woodpeckers prefer more open canopy cover (<50%) and dispersed midstory vegetation (0.6-6.1 m in height) (Figure 47).

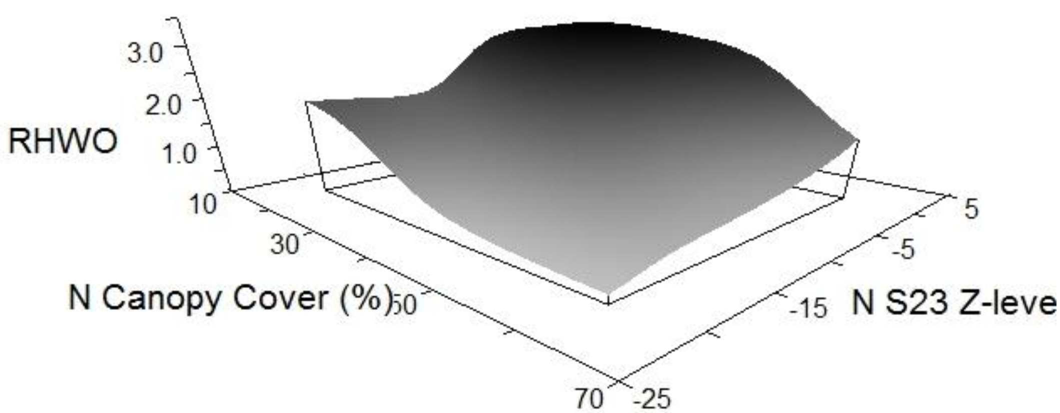

Figure 47. 3D Response Variable for the RHWO as the predictor and the two strongest predictors: fine scale (100m) canopy cover and S2+S3 z-level.

Forest-edge species

The model for the Blue Grosbeak, a low-shrub level nesting species of ecotones, indicated a preference towards lower maximum canopy heights and an avoidance of 70-90% canopy canopy cover.

The Carolina Wren and White-eyed Vireo presented preferences for a highly clustered vegetation pattern in the shrub levels (between 1.5-6.1 m and 0.6-6.1 m, respectively), Stratum 3 between 1.5-6.1 m), with smaller influences of high vegetation cover of the same midstory strata (Figure 48). However, the Yellow-breasted Chat, often classified in the same guild due to its nesting preference in midstory thickets, indicated suitable habitat with relatively low high shrub level cover (1.5-6.1 m) and high mean canopy heights.

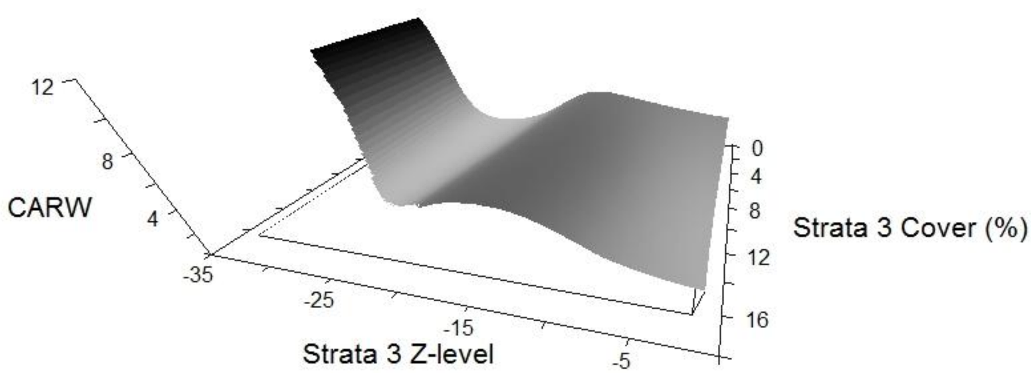

Figure 48. 3D Response Variable for the CARW as the predictor and the two strongest predictors: fine scale (100 m buffer) S3 Cover and S3 z-value.

Discussion

Temporal and spatial variability of the frequency of woodland bird species is very high in pine-hardwood woodlands. The annual change in bird abundance for the same spatial location has strong modeling and management implications. Compounding this temporal variability (Bulluck et al., 2006;Hinsley et al., 2006) with the strong response of woodland bird species to habitat structure at variety of spatial scales (Díaz et al., 2005;Seavy et al., 2009) has made habitat suitability modeling a challenge. Predictive models have to be constructed from temporally coherent data - synchronous predictor and response variables - and at a variety of spatial scales, to allow a fine-tuned habitat suitability model to be constructed. Management of species at individual or community scale needs a dynamic approach, and monitoring of key direct or indirect targets (e.g. habitat quality, species occurrence) has to take temporal changes into account.

Habitat structure is a key predictor for species distribution and abundance (MacArthur and MacArthur, 1961;Clawges et al., 2008;Müller et al., 2010). Ecological concepts, such as “Niche-Gestalt” (James, 1971;James et al., 1996) have highlighted the importance of vegetation structure for avian woodland species’ distributions, and extensive effort was placed in describing these relationships using field methods. Active remote sensing tools, such as airborne LiDAR, have been filling the void of horizontal and vertical heterogeneity in habitat and management approaches (Foody, 2008;Bergen et al., 2009). In this study, LiDAR extracted structural habitat variables, when combining coarse and fine spatial predictors provided up to 54% of predictive power for selected bird species' abundance, higher than previous studies (Müller et al., 2009). When describing the habitat structure-distribution relationship at an individual species scale, explanatory power was as high as xr^2 of 0.69.

Incorporating both coarse and fine scale structural variables increase the overall predictability of structure in modeling preferences, especially at the individual species scale. Ecologically, predation risk and breeding success are highly impacted by local structure, with the spatial scale of impact directly linked to individual species behavior. Recently, structural heterogeneity at several spatial scales has been found to be important in modeling habitat quality at the individual species level (Bradbury et al., 2005;Seavy et al., 2009). For the ten individual habitat suitability models constructed in this study, four used exclusively coarse spatial scale predictors (Northern Bobwhite, Blue Grosbeak, Yellow-breasted Chat, and Pine Warbler), and the remaining species (i.e. Bachman's Sparrow, Indigo Bunting, Carolina Wren, White-eyed Vireo, Eastern Wood-pewee, and Red-headed Woodpecker) had better predictors using only fine scale structural predictors.

