5-1-2009

Testing the accuracy of LiDAR forest measurement replications in operational settings

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TESTING THE ACCURACY OF LIDAR FOREST MEASUREMENT REPLICATIONS IN OPERATIONAL SETTINGS

By

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A Thesis
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Master of Science
in Forestry
in the Department of Forestry

Mississippi State, Mississippi

May 2009

TESTING THE ACCURACY OF LIDAR FOREST MEASUREMENT

REPLICATIONS IN OPERATIONAL SETTINGS

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Title of Study: TESTING THE ACCURACY OF LIDAR FOREST MEASUREMENT REPLICATIONS IN OPERATIONAL SETTINGS

Pages in Study: 57

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The repeatability of stand measurements derived from LiDAR data was tested in east-central Mississippi. Data collected from LiDAR missions and from ground plots were analyzed to estimate stand parameters. Two independent LiDAR missions were flown in approximate orthogonal directions. Field plots were generated where the missions overlapped, and tree data were taken in these plots. LiDAR data found 86-100% of mature pine trees, 64-81% of immature pine trees, and 63-72% of mature hardwood trees. Immature and mature pine tree heights measured from LiDAR were found to be significantly different (α= 0.05) than field measured heights. Individual tree volumes and plot volume for mature pines were precisely predicted in both flight directions. The

results of this study showed that LiDAR repeatability in mature pines can be accurately achieved, while immature pine and hardwood plots were unable to match the repeatability of the mature pine plots.

ACKNOWLEDGEMENTS

After every chapter of a text book, there is always a review section where important points in the chapter are mentioned; points that one should keep in mind. Now that another chapter of my life has ended, I would like to look back and review some people who have played an important part in this section of my life; people who will always be kept in my mind and especially in my heart.

On the top of my list would be my shepherd, our Lord God; he who guides me and loves me unconditionally; the One who gave me a blessed and meaningful life. I would like to thank You Lord God for this and especially for these people that You sent to my life who have kept me going, even when I wanted to give up. For the love they are giving me, may You bless them Lord and guide them all throughout their lives.

To my major professor, Dr. David Evans and committee members, Dr. Robert Parker and Dr. Emily Schultz who have helped me with every problem I had. Their patience and good nature have touched my life so much.

To my family who has always been patient with me, my parents, David and Judy Arnold, my sister, Myra Purvis, all my grandparents, aunts, uncles, and cousins. Finally, after years of waiting, I'm through and thanks to all of you for believing in me.

To the person who helped me bring back my faith in myself. He pulled me up when I was so down. Thank you, David Wilkinson, for encouraging me and always being there.

To Drew Ashworth and Tabatha Kelly who were my constant companions during the trying times that are graduate school. Your friendships have kept me strong until now, thank you.

To the Spatial Information Technologies Laboratory members and fellow graduate students, as well as Curtis Collins and others who have already moved on with the next part of their lives, thank you all for help and direction.

To the friends and people who have made my time at MSU very memorable. And to the people that I failed to mention, thank you so much for making my MSU life unforgettable. May the Lord bless you all!

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CHAPTER I

INTRODUCTION

Having information on the structural characteristics of a forest is important for any management scheme, whether it is for timber growth and harvest, wildlife habitat, recreational areas, or forest inventory. The vertical composition of forests such as tree size and spacing can be detected by remote sensing techniques including aerial photographs and laser scanner systems. Lefsky *et al.* (2001) examined several remote sensors including light detection and ranging (LiDAR) and evaluated the ability of each to predict forest stand structure attributes. LiDAR is an active airborne sensor that records the x, y, z coordinates of objects that laser pulses reflect off of on their way to the ground, as well as the ground itself. LiDAR systems are composed of three independent devices. 1) The ranging device records the length of time between the emission and reception of a laser pulse that is used to calculate the distance from the platform to the object (half of the recorded time); the scanning system determines the angle at which laser pulses are emitted. 2) A Differential Global Positioning System (DGPS) is employed to record the location of the laser at each pulse. 3) An internal Inertial Measurement Unit (IMU) records the "three-axis orientation (angular roll, pitch, and yaw) of the aircraft." The information from these systems is combined to determine the exact location of each laser pulse return (Evans *et al.*, 2006). Many studies have been performed to test the ability of small-footprint LiDAR to estimate stand characteristics such as: tree height, number of stems per plot, basal area, volume, crown properties - including height from ground to crown and crown length as a proportion of tree height of individual trees, mean tree height, trees per acre, and predicted diameter breast height (DBH) (Means *et al.*, 2000; Næsset and Bjerknes, 2001; Næsset and Økland, 2002; Parker and Evans, 2004).

Parker and Glass (2004) compared high- and low-posting-density, small-footprint, multi-return LiDAR data for estimating tree heights and stem density to predict volume. Posting density is the average number of LiDAR footprints per unit area. The low-density LiDAR had a footprint (area covered on the ground) diameter of 0.213 meters and posting spacing of 1 meter; the high-density LiDAR had a footprint of 0.122 meters and posting spacing of 0.5 meters. Of their 1,410 total LiDAR plots, every tenth plot was assigned to be a ground plot for field measurements. The low-density LiDAR yielded higher estimates of number of trees than either the high-density LiDAR or the ground plots. No statistical differences were found between the double-sample regression volume estimates with high- or low-density LiDAR data, but the standard errors and sampling errors were lower with low-density data than with high-density data.

Parker and Glass (2004) concluded that low-density LiDAR data will produce adequate volume results when used with a double-sampling procedure.

Parker and Mitchell (2005) compared smoothed and unsmoothed small-footprint LiDAR for estimating tree heights and trees per acre. The canopy height model derived from LiDAR data was smoothed by using a 5x5 pixel (1 m^2) window that averaged the pixel values in the window and assigned the center pixel the average value. Their research used the same high- and low-density LiDAR and ground data as Parker and Glass (2004). There were statistically significant differences between estimated average tree height from ground plots and from smoothed and unsmoothed, high- and low-density LiDAR data. The relationship between high- and low-density LiDAR and ground tree heights was improved by smoothing the heights on the LiDAR crown surfaces; additionally, this smoothing reduced height biases for hardwoods, increased height biases for pines, and improved accuracy rates in the number of trees per acre estimates. The authors concluded that low-density unsmoothed LiDAR data will produce adequate volume results when used with a double-sampling procedure.

Andersen *et al.* (2005) compared high-density LiDAR data sets from 1999 and 2003 for the same location in Washington State. The research determined that if high-density LiDAR data are collected in different years, measurements of individual tree height growth can be obtained for an entire forest area, allowing for detailed, spatially explicit analyses of site quality and productivity. LiDAR canopy surface measurements were extracted by filtering out the highest return within each 1 meter grid cell area. Those returns were gridded into a canopy surface model using an inverse distance interpolation algorithm and a 3-sector search with a radius of 3 meters. They also measured at plot and individual-tree levels. They determined that only trees in the overstory could be accurately segmented and measured, but that is not a serious limitation because typically only overstory trees comprise the majority of the volume in a commercial forest inventory. From the two sets of LiDAR data, individual tree height measurements were extracted and it was determined that small differences in growth between thinning treatments could be detected.