The most influential structural predictors in separating individual bird species and assemblages (i.e. ground open nesting species, shrub, and mature tree nesters in forest edge versus pine-grassland habitats) were the overall canopy cover, midstory cover (Strata 2 and 3 combined, or between 0.6-6.1 m in height), and, in direct opposition to these, ground level cover (0-0.6 m). In addition, spatial heterogeneity of vegetation across different height strata (represented by z-values, or a measure of standard deviation of a random distribution), in particular, the overstory (>6.1 m) vegetation was another very important factor in the distribution and abundance of woodland bird species. Height data, such as mean and maximum height, has, overall, very little impact in the distribution of bird species, when other structural variables that describe the vertical and horizontal distribution of vegetation were included. Habitat quality determinations and suitability modeling using LiDAR data are commonly performed with tree height predictors only (Hinsley et al., 2002;Hill et al., 2004;Bradbury et al., 2005;Hinsley et al., 2006), or a combination (Hinsley et al., 2009) of canopy height and cover. Improvements in quantitative modeling to answer species-specific ecological questions need to include variables that describe the canopy heterogeneity and three-dimensionality. With the advances of remote sensing, canopy profiles are just starting to be included in species diversity and abundance studies (Goetz et al., 2007;Vierling et al., 2008;Goetz et al., 2010).

Non-parametric multiplicative regressions (NPMR) (HyperNiche 2, 2009) provided strong cross-validation r^2 for several species, in particular Bachman's' Sparrow, Blue Grosbeak, Northern Bobwhite, Pine Warbler, and Red-headed Woodpecker (xr^2 >0.55). The use of parsimonious predictors and incorporation of multiplicative interactions between predictors (McCune, 2006), allowed the interpretation of the best predictors at specific spatial scales to be detected for individual bird species. In general, species that prefer forest edge habitats (i.e. Carolina Wren and White-eyed Vireo) showed preference for highly clustered shrub layer, with relative high shrub cover. Carolina Wren appeared, in independent studied (Masters et al., 2002) to be positively related to shrub-level foliage under 2 m. Pine-grassland species, benefited, in general from lower canopy covers, in agreement to the general consensus (Masters et al., 2002), but predictors with greatest weight varied depending on nesting preference. The strongest predictors for ground-nesting species, such as Northern Bobwhite, were low overall canopy cover and high groundcover percentages. Tree or cavity nesting species, i.e. Red-headed Woodpecker, still preferred open canopy cover (<50%) but also seem to be associated with dispersed midstory vegetation (0.6-6.1 m in height) habitat. Individual species, even within the same apparent habitat (Northern bobwhite versus Bachman's Sparrow), do have unique predictors: for the Bachman's Sparrow, dispersed distribution of low shrub is a stronger predictor of suitability than high groundcover values. Individuality of preferences among species requires management of these preferences which involves assessing and monitoring spatial and vertical habitat heterogeneity,

Future validation of these models with independent datasets would further improve their use in predicting suitable habitat using remotely sensed data. Independent validation attempted in this study performed weakly, potentially due to the large temporal discrepancy between structural predictor dataset (2002) and response variable data (1999 bird occurrences).

Management Implications

This study provides valuable wildlife and conservation management lessons. High spatial and temporal variability have to be taken into account when managing at the individual species or community level. Monitoring of management goals has to be an ongoing task, taking place at relatively frequent intervals, and airborne LiDAR can provide valuable datasets which can improve decision-making in a timely manner (Vierling et al., 2008;Bergen et al., 2009).

Individual species habitat preferences, particularly those of management and conservation concern, can often only be characterized with fine spatial scale habitat structural data (Michel et al., 2008;Vierling et al., 2008). Airborne LiDAR data can provide a rapid three-dimensional assessment of structure at user-specified scales, reducing the time-consuming and costly effort of manual field structural data collection. The ability to obtain data at fine vertical scale and broad horizontal scales allow modeling of individual species to be more quantitative and have greater predictive power. Woodland bird species, even the ones classified within the same guild by nesting preferences, had clearly distinct habitat structural preferences. For example, while the Eastern wood-pewee indicated preference for canopy cover values between 40-45% and a high mean height, the Pine Warbler preferred low shrub cover (between 1.5-6.1 m) and highly dispersed groundcover vegetation (<0.5 m).

Spatial heterogeneity of vegetation at different vegetation structural levels might be an element as important as percentage cover for these same strata. In this study we looked at the average nearest neighbor distance of the point cloud data of the four height strata represented as a z-statistic value. The dispersed or clumped nature of the vegetation was a powerful predictor in several individual species models. The Red-headed Woodpecker, for example, a species targeted for conservation and highly dependent from frequent fires in savanna-woodlands (Grundel and Pavlovic, 2007), appeared to be best predicted by a combination of low-medium (30-55%) canopy cover and a dispersed shrub vegetation layer (0.6 -6.1 m). This closely corresponds to findings by (Masters et al., 2002) of the negative relationship between Red-headed Woodpecker and both canopy cover and midstory vegetation.

Understanding the predictors key for suitability of individual species, allows appropriate management goals to be set, and, consequently, appropriate treatments to be imposed. For example, the Northern bobwhite, a game species of high interest in the SE pine-hardwood woodlands, is often managed by improving habitat quality with supplementing feeding and introduction of frequent fire return intervals using controlled burns. There is general consensus on the need to maintain persistent woody cover under 2 m in height (Masters et al., 2006). Also, low basal areas and open canopies are preferential (Cram et al., 2002). Using NPMR modeling with detailed LiDAR derived structural predictors, a much more detailed understanding of suitability can be determined (Figure 46): the preferential habitat characteristics are low canopy cover between 20-40% combined with a high cover (20-30%) in 0-0.6 m high vegetation. Similar modeling could be performed for all species of management and conservation concern using a larger sampling effort and validation of the results in a wide range of study areas, for which both synchronous LIDAR and bird occurrence data are available.

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APPENDIX A: PICTURES OF THE STODDARD FIRE PLOTS, TTRS, FL

Figure 49. Stoddard Plot W1A (1-year fire return interval).

Figure 50. Stoddard Plot W1B (1-year fire return interval).