Yu *et al*. (2004) studied the usefulness of high-density airborne laser scanners for the detection of harvested trees and estimation of tree growth. Two LiDAR missions were flown in September 1998 and June 2000 over the study area in Kalkkinen, Finland. Fallen or harvested trees were located in the field. Difference imaging was used to detect harvested trees. Each pixel value from the 2000 canopy height model was subtracted from the corresponding pixel of the 1998 canopy height model. The harvested trees were detected with high accuracy (61 out of 83 trees correctly detected). To estimate tree height growth, they developed a tree-to-tree matching algorithm to locate the trees that were present at both data collection periods. Single tree heights were taken as the highest point in each tree segment. The calculated tree height growth was attained by subtracting the 1998 data height from the 2000 data height. The standard errors were generally less than 5 cm and in all cases less than 10 cm. All the trees from the selected stands were not matched; the percentage of correct matches for the 20 selected stands ranged from 39-70%. The same tree-to-tree matching algorithm and the same 20 stands that were used to locate trees were used to analyze the change in crown cover percentage. A trend showing that young trees grow horizontally more rapidly than older trees was discovered though, these findings were not field validated. The authors concluded these methods will be usable in large-area forest inventories where permanent sample plots are used.

Objectives

Few studies have examined the repeatability of LiDAR measurements in the context of inventory. The objective of this study was to test repeatability of individual tree measurements derived from LiDAR data in operational settings such as long term forest inventory, repetitive regional forest inventories, or site productivity determinations.

Questions to be answered:

- Are the same trees identified on different LiDAR canopy surfaces and do they match with field data?
- Are the heights of trees identified on different LiDAR canopy surfaces the same, and are they more precise than field measurements?
- Is the individual tree volume as determined from different LiDAR surfaces the same, and is it more precise than calculated field volume?
- Is the timber volume per plot as estimated from different LiDAR surfaces the same, and is it more precise than calculated field volume?

CHAPTER II

METHODS

Data collected from aerial LiDAR missions flown in July of 2006 and from fieldwork were analyzed to estimate parameters such as tree height, individual tree volume, and computed plot volume. Three forest types were studied with mature pine having 16 field plots, mature hardwood having 15 field plots, and immature pine having 18 field plots (49 total plots). The LiDAR missions were compared to each other and the ground measurements for statistical differences. The manipulation and analysis of both the aerial and field data were completed in January 2009.

Study Site

The study area is located 8.9 km (5.5 miles) south of Starkville, MS, and encompasses parts of the John W. Starr Memorial Forest and Noxubee National Wildlife Refuge (Figure 2.1). The area is approximately 3.4 km (2.1miles) across and 11.8 km (7.3 miles) long. Timber types found on the area include mature pine, immature pine, immature hardwoods, mature hardwoods, and mixed pine-hardwood stands.

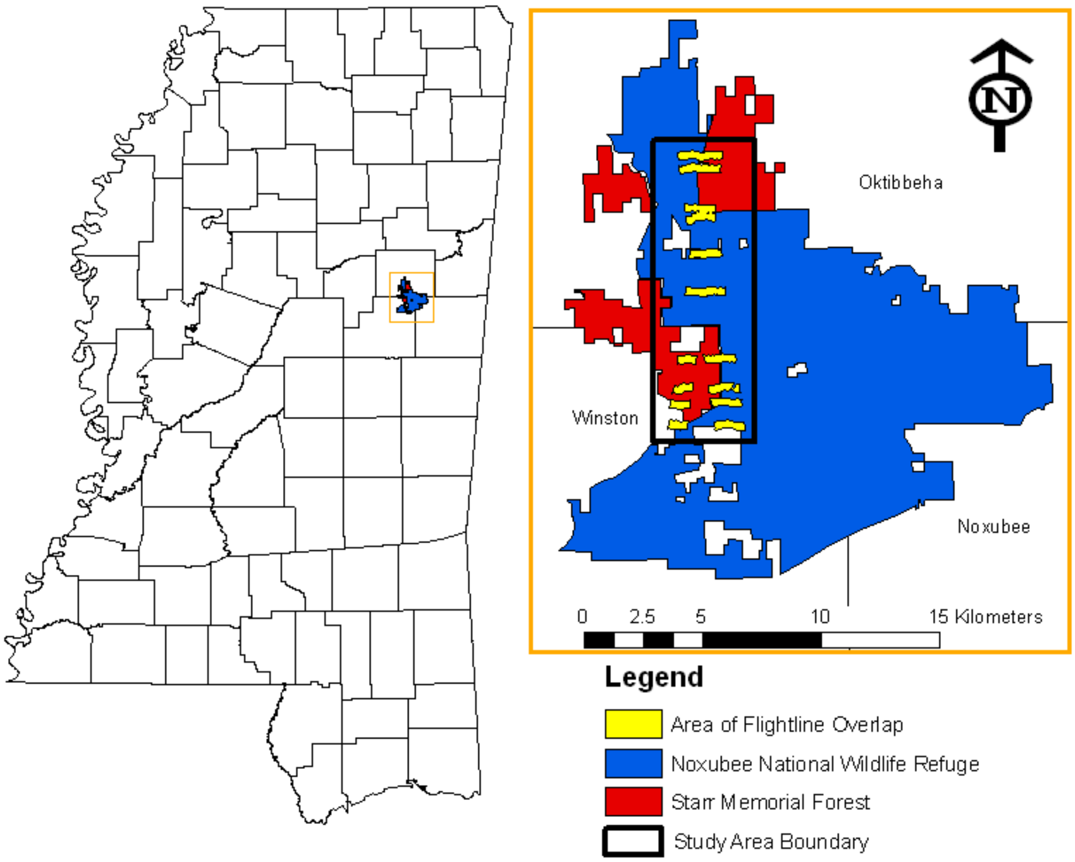


Figure 2.1 Location of the study area within portions of the John W. Starr Memorial Forrest and Noxubee National Wildlife Refuge in Okitbbeha, Noxubee, and Winston Counties, Mississippi.

Aerial Measurements

Two independent LiDAR missions were flown in approximate orthogonal directions (NS vs. EW) in July 2006. These two independent data sets were tested for accuracy of rectification and tree/plot measurements by the establishment of ground plots in the intersections of the LiDAR flight lines. The LiDAR data were delivered by the University of Texas in ASCII text format with Universal Transverse Mercator (UTM) coordinates. The data included a timestamp, "X" coordinates for the first and last return, "Y" coordinates for the first and last return, "Z" height above ellipsoid (HAE) in meters for the first return and last return, and intensity of the first and last return. HAE precision of 0.0000001 was maintained throughout processing. The data were collected at a posting spacing of 0.75 m within the center 50% of the flight swath (approximately 300 m wide). The ground footprint size ranged from 0.25 m to 0.6 m. The scan angle did not exceed 20 degrees from nadir. Data were collected in an elongated X pattern from roughly north to south (NS) and 10 lines were flown from east to west (EW). A digital elevation model (DEM) of each plot was generated from the LiDAR data to help in determining heights of trees identified from LiDAR surfaces.