Figure 51. Stoddard Plot W1C (1-year fire return interval).

Figure 52. Stoddard Plot W2A (2-year fire return interval).

Figure 53. Stoddard Plot W2B (2-year fire return interval).

Figure 54. Stoddard Plot W2C (2-year fire return interval).

Figure 55. Stoddard Plot W3A (3-year fire return interval).

Figure 56. Stoddard Plot W3B (3-year fire return interval).

Figure 57. Stoddard Plot W3C (3-year fire return interval).

Figure 58. Control Plot UA (fire suppressed).

Figure 59. Control Plot W75B (fire suppressed).

APPENDIX B: PICTURES OF THE FIELD TRANSECTS AT TTRS, FL

Figure 60. Field transect location 8 (eastern view).

Figure 61. Field transect location 8 (western view).

Figure 62. Field transect location 9 (eastern view).

Figure 63. Field transect location 9 (southern view).

Figure 64. Field transect location 14 (eastern view).

Figure 65. Field transect location 14 (southern view).

Figure 66. Field transect location 16 (eastern view).

Figure 67. Field transect location 14 (southern view).

Figure 68. Field transect location 18 (eastern view).

Figure 69. Field transect location 18 (southern view).

Figure 70. Field transect location 20 (eastern view).

Figure 71. Field transect location 20 (southern view).

Figure 72. Field transect location 21 (eastern view).

Figure 73. Field transect location 21 (southern view).

Figure 74. Field transect location 25 (eastern view).

Figure 75. Field transect location 25 (southern view).

Figure 76. Field transect location 26 (eastern view).

Figure 77. Field transect location 26 (southern view).

Figure 78. Field transect location 27 (eastern view).

Figure 79. Field transect location 27 (southern view).

Figure 80. Field transect location 28 (eastern view).

Figure 81. Field transect location 28 (southern view).

Figure 82. Field transect location 29 (eastern view).

Figure 83. Field transect location 29 (southern view).

Figure 84. Field transect location 30 (eastern view).

Figure 85. Field transect location 30 (southern view).

Figure 86. Field transect location 32 (eastern view).

Figure 87. Field transect location 32 (southern view).

Figure 88. Field transect location 45 (eastern view).

Figure 89. Field transect location 45 (southern view).

APPENDIX C: PICTURES OF THE PLOTS AND TRANSECTS AT PEBBLE HILL AND ARCADIA PLANTATIONS, GA

Figure 90. Arcadia Plot 1, Wade Tract (old-growth with 2-year fire return interval).

Figure 91. Mid-story thicket in a pocket of Arcadia Plot 1, Wade Tract.

Figure 92. Arcadia Plot 2, Wade Tract (old-growth with 2-year fire return interval).

Figure 93. Arcadia Plot 3, Wade Tract (old-growth with 2-year fire return interval).

Figure 94. Arcadia Transect 1, Wade Tract (old-growth with 2-year fire return interval).

Figure 95. Arcadia Transect 2, Wade Tract (old-growth with 2-year fire return interval).

Figure 96. Arcadia Transect 3, Wade Tract (old-growth with 2-year fire return interval).

Figure 97. Pebble Hill Plot 1 (secondary-growth with 2-year fire return interval).

Figure 98. Pebble Hill Plot 2 (secondary-growth with 2-year fire return interval).

Figure 99. Pebble Hill Plot 3 (secondary-growth with 2-year fire return interval).

Figure 100. Pebble Hill Transect 1 (secondary-growth with 2-year fire return interval).

Figure 101. Pebble Hill Transect 2 (secondary-growth with 2-year fire return interval).

Figure 102. Pebble Hill Transect 3 (secondary-growth with 2-year fire return interval).

APPENDIX D: SUPPLEMENTAL TABLES, CHARTS OF MULTIVARIATE ORDINATION ANALYSES AND 3D SURFACE MODELS FOR CHAPTER 4

Table 20. Bird occurrence data for the ten species of interest grouped by guilds (1999 and 2008 survey points).

Station ID	Year	Ground-Nesting Pine-Grass			Low-Shrub Pine-Grass			Mid-Story Thickets				Mature Pine/Hardwood Trees			
		BACS	NOBO	Total	BLGR	INBU	Total	CARW	WEVI	YBCH	Total	EAWP	PIWA	RHWO	Total
1	2008	3	5	8	0	6	6	1	2	1	4	0	1	1	2
2	2008	2	9	11	4	2	6	1	1	1	3	0	2	6	8
3	2008	3	6	9	0	5	5	4	1	6	11	1	1	4	6
4	2008	0	6	6	4	5	9	2	1	5	8	1	0	1	2
5	2008	0	5	5	2	5	7	12	1	1	14	2	0	0	2
6	2008	2	3	5	1	4	5	1	1	2	4	2	0	2	4
7	2008	6	8	14	3	9	12	7	0	5	12	3	1	1	5
8	2008	6	3	9	3	3	6	5	0	0	5	3	1	7	11
9	2008	1	4	5	5	3	8	4	0	1	5	3	2	2	7
10	2008	0	1	1	0	3	3	4	4	2	10	4	4	3	11
11	2008	2	8	10	1	7	8	4	0	3	7	1	2	3	6
12	2008	3	8	11	3	8	11	6	0	3	9	2	5	3	10
13	2008	4	6	10	3	3	6	3	0	3	6	3	1	4	8
14	2008	0	1	1	1	4	5	4	0	3	7	0	0	1	1
15	2008	0	2	2	1	0	1	7	3	1	11	2	0	2	4
16	2008	0	0	0	0	0	0	4	0	0	4	0	0	0	0
17	2008	3	4	7	1	7	8	0	0	3	3	3	1	0	4
18	2008	0	0	0	0	0	0	7	2	0	9	0	2	0	2
19	2008	2	7	9	3	4	7	1	0	1	2	0	0	3	3
20	2008	0	5	5	1	6	7	3	1	2	6	0	1	0	1
N1	1999	2	13	15	4	7	11	9	3	6	18	4	13	6	23
N2	1999	11	12	23	2	11	13	15	0	2	17	6	5	4	15
N3	1999	2	9	11	8	5	13	16	3	3	22	6	11	2	19
N4	1999	3	8	11	5	5	10	18	4	2	24	7	8	3	18
N5	1999	4	17	21	5	11	16	8	4	7	19	9	10	6	25
N6	1999	12	12	24	13	10	23	4	1	2	7	12	9	5	26
N7	1999	12	5	17	5	6	11	13	4	4	21	3	7	0	10
N8	1999	10	8	18	3	13	16	15	5	6	26	4	3	3	10
N9	1999	4	8	12	9	17	26	16	0	6	22	4	8	5	17
S1	1999	1	15	16	1	7	8	13	5	0	18	7	11	0	18
S2	1999	11	8	19	6	17	23	16	0	0	16	2	11	4	17
S3	1999	2	7	9	2	17	19	17	6	0	23	1	7	2	10
S4	1999	0	8	8	9	9	18	8	2	0	10	8	4	0	12
S5	1999	8	6	14	9	10	19	18	0	8	26	5	3	0	8
S6	1999	1	10	11	8	8	16	11	1	1	13	9	4	7	20
S7	1999	7	3	10	12	10	22	16	3	0	19	4	3	6	13
S8	1999	13	6	19	2	15	17	10	6	1	17	7	8	4	19
S9	1999	4	2	6	9	9	18	18	3	0	21	7	16	1	24