Field Measurements

Field work was completed in May 2007. Field plot locations were generated at random within strata defined by the Landsat-based classification described in Collins *et al.* (2005) in the areas where the LiDAR data collection overlapped. Plot centers were located and recorded with a Wide Area Augmentation System (WAAS)-enabled twelve-channel Garmin[1] GPS with real-time differential correction. The GPS, operated by a handheld LandMark Systems Recon 400X data recorder, had a reported position accuracy of <3 m on average (Garmin, 2005). Canopy trees in the plots were classified as either hardwood or pine and their crown class (dominant, co-dominant, intermediate, or suppressed) was recorded. Suppressed trees were recorded but not used in analysis because this study was only interested in detection of canopy trees that could be identified by LiDAR and substantially contribute to the wood volume accounted for in an inventory. Plot size varied between stand types with the mature pine having a 0.04 ha (0.1 acre) plot, the immature pine having a 0.020 ha (0.05 acre) plot, and the mature hardwood having a 0.081 ha (0.5 acre) plot. Total tree heights and height to live crown were measured to the nearest 0.1 m twice by different people using separate Haaglof Forestor Vertex hypsometers. These double measurements were taken to be compared to each other and the

[1] Mention of company or product names is for information only and does not constitute official endorsement by the author or Mississippi State University

processed LiDAR data. Tree diameter at breast height (DBH; 1.4m above ground) was recorded to the nearest 0.254 cm (0.1 inch) with a Spencer® 50'L loggers diameter tape. All canopy trees in the plots were stem mapped, using an Advantage® from Laser Atlanta to determine azimuth and distance for trees more than 2.44 m (8 feet) away from plot center. A tape measure was used to determine the distance from plot center for trees less than 2.44 m away because the laser does not accurately measure distances less than 2.44 m. Also, crown radii were taken in the cardinal directions to nearest 0.1 m using a tape measure or a Haglof 201 Distance Measuring Equipment (DME).

In Microsoft Excel, the coordinates of the plot center were used along with the stem mapped information to create a table of tree location coordinates that were converted to a shapefile of tree locations in ESRI ArcMap. This shapefile was used along with the crown radius measurements to create a shapefile of tree crown polygons.

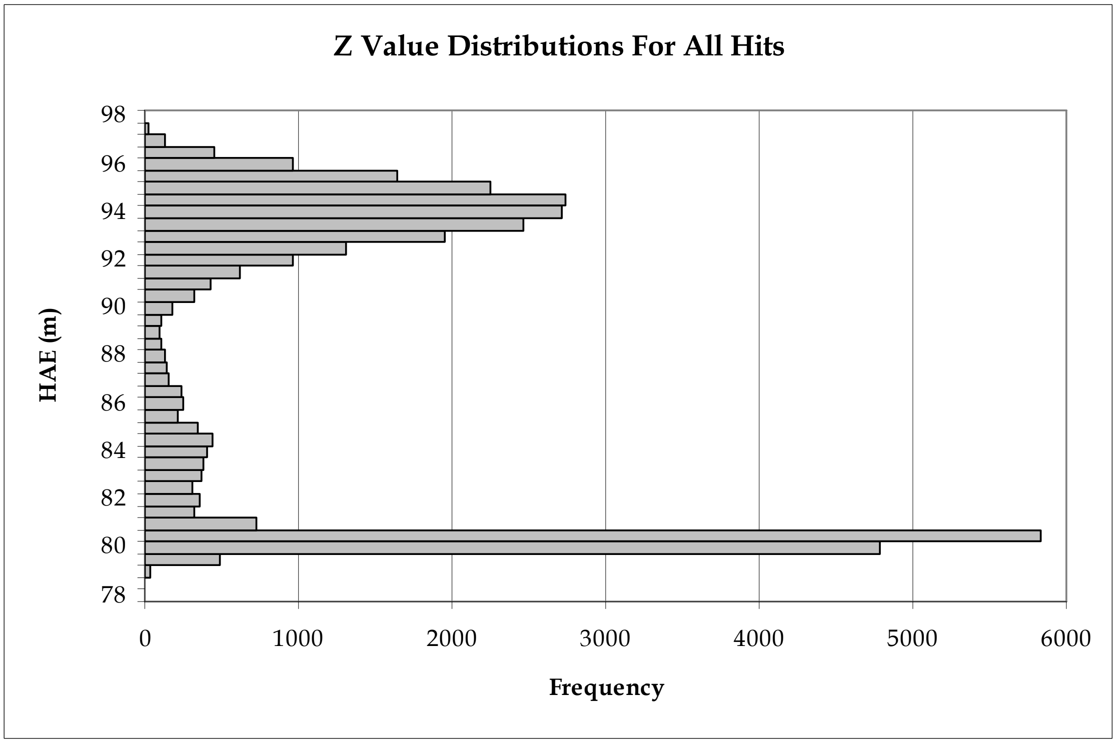
LiDAR Data Processing

The AWK text-processing programming language was used on a Unix workstation to process the text files. Individual flight lines were first clipped by the imprinted time stamp. From those files of individual flight lines, the areas around the plots were clipped using X and Y coordinates. This process was performed for the NS flight lines as well as the EW flight lines. The last returns were used to create the bare earth layer, and the first returns were used to create the tree canopy surface.

Bare Earth Layer Generation

Since not every last return is a ground hit, JMP IN Version 4.0.4 (Academic) software was used on the clipped files separate out and keep only the LiDAR points that appeared to be under the main canopy (Figure 2.2). This resulted in most plot files used to generate the bare earth layer having only points less than 90 meters in height, eight files had points less than 95 meters, and 4 files had points less than 80 meters.

LIDAR Analyst® for ArcGIS version 4.2.0.11 was run in ESRI® ArcMAP™ 9.1 to make a bare earth layer. First, the LiDAR text files for each plot were converted into LAS files, and using only those last returns selected previously, the program extracted the uncorrected bare earth for each plot. In ERDAS IMAGINE 8.7, a DEM downloaded from MARIS with 10 m resolution was subset to each of the plot files. The heights in the DEM file were converted from feet to meters so the two corresponding files (uncorrected LiDAR bare earth and DEM) were comparable. They were then differenced using a model built in IMAGINE. In LIDAR Analyst the uncorrected bare earth file was used to create a modification layer. This layer was composed of points that were used to



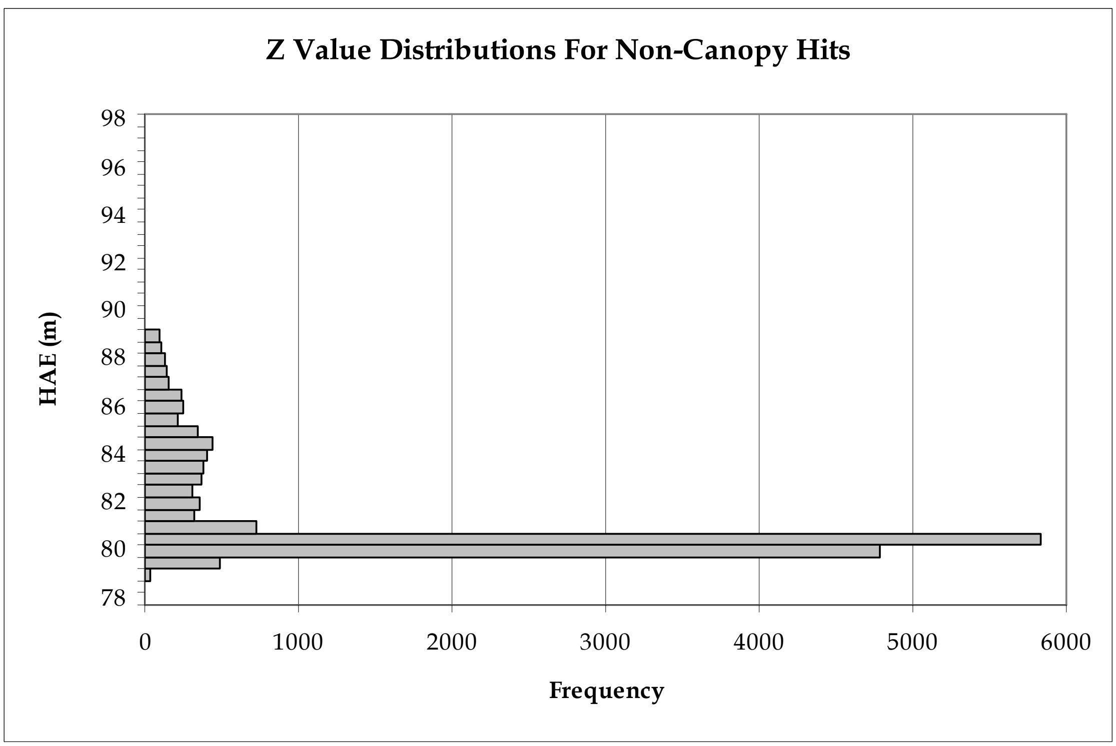


Figure 2.2 Distributions of Z values in height above ellipsoid (HAE) before (above) taking out LiDAR canopy hits and after (bottom) taking out canopy hits (includes mid- and understory hits).

interpolate the bare earth layer. The high spots in particular were obviously dense clumps of vegetation that were not penetrated by the LiDAR. There are no earthen mounds of this sort in the areas that were field surveyed. Therefore, the points associated with these high points were deleted before final bare earth layer production. The general cutoff value was interpreted to be 1.5 meters for false ground returns. The differenced image was viewed on screen along with the modification layer, and the raster value of the differenced image was attributed to the points in the modification layer. In the attribute table of the modification layer, all points greater than 1.5 meters were selected and deleted (Figure 2.3) because these points were assumed to be false ground points that would bias the final bare earth layer. The modification layers for each plot region were then re-interpolated without the bad points, creating a final bare earth layer.

Tree Canopy Surface Generation

Tree canopy surfaces were created in IMAGINE by means of the linear rubber sheeting interpolation method using all first return points. The output cell size for these layers was 0.5 meter. This tree canopy surface, along with the previously mentioned final bare earth layer, was used in a model to produce a tree height layer. To prevent a negative height, the tree height model made each

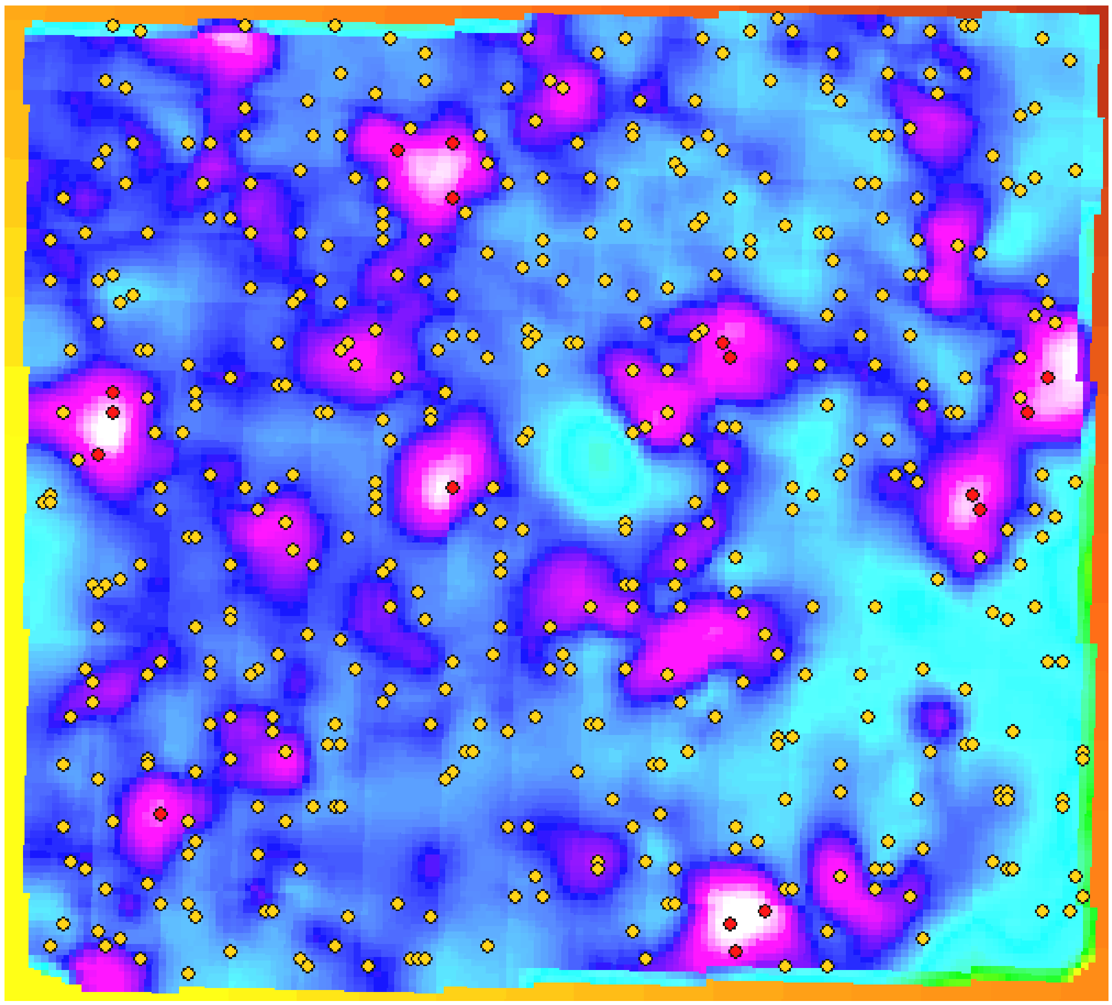


Figure 2.3 A small subset of the initial bare ground surface viewed with LiDAR Analyst in ArcMap. The dots shown are the predicted LiDAR ground points. The red dots are predicted ground points that were greater than 1.5 meters different from the 10m DEM. These points were removed before final interpolation.

output cell value zero if the bare earth layer was a larger value than the canopy surface layer, otherwise it output the difference between the canopy surface and the bare earth layer. The bare earth layer could be higher than the canopy surface if the bare earth layer smoothed out a dip that the canopy model did not. The tree height layers for each plot were combined together by plot type, and then processed in additional models to get tree locations and heights.