Table 21. Means and standard deviations of selected bird species abundance for the 2008-1020 data collection events.

Station	BACS		BLGR		CARW		EAWP		INBU		NOBO		PIWA		RHWO		WEVI		YBCH	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
1	5.00	1.73	2.67	2.52	1.33	0.58	0.67	0.58	4.33	2.89	4.67	1.53	0.33	0.58	1.33	0.58	1.67	1.53	2.67	2.08
2	6.67	4.04	3.33	1.15	0.67	0.58	0.67	0.58	4.67	2.52	10.33	1.15	2.67	2.08	4.67	1.15	0.33	0.58	3.33	3.21
3	4.33	3.21	1.00	1.00	3.33	0.58	2.00	1.00	5.00	3.00	7.33	2.31	2.67	1.53	4.00	0.00	0.33	0.58	5.67	0.58
4	2.33	2.52	4.33	1.53	2.67	1.15	1.33	0.58	6.33	2.31	5.33	0.58	1.00	1.00	1.67	2.08	0.33	0.58	4.67	0.58
5	2.00	2.65	1.33	0.58	9.00	3.00	2.67	0.58	5.67	1.15	6.67	1.53	0.33	0.58	2.67	3.06	0.33	0.58	1.33	0.58
6	3.67	1.53	2.00	1.00	1.67	2.08	1.67	0.58	4.33	0.58	4.33	3.21	1.00	1.00	4.00	2.00	1.00	1.00	3.33	1.53
7	5.33	1.15	2.00	1.00	5.00	3.46	2.33	0.58	8.33	1.15	7.00	2.65	1.67	2.08	3.33	2.52	0.00	0.00	4.67	0.58
8	6.33	2.52	2.33	1.15	6.33	1.53	2.33	0.58	5.33	2.52	4.00	2.65	2.00	1.73	5.67	1.53	0.67	0.58	0.33	0.58
9	3.33	3.21	4.00	1.00	4.00	1.00	1.67	1.53	2.67	0.58	6.00	2.00	3.67	1.53	4.00	2.00	0.00	0.00	2.67	2.08
10	1.67	2.89	1.33	1.15	3.33	1.15	4.00	0.00	3.67	2.08	2.67	2.89	5.67	2.08	2.00	1.73	2.33	1.53	2.00	1.00
11	3.33	1.53	1.67	0.58	3.33	0.58	1.67	2.08	5.00	2.00	4.33	4.04	1.67	0.58	5.00	2.00	0.33	0.58	3.33	0.58
12	5.33	2.08	2.00	1.00	4.67	1.15	3.33	1.15	5.67	2.08	6.67	3.21	3.33	1.53	3.00	1.00	0.33	0.58	3.67	2.08
13	3.67	3.51	2.33	1.15	3.33	1.53	3.00	1.00	3.00	1.00	4.67	1.53	1.33	1.53	4.00	1.00	0.00	0.00	3.33	0.58
14	0.00	0.00	3.33	2.52	4.67	2.08	0.00	0.00	5.00	1.73	3.33	2.08	1.00	1.00	1.00	0.00	1.67	1.53	5.00	3.46
15	0.00	0.00	0.33	0.58	5.67	1.53	1.00	1.00	0.67	0.58	2.33	0.58	0.67	1.15	0.67	1.15	1.67	1.15	0.33	0.58
16	0.00	0.00	0.00	0.00	5.33	1.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	3.33	0.58	1.00	1.00	3.33	2.89	3.33	0.58	6.33	1.15	5.00	1.00	2.33	1.15	2.33	2.08	1.33	1.53	2.33	0.58
18	0.00	0.00	0.67	1.15	5.67	1.53	1.67	2.08	0.00	0.00	0.00	0.00	3.67	2.89	0.00	0.00	1.67	0.58	0.00	0.00
19	2.33	1.53	3.67	0.58	2.00	1.00	1.00	1.00	3.00	1.00	9.00	3.46	1.33	1.53	4.33	1.53	0.00	0.00	2.00	1.00
20	3.00	2.65	1.67	0.58	3.67	2.08	1.00	1.00	5.00	1.73	5.67	2.08	0.67	0.58	0.33	0.58	1.33	0.58	2.33	1.53