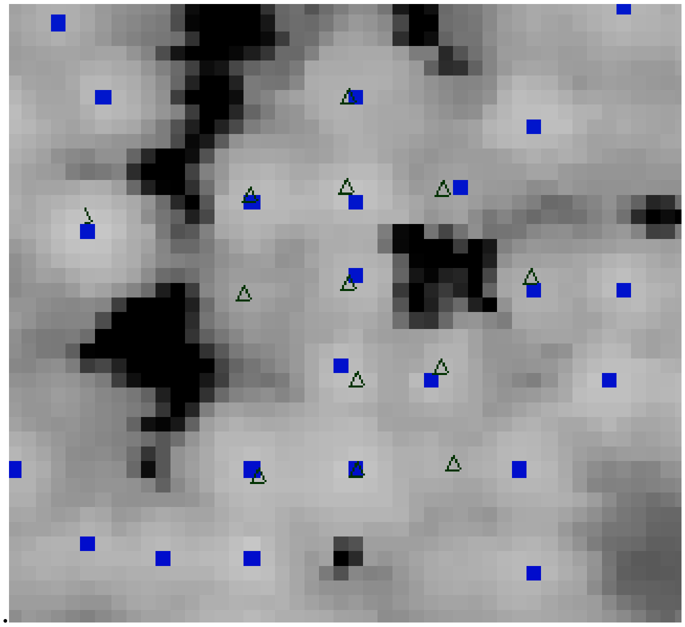
Tree Location Extraction

Tree location extraction models were adapted to each of the tree plot types. The two models for tree identification used were originally developed by McCombs et al. (2003) and these original models were modified for this study. The main modification to the first model had to do with using tree height for the search criterion rather than the relative target density that the original model utilized. The second modification deals with how clumps (assumed tree locations) are formed relative to tree size, rather than using the same constraints for all trees. The model used after combining the tree height layers together was a heights-to-clumps model that converted the tree height layer to output clump locations. The clumps are groups of pixels that represent tree crowns. To identify clumps, the model uses the overall range of possible tree heights to determine which focal search to apply, and couples tree height to assume relative crown size regardless of density. To make the clumps, a Focal Mean function is first incremented with a moving kernel over the tree height layer and returns the mean of the pixels in that search window. This is done to smooth the input surface to reduce the variability in the canopy layer within tree crowns that would potentially result in false tree identification. Then three Focal Rank functions are performed making the output pixel value 1 if it was greater than a fixed percentage of the other pixels (this varied by plot type) in the search window, or 0 if not. This results in binary data sets that represent clumps of different sizes. Next, the maximum possible height value of the original tree height surface and the clump outputs are processed using a conditional statement that only keeps clumps that have a mean vegetation height greater than a certain percentage of the maximum height. A contiguity analysis function was then performed on the clumps to give them a unique identifier, and finally, a Zonal Max function returns the maximum height value for each clump.

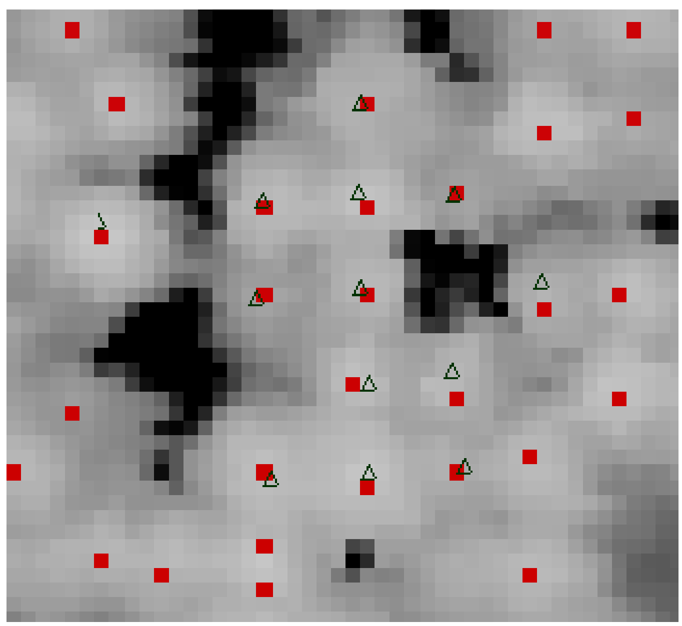
The second model used after combining the tree height layers together was a clumps-to-trees model in which the clumps are processed through a series of sieve tables with thresholds to discard false clumps, such as, a single pixel clump that is greater than 80 percent of the max height or a very large clump that is less that 30 percent of the max height. This model was also modified from the original in McCombs et al. (2003) so that it would detect small trees. The grid cells produced from the sieve tables were added together and subjected to a conditional statement that keeps the highest value pixel in the clump. The output raster layer indicates tree locations and corresponding heights. Tree output locations were assigned unique identities and an additional column "tree id" was added to the attribute table.

Ground and LiDAR Tree Matching

IMAGINE was used to visually match the trees identified in the LiDAR data with the trees that were stem mapped in the field. Because of the many contributing factors such as GPS errors recording the plot location under forest canopy, error in position of LiDAR points, error in angle and distance from plot center of trees, and error due to tree leaning (highest point in crown not centered over the ground location of the stem), the field plot locations had to be adjusted in order to line up correctly with the LiDAR data. Two immature pine plots could not be matched to their LiDAR data so they were not used in any analysis. The two sets of LiDAR trees (NS and EW) were matched with field data in IMAGINE by overlapping the three sets of tree locations (Figure 2.4). The field trees were given a reference number that was used in analysis to match ground and LiDAR observations. The LiDAR tree location attribute tables were opened and the corresponding tree number from the field tree location file was entered in the "tree id" column. Any LiDAR trees found that did not have corresponding field trees were labeled as the plot number and .999 for use in generating an accuracy assessment.



EW



NS

Figure 2.4 Example views of LiDAR found trees and actual ground tree locations displayed over canopy surfaces. The red and blue pixels represent trees identified by the tree finding model. The surface on the top shows the EW trees (red pixels); and the surface on the bottom shows the NS trees. The green triangles represent field location of trees.

Statistical Analysis

LiDAR Tree Finding Accuracy

After making all possible tree matches in the NS and EW data sets, the LiDAR attribute data were exported as a .dbf file and converted to an .xls file to be managed in Excel where the LiDAR trees were matched with their corresponding ground trees using the tree number that had been previously assigned.

Analysis was performed using two plot selection criteria. The first analysis was made using all plot locations (further referred to as "all plots"). The second set disregarded those plots located on the edge of LiDAR scans (further referred to as "no edge plots"). LiDAR surfaces near the edges of scans exhibited distortions due to different canopy penetration by LiDAR pulses. The selection of those plots was performed based on *a priori* knowledge of the stand conditions. Only 14 plots out of 47 did not fall on the edge of a flightline. Of those 14 plots, 1 was mature pine, 4 were hardwood, and 9 were immature pine. Tree finding omission and commission errors were calculated using the methods described in Congalton and Green (1999), and a two-tailed Chi-squared test, described in Conover (1999), was used to test the accuracies for significant differences. Also calculated was percent of trees found by crown class.

Tree Measurements

Height Analysis

In Excel, trees that had matches for both NS and EW flight lines were separated and analyzed with SAS 9.1.3 to compare statistical differences between individual heights, individual tree volume estimated from the two LiDAR data sets and the ground measurements, and plot volume estimated from the two LiDAR data sets and the ground measurements. Paired t-tests were performed on the matched trees to test mean height differences between the parameters listed in Table 2.1.

Table 2.1 Parameters used to test mean height differences between matched trees in paired t-tests in east-central Mississippi.

NS - EW	=	heights predicted for the NS flightlines	-	heights predicted for the EW flightlines
Hyp1 - Hyp2	=	heights determined by hypsometer 1	-	heights determined by hypsometer 2
NS - Hyp1	=	heights predicted for the NS flightline	-	heights determined by hypsometer 1
NS - Hyp2	=	heights predicted for the NS flightline	-	heights determined by hypsometer 2
EW - Hyp1	=	heights predicted for the EW flightline	-	heights determined by hypsometer 1
EW - Hyp2	=	heights predicted for the EW flightline	-	heights determined by hypsometer 2

Volume Analysis

Ground tree heights from 111 hardwood trees, 115 mature pine trees, and 118 immature pine trees were compared with corresponding predicted LiDAR tree heights derived from the tree finding models using Simple Linear Regression (SLR) with the model:

$$H_{gr} = b_0 + b_1 H_{Li} \quad (2.1)$$

where:

H_{gr} = average measured ground height of the tree (m)

H_{Li} = predicted height of the same tree (m) from the difference of the LiDAR canopy and ground surfaces

Regression coefficients were produced in SAS using Proc Reg to fit the average hypsometer height to the LiDAR derived NS and EW height. To test the differences between the regression coefficients in SAS, Proc GLM was performed with a contrast statement. The DBH for corresponding adjusted LiDAR-derived heights was interpolated for each plot type using a regression equation that was derived from the field heights and DBHs using NLREG (Sherrod, 2001). DBH and height from 106 immature pine, 100 mature pine, and 109 hardwood trees were used to produce the equations. LiDAR heights were adjusted to the ground tree height because previous studies have found differences between LiDAR derived heights and ground measured tree heights. Roberts et al. (2005) found significant differences between the average ground measured heights of trees and the average LiDAR estimated heights. Volume was calculated per tree using Minor's form class equation (Merrifield and Foil, 1967). Paired t-tests were processed in SAS to compare between (1) mean volume differences of individual matched trees (2) mean volume differences by plot of all trees found by LiDAR and measured on the ground for the parameters listed in Table 2.2.

Table 2.2 Parameters used to test mean volume differences between individual matched trees in paired t-tests in east-central Mississippi.

NS-EW	=	volume predicted by the adjusted heights for the NS flightlines	-	volume predicted by the adjusted heights for the EW flightlines
Vol1-Vol2	=	volume calculated for the heights determined by hypsometer 1	-	volume calculated for the heights determined by hypsometer 2
NS- Vol1	=	volume predicted by the adjusted heights for the NS flightlines	-	volume calculated for the heights determined by hypsometer 1
NS- Vol2	=	volume predicted by the adjusted heights for the NS flightlines	-	volume calculated for the heights determined by hypsometer 2
EW- Vol1	=	volume predicted by the adjusted heights for the EW flightlines	-	volume calculated for the heights determined by hypsometer 1
EW- Vol2	=	volume predicted by the adjusted heights for the EW flightlines	-	volume calculated for the heights determined by hypsometer 2
NS-Avg	=	volume predicted by the adjusted heights for the NS flightlines	-	volume calculated for heights determined by the average of hypsometer 1 and 2
EW-Avg	=	volume predicted by the adjusted heights for the EW flightlines	-	volume calculated for heights determined by the average of hypsometer 1 and 2

CHAPTER III

RESULTS

LiDAR Tree Finding Accuracy

The analysis of accuracy of the tree finding model for all plots indicated that mature pine plots had the highest percent of correctly matched trees (Table 3.1) with immature pine and hardwood plots having about the same accuracies. Mature pine plots also had the lowest omission errors with immature pine plots and hardwood plots having about the same omission errors. For the NS flightlines, commission errors were similar for both mature and immature pine plots, but for EW flightlines the commission errors were greater for the mature pine plots than immature pine plots. Hardwood plots had commission errors that were higher than mature or immature pine plots.

Tree finding model accuracies for no edge plots (Table 3.2) were to some extent different than accuracies for all plots. The only mature pine plot contained 5 trees and had 100 percent of trees correctly matched with no omission or commission errors. Compared to the analysis on all plots (Table 3.1), immature pine plot overall accuracy was higher, omission errors were lower, and commission errors were similar for NS flightlines and decreased slightly for

Table 3. 1 LiDAR tree finding model accuracies for all plots in east-central Mississippi.

Immature Pine	Field Total	Total Trees Found by LiDAR	Total LiDAR trees w/ Field match	Correctly matched trees (%)	Omission (%)	Commission (%)
North-South	193	127	123	64	36	2
East-West	193	162	143	74	26	10
Mature Pine	Field Total	Total Trees Found by LiDAR	Total LiDAR trees w/ Field match	Correctly matched trees (%)	Omission (%)	Commission (%)
North-South	138	122	118	86	14	3
East-West	138	155	122	88	12	24
Hardwood	Field Total	Total Trees Found by LiDAR	Total LiDAR trees w/ Field match	Correctly matched trees (%)	Omission (%)	Commission (%)
North-South	174	251	120	69	31	75
East-West	174	316	127	73	27	109

Table 3. 2 LiDAR tree finding model accuracies for no edge plots in east-central Mississippi.

Immature Pine	Field Total	Total Trees Found by LiDAR	Total LiDAR trees w/ Field match	Correctly matched trees (%)	Omission (%)	Commission (%)
North-South	107	79	76	71	29	3
East-West	107	93	87	81	19	6
Mature Pine	Field Total	Total Trees Found by LiDAR	Total LiDAR trees w/ Field match	Correctly matched trees (%)	Omission (%)	Commission (%)
North-South	5	5	5	100	0	0
East-West	5	5	5	100	0	0
Hardwood	Field Total	Total Trees Found by LiDAR	Total LiDAR trees w/ Field match	Correctly matched trees (%)	Omission (%)	Commission (%)
North-South	62	60	41	66	34	31
East-West	62	75	39	63	37	58

EW flightlines. Hardwood plot percent of correctly matched trees and commission errors decreased and omission errors increased when compared to analysis on all plots.

Tree Finding Accuracy Comparison

The EW flight line overall accuracies for all plots were higher in all cases. To test the statistical difference between these accuracies, a Chi-squared test was performed using a 2x2 contingency table. In addition to testing the differences within plot types, the accuracies were also tested across plot types. In order to be statistically different, the t-value had to be less than -1.9600 or greater than 1.9600 ($\alpha=0.05$) (Conover, 1999). The difference between the two flightlines was only statistically different within plot types for immature pine (Table 3.3). When testing across plot types, there were statistical differences between mature pine NS and EW against every plot type they were compared against.

Table 3.3 Chi-squared test for differences of tree finding model accuracies for all plots.

Within Plot Types			t Value	n
Immature Pine NS	vs	Immature Pine EW	-2.1993*	386
Mature Pine NS	vs	Mature Pine EW	-0.7149	267
Hardwood NS	vs	Hardwood EW	-0.8268	348
Across Plot Types				
Hardwood NS	vs	Mature Pine EW	-3.2133*	312
Hardwood NS	vs	Mature Pine NS	-2.5073*	312
Hardwood NS	vs	Immature Pine NS	-4.3903*	367
Hardwood NS	vs	Immature Pine EW	-5.0473*	367
Hardwood EW	vs	Mature Pine EW	-4.8825*	312
Hardwood EW	vs	Mature Pine NS	-3.4117*	312
Hardwood EW	vs	Immature Pine NS	1.0587	367
Hardwood EW	vs	Immature Pine EW	-1.0885	367
Immature Pine EW	vs	Mature Pine EW	-3.3692*	331
Immature Pine EW	vs	Mature Pine NS	-2.6744*	331
Immature Pine NS	vs	Mature Pine NS	-1.9004	331
Immature Pine NS	vs	Mature Pine EW	-0.2397	331

* denotes significant difference at $\alpha = 0.05$

The analysis of no edge plots showed that the overall accuracies were higher for the EW flightline for immature pine and higher for the NS flightline for hardwood. There was only one mature pine plot that was not on the edge for either NS or EW and all trees in that plot were found. To test the statistical difference between these accuracies, a Chi-squared test was performed using a 2x2 contingency table. The difference between the two flightlines was not significant among plot types (Table 3.4); but the difference between immature pine EW and both hardwood NS and EW was significant.

Table 3.4 Chi-squared test for differences of tree finding model accuracies for no edge plots.

Within Plot Types			t Value	n
Immature Pine NS	vs	Immature Pine EW	-1.7649	214
Mature Pine NS	vs	Mature Pine EW	-------	
Hardwood NS	vs	Hardwood EW	0.3754	124
Across Plot Types				
Hardwood NS	vs	Mature Pine EW	-1.5705	67
Hardwood NS	vs	Mature Pine NS	-1.5705	67
Hardwood NS	vs	Immature Pine NS	-0.6650	169
Hardwood NS	vs	Immature Pine EW	-2.2187*	169
Hardwood EW	vs	Mature Pine EW	-1.6806	67
Hardwood EW	vs	Mature Pine NS	-1.6806	67
Hardwood EW	vs	Immature Pine NS	-1.0917	169
Hardwood EW	vs	Immature Pine EW	-2.6476*	169
Immature Pine EW	vs	Mature Pine EW	-1.0667	112
Immature Pine EW	vs	Mature Pine NS	-1.0667	112
Immature Pine NS	vs	Mature Pine NS	-1.4153	112
Immature Pine NS	vs	Mature Pine EW	-1.4153	112

* denotes significant difference at $\alpha = 0.05$

Crown Class

In all plot types, dominant trees had the highest percentage of trees found, codominant the second highest, and intermediate the lowest percentage of trees found (Table 3.5).

Table 3.5 Percent trees found by crown class for all plots in east-central Mississippi.

	Dominant	Codominant	Intermediate
Immature Pine:			
North-South	92	63	16
East-West	92	72	50
Mature Pine:			
North-South	94	92	35
East-West	100	94	41
Hardwood:			
North-South	97	75	40
East-West	90	79	51

Tree Measurements

Height Analysis

The plots were evaluated by plot type. Two immature pine plots were not matched to their field data so they were eliminated from the analysis. Normal distribution and independence were assumed for the paired data based on examination of the normal probability plot and random sampling. As indicated by the t-tests test statistics, heights were not significantly different for immature pine measurements of hypsometer 1 – hypsometer 2 heights, and heights were not significantly different for mature pine LiDAR measurements of NS -EW heights and measurements of hypsometer 1 – hypsometer 2 heights. Hardwood height measurements were not significant for any comparison (Table 3.6).

Table 3.6 Paired Student's t test values for comparisons of mean height differences by forest type of all plots in east-central Mississippi.

<table>
<tr><th></th><th>Immature Pine:</th><th></th><th></th><th>Mature Pine:</th><th></th><th></th><th>Hardwood:</th><th></th><th></th></tr>
<tr><th>Difference</th><th>df</th><th>t Value</th><th>Pr > |t|</th><th>df</th><th>t Value</th><th>Pr > |t|</th><th>df</th><th>t Value</th><th>Pr > |t|</th></tr>
<tr><td>NS height - EW height</td><td>117</td><td>4.39</td><td><.0001*</td><td>114</td><td>1.05</td><td>0.2941</td><td>110</td><td>0.68</td><td>0.4975</td></tr>
<tr><td>Hypsometer 1 height – Hypsometer 2 height</td><td>117</td><td>-0.94</td><td>0.3481</td><td>114</td><td>-0.45</td><td>0.6557</td><td>110</td><td>-1.32</td><td>0.1898</td></tr>
<tr><td>NS height – Hypsometer 1 height</td><td>117</td><td>-11.56</td><td><.0001*</td><td>114</td><td>-9.4</td><td><.0001*</td><td>110</td><td>-1.53</td><td>0.1297</td></tr>
<tr><td>NS height – Hypsometer 2 height</td><td>117</td><td>-13.6</td><td><.0001*</td><td>114</td><td>-9.1</td><td><.0001*</td><td>110</td><td>-2.22</td><td>0.0288</td></tr>
<tr><td>EW height – Hypsometer 1 height</td><td>117</td><td>-13.56</td><td><.0001*</td><td>114</td><td>-10.09</td><td><.0001*</td><td>110</td><td>-1.65</td><td>0.1011</td></tr>
<tr><td>EW height – Hypsometer 2 height</td><td>117</td><td>-17.2</td><td><.0001*</td><td>114</td><td>-9.95</td><td><.0001*</td><td>110</td><td>-2.25</td><td>0.0267</td></tr>
</table>

* denotes significant difference at $\alpha = 0.05$

No edge plots measurements of hypsometer 1 – hypsometer 2 heights for all plot types were not significantly different. For mature pine, LiDAR measurements of NS -EW heights, NS – hypsometer 1 heights, and EW– hypsometer 1 heights were not statistically different. Also for hardwood, NS – hypsometer 1 heights, NS – hypsometer 2 heights, and EW – hypsometer 2 heights were not significantly different. For immature pine, NS – EW heights, NS – hypsometer 1 heights, NS – hypsometer 2 heights, EW – hypsometer 1 heights, and EW – hypsometer 2 heights were significantly different. Significant differences for mature pine are NS – hypsometer 2 heights and EW – hypsometer 2 heights, and significant differences for hardwood are NS – EW heights and EW – hypsometer 2 heights (Table 3.7).

Height Discrepancies

Regression coefficients and R^2 values used for equation (2-4) to adjust the predicted LiDAR tree height are displayed in Table 3.8. To test the differences between the regression coefficients, SAS's Proc GLM was performed with a contrast statement. There was a significant difference between the regression coefficients for hardwood EW against all other plot types except hardwood NS for all plots (Table 3.9). For no edge plots there was a significant difference

Table 3.7 Paired Student's t test values for comparisons of mean height differences by forest type of no edge plots in east-central Mississippi.

	Immature Pine:			Mature Pine:			Hardwood:		
Difference	df	t Value	Pr > |t|	df	t Value	Pr > |t|	df	t Value	Pr > |t|
NS height - EW height	74	3.36	0.0005*	4	-0.42	0.6961	36	-3.64	0.0008*
Hypsometer 1 height – Hypsometer 2 height	74	-1.91	0.0597	4	-2.18	0.0943	36	-0.40	0.6888
NS height – Hypsometer 1 height	74	-9.74	<.0001*	4	-3.21	0.0325	36	2.01	0.0519
NS height – Hypsometer 2 height	74	-11.86	<.0001*	4	-5.52	0.0053*	36	1.47	0.1500
EW height – Hypsometer 1 height	74	-12.34	<.0001*	4	-3.08	0.0368	36	3.09	0.0039*
EW height – Hypsometer 2 height	74	-15.47	<.0001*	4	-5.13	0.0068*	36	2.21	0.0333

* denotes significant difference at $\alpha = 0.05$

Table 3.8 Regression coefficients and R^2 values for the adjustment of LiDAR heights (m) with the model $H_{gr} = b_0 + b_1(H_{Li})$.

Plot type	Flight direction	b_0	b_1	R^2	RMSE
Immature Pine	NS	-0.380	1.115	0.929	1.290
	EW	0.829	1.065	0.933	1.259
Mature Pine	NS	-0.508	1.080	0.900	1.825
	EW	-0.167	1.070	0.911	1.718
Hardwood	NS	1.218	0.985	0.528	3.913
	EW	4.763	0.873	0.437	4.275

Table 3.9 Statistical comparison of regression coefficients for adjusting predicted LiDAR tree heights of all plots in east-central Mississippi.