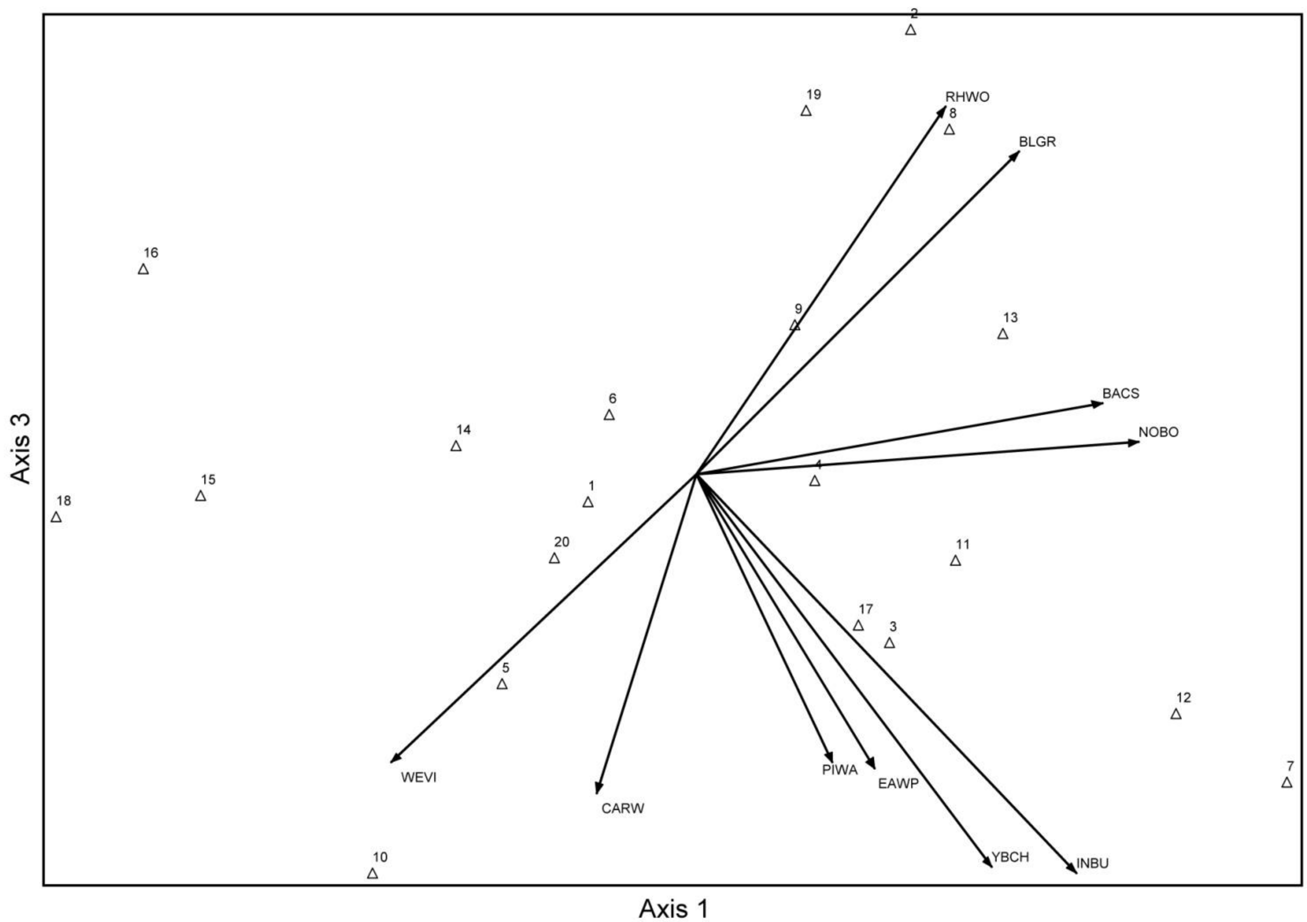

Figure 103. PCA Results for 2008 Bird Abundance Ordination (Axes 1 and 3). The point centers are represented by the triangles and species as Eigenvectors.

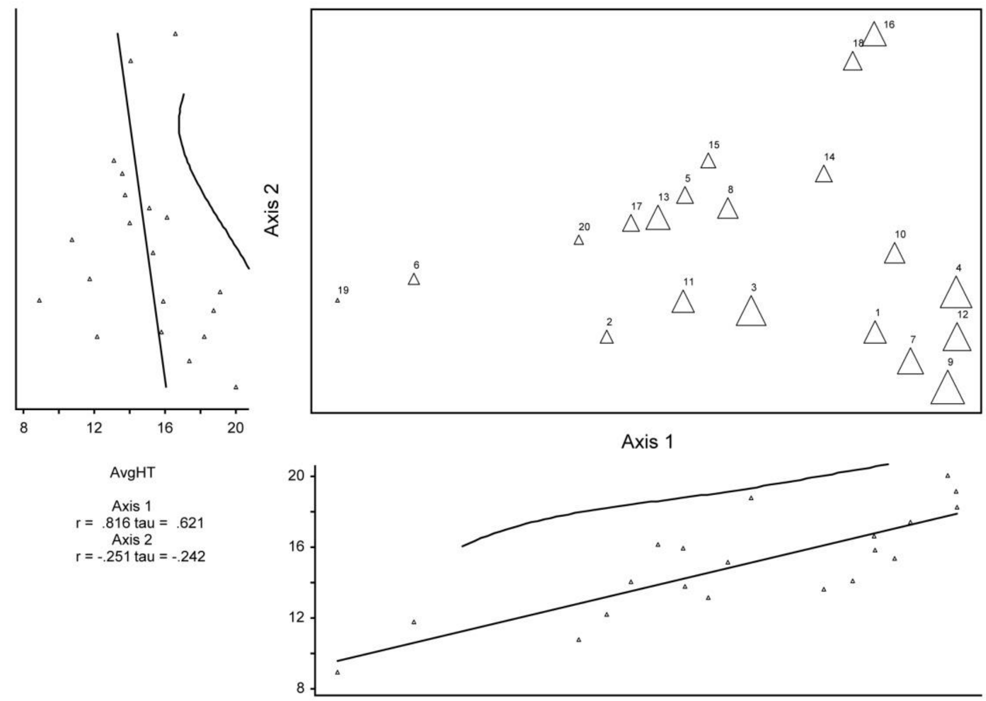

Figure 104. NMS and r-value results for the Average Height across Axes 1 and 2.

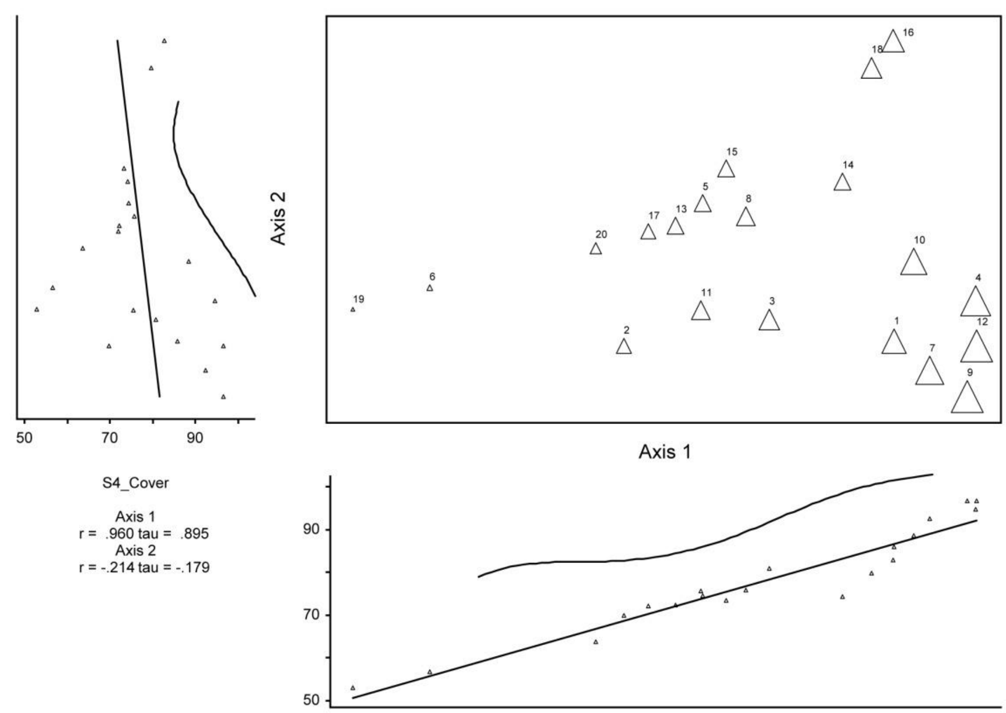

Figure 105. NMS and r-value results for the vegetation stratum 4 (>6.1 m) cover across Axes 1 and 2.

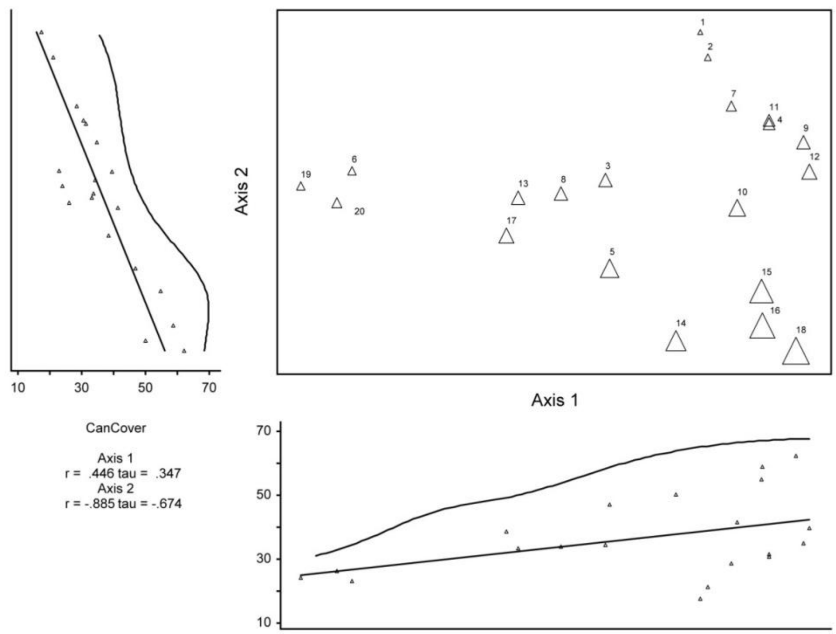

Figure 106. NMS and r-value results for the Canopy Cover across Axes 1 and 2.

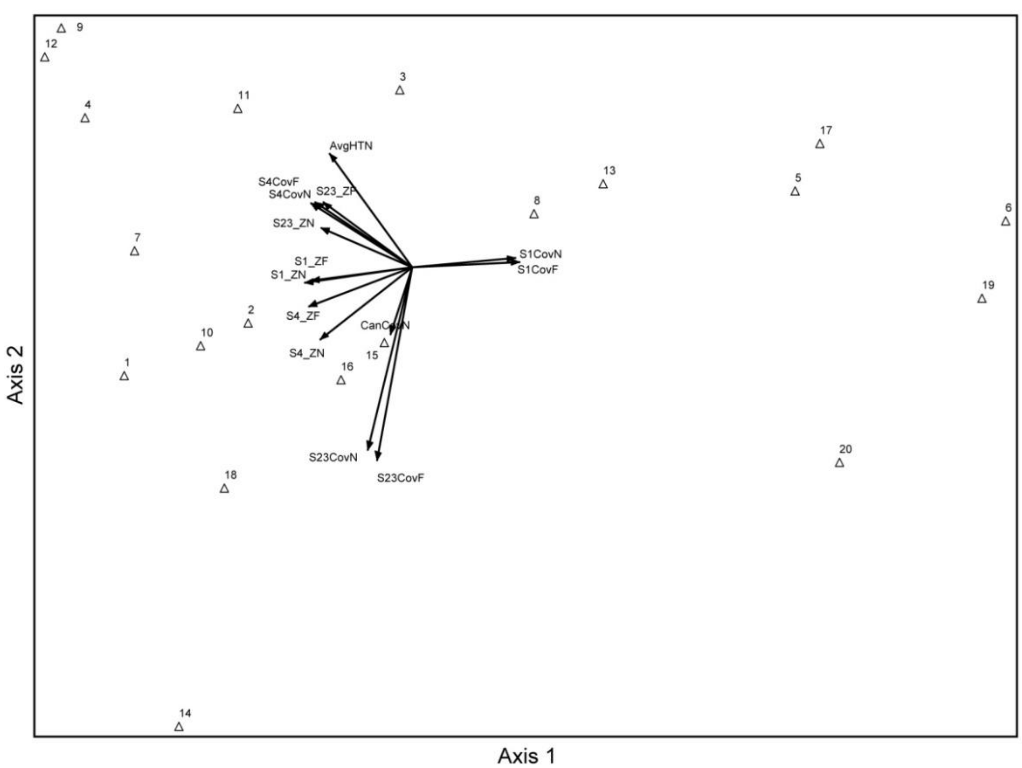

Figure 107. PCA Results for 2008 LiDAR-derived Structural Variables for the both spatial scales (N=narrow or 100 m buffer and F=farther or 200 m buffer) around point survey locations.