Contrast			Contrast SS	Mean Square	F Value	Pr > F
Immature Pine NS	vs	Immature Pine EW	2.68685755	2.68685755	0.38	0.5365
Immature Pine NS	vs	Mature Pine EW	2.48538179	2.48538179	0.35	0.5522
Immature Pine NS	vs	Mature Pine NS	1.49355663	1.49355663	0.21	0.6449
Immature Pine NS	vs	Hardwood NS	16.74143225	16.74143225	2.38	0.1231
Immature Pine NS	vs	Hardwood EW	59.29774005	59.29774005	8.44	0.0038*
Immature Pine EW	vs	Mature Pine NS	0.27951987	0.27951987	0.04	0.842
Immature Pine EW	vs	Mature Pine EW	0.03090649	0.03090649	0	0.9471
Immature Pine EW	vs	Hardwood NS	6.60787354	6.60787354	0.94	0.3325
Immature Pine EW	vs	Hardwood EW	39.00201176	39.00201176	5.55	0.0188*
Mature Pine NS	vs	Mature Pine EW	0.14618673	0.14618673	0.02	0.8853
Mature Pine NS	vs	Hardwood NS	10.3945658	10.3945658	1.48	0.2243
Mature Pine NS	vs	Hardwood EW	50.81013274	50.81013274	7.23	0.0073*
Mature Pine EW	vs	Hardwood NS	8.42776903	8.42776903	1.2	0.2738
Mature Pine EW	vs	Hardwood EW	46.61128046	46.61128046	6.63	0.0102*
Hardwood NS	vs	Hardwood EW	12.29105402	12.29105402	1.75	0.1864

* denotes significant difference at $\alpha = 0.05$

for the regression coefficients for immature pine NS against both hardwood NS and EW (Table 3.10).

DBH Equations

The equations used to predict DBH from adjusted LiDAR height were:

Immature pine:

$$\frac{1}{DBH} = 5.03160545 - 2.27763577 \times (\ln HT) + 0.262349655 \times (\ln HT^2) \qquad (3.1)$$

$R^2 = 0.7639$

Mature pine:

$$\frac{1}{DBH} = 0.428840189 - 0.0800954334 \times (\ln HT) \qquad (3.2)$$

$R^2 = 0.7399$

Hardwood:

$$\frac{1}{DBH} = 0.54412923 - 0.104767024 \times (\ln HT) \qquad (3.3)$$

$R^2 = 0.5928$

Volume Analysis by Individual Matched Trees

The adjusted LiDAR-derived heights and estimated DBHs were used to calculate volume using a Minor's form class equation. Paired t-tests were used to look for statistical differences between predicted volume of the matched trees for the NS and EW flightlines and the volume of the matched trees from hypsometer

Table 3.10 Statistical comparison of regression coefficients for adjusting predicted LiDAR tree heights for no edge plots in east-central Mississippi.

Contrast			Contrast SS	Mean Square	F Value	Pr > F
Immature Pine NS	vs	Immature Pine EW	13.81877694	13.81877694	1.26	0.2625
Immature Pine NS	vs	Mature Pine EW	0.58216598	0.58216598	0.05	0.8179
Immature Pine NS	vs	Mature Pine NS	0.1922153	0.1922153	0.02	0.8947
Immature Pine NS	vs	Hardwood NS	87.36072848	87.36072848	7.98	0.0052*
Immature Pine NS	vs	Hardwood EW	47.35802183	47.35802183	4.32	0.0387*
Immature Pine EW	vs	Mature Pine NS	0.48638465	0.48638465	0.04	0.8333
Immature Pine EW	vs	Mature Pine EW	0.99482757	0.99482757	0.09	0.7634
Immature Pine EW	vs	Hardwood NS	40.736025	40.736025	3.72	0.0550
Immature Pine EW	vs	Hardwood EW	15.59477688	15.59477688	1.42	0.2340
Mature Pine NS	vs	Mature Pine EW	0.0739208	0.0739208	0.01	0.9346
Mature Pine NS	vs	Hardwood NS	1.43742709	1.43742709	0.13	0.7175
Mature Pine NS	vs	Hardwood EW	1.04159967	1.04159967	0.1	0.7581
Mature Pine EW	vs	Hardwood NS	2.10582194	2.10582194	0.19	0.6614
Mature Pine EW	vs	Hardwood EW	1.66332875	1.66332875	0.15	0.6971
Hardwood NS	vs	Hardwood EW	3.72199993	3.72199993	0.34	0.5605

* denotes significant difference at $\alpha = 0.05$

1 and 2 and the volume of matched trees from the average of hypsometer 1 and 2 using p-value < 0.025 (two-tailed test, ½ of α=0.05). The analysis of all plots showed that NS volumes were not significantly different from EW volumes in immature pine and hardwood plots, and volume based on height measurements from hypsometer 1 was not significantly different from volume based on height measurements from hypsometer 2. In mature pine plots, no tested estimates were significantly different from each other (Table 3.11).

The analysis of no edge plots showed that immature pine had significant differences between EW-Average and EW-Vol2. In mature pine, the comparisons of NS-EW and Vol1-Vol2 were not significantly different, but all other comparisons were. In hardwood plots, the comparison between NS-EW was significantly different but all other comparisons were not (Table 3.12).

Volume Analysis by Plot

Paired t-tests were used to look for statistical differences by plot between the NS and EW flightline volumes predicted from all LiDAR found trees and the volume from hypsometer 1 and 2 and the volume from the average of hypsometer 1 and 2 using p-value < 0.025 (two-tailed test, ½ of α=0.05). Analysis of all plots indicated that NS volume measurements were significantly different from EW volume measurements, volume based on height measurements from hypsometers 1 and 2, and volume from the average of hypsometers 1 and 2 for

Table 3.11 Paired Student's t test values for comparisons of mean volume differences of individual matched trees by forest type of all plots in east-central Mississippi.

	Immature Pine:			Mature Pine:			Hardwood:		
Difference	df	t Value	Pr > |t|	df	t Value	Pr > |t|	df	t Value	Pr > |t|
NS - EW	117	-0.16	0.8769	114	-0.29	0.7698	110	0.91	0.3648
Vol1 – Vol2	117	-0.53	0.5986	114	-1.03	0.3045	110	-0.88	0.3781
NS – Avg	117	-2.77	0.0065*	114	-0.32	0.7465	110	-3.94	0.0001*
EW - Avg	117	-2.75	0.0068*	114	-0.28	0.7823	110	-4.11	<.0001*
NS – Vol1	117	-2.71	0.0078*	114	-0.27	0.7859	110	-3.95	0.0001*
NS – Vol2	117	-2.82	0.0057*	114	-0.28	0.7085	110	-3.91	0.0002*
EW – Vol1	117	-2.69	0.0082*	114	-0.22	0.8252	110	-4.13	<.0001*
EW – Vol2	117	-2.81	0.0058*	114	-0.33	0.7410	110	-4.07	<.0001*

* denotes significant difference, Vol1 = volume derived from the height given by hypsometer 1, Vol2 = volume derived from the height given by hypsometer 2, Avg = volume derived from the averaged heights of both hypsometers at $\alpha = 0.05$

Table 3.12 Paired Student's t test values for comparisons of mean volume differences of individual trees by forest type of no edge plots in east-central Mississippi.

	Immature Pine:			Mature Pine:			Hardwood:		
Difference	df	t Value	Pr > |t|	df	t Value	Pr > |t|	df	t Value	Pr > |t|
NS - EW	74	1.46	0.1473	4	-1.83	0.1411	36	-2.42	0.0207*
Vol1 – Vol2	74	-1.51	0.1348	4	-2.58	0.0616	36	-1.38	0.1753
NS – Avg	74	-2.17	0.0335	4	-4.69	0.0094*	36	-2.00	0.0532
EW - Avg	74	-2.39	0.0194*	4	-4.60	0.0100*	36	-1.76	0.0878
NS – Vol1	74	-2.06	0.0429	4	-4.51	0.0107*	36	-2.00	0.0526
NS – Vol2	74	-2.26	0.0267	4	-4.87	0.0082*	36	-1.99	0.0542
EW – Vol1	74	-2.28	0.0253	4	-4.43	0.0114*	36	-1.75	0.0886
EW