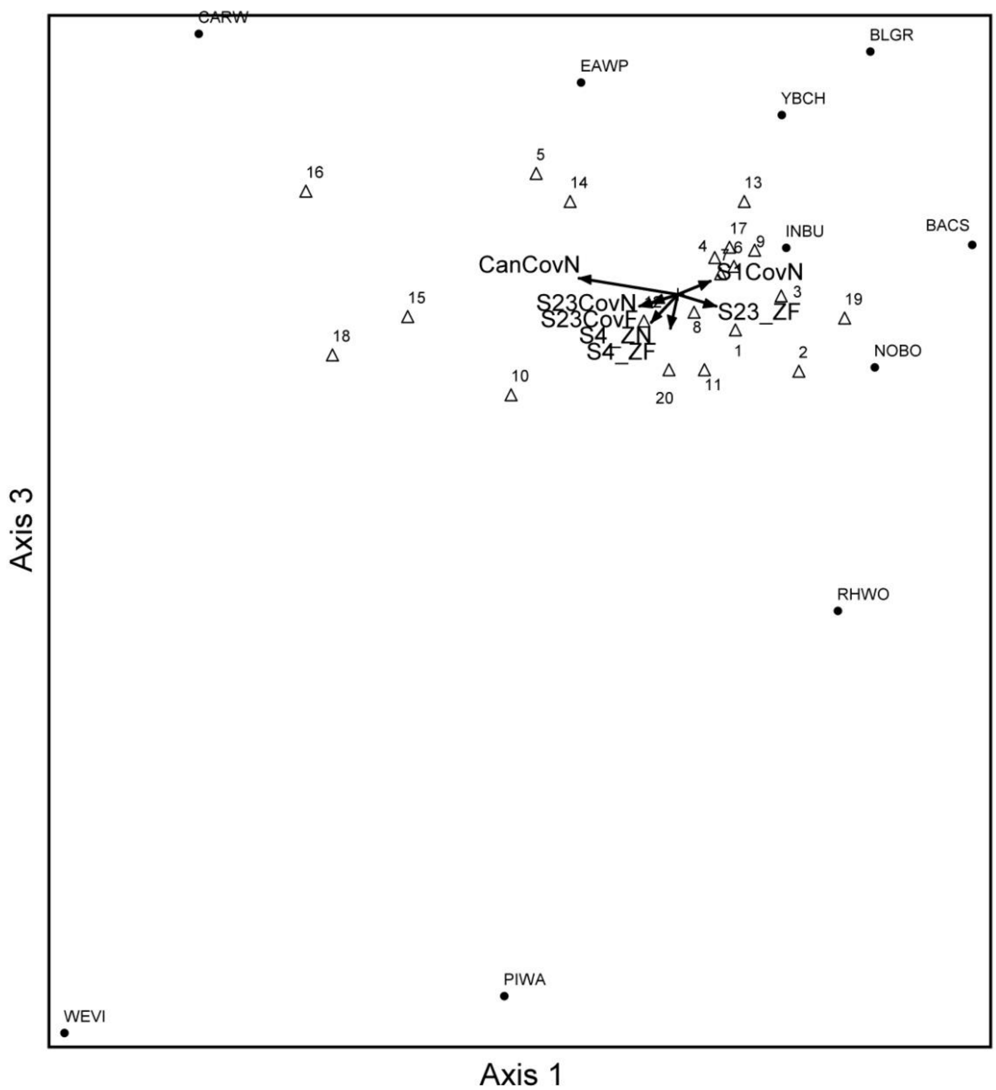

Figure 108. Canonical Correspondence Analysis Biplot for species and LiDAR-derived structural habitat attributes for 2008 survey point location data.

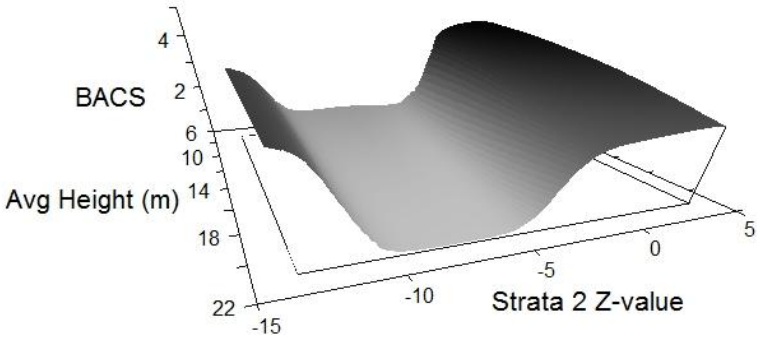

Figure 109. 3D Response Variable for Bachman's Sparrow as the predictor and the two strongest predictors: fine scale (100 m buffer) average height and Stratum 2 z-value.

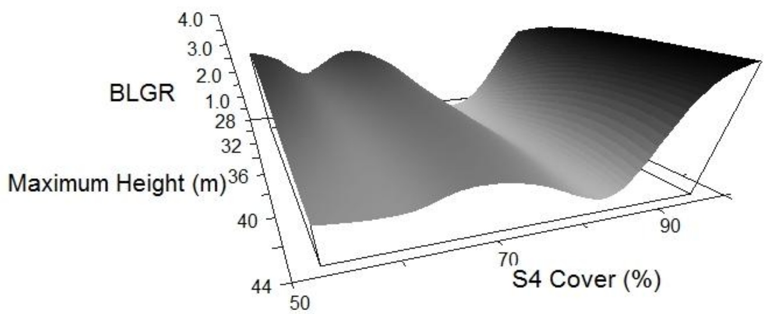

Figure 110. 3D Response Variable for the Blue Grosbeak as the predictor and the two strongest predictors: course scale (200 m buffer) maximum height and Stratum 4 cover.

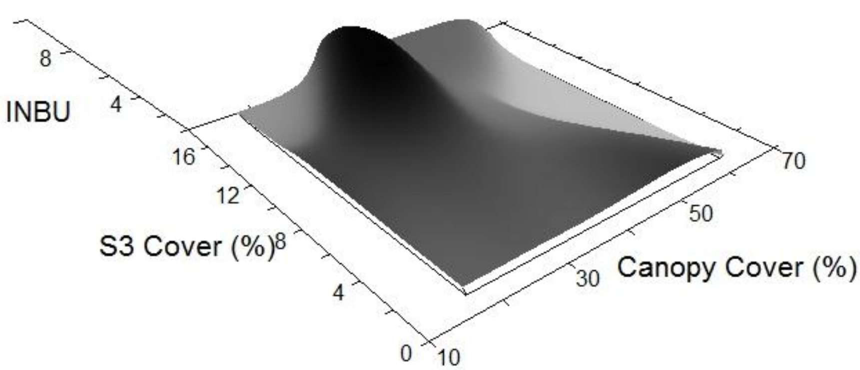

Figure 111. 3D Response Variable for the Indigo Bunting as the predictor and the two strongest predictors: fine scale (100 m buffer) canopy cover and Stratum 3 cover.

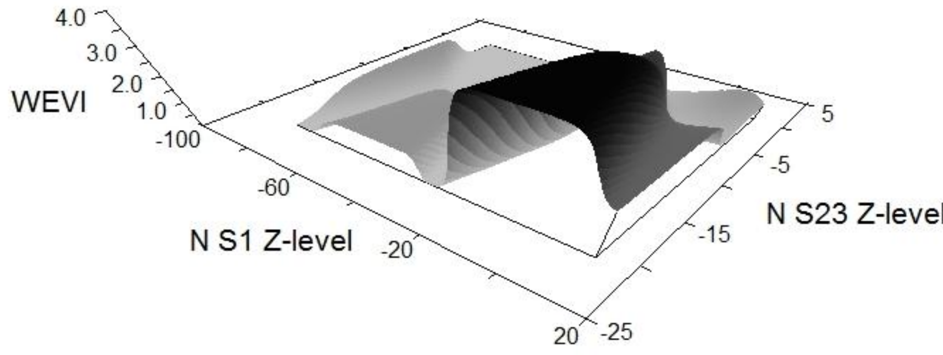

Figure 112. 3D Response Variable for the White-eyed Vireo as the predictor and the two strongest predictors: fine scale (100m) Stratum 1 z-value and Strata 2+3 z-level.

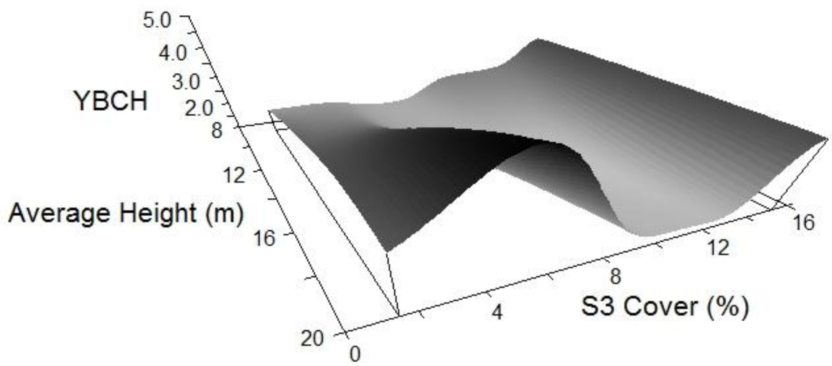

Figure 113. 3D Response Variable for the Yellow-breasted Chat as the predictor and the two strongest predictors: coarse scale (200m) average height and Stratum 3 cover.

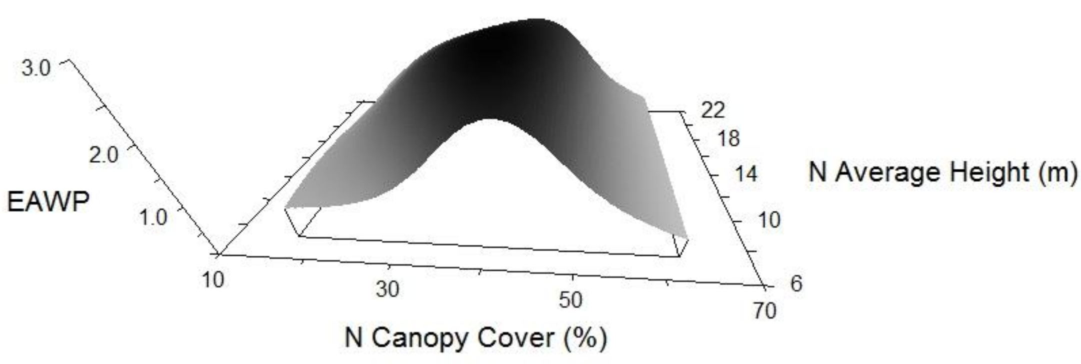

Figure 114. 3D Response Variable for the Eastern Wood-pewee as the predictor and the two strongest predictors: fine scale (100 m buffer) average height and Stratum 2 z-value.

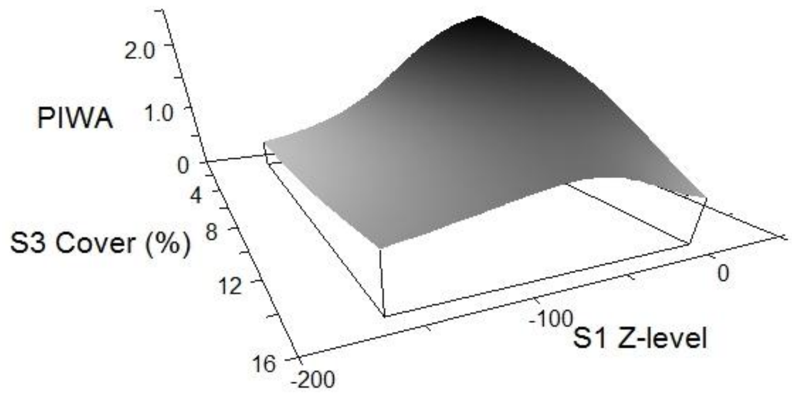

Figure 115. 3D Response Variable for the Pine Warbler as the predictor and the two strongest predictors: coarse scale (200 m buffer) Stratum 3 Cover and Stratum 1 z-value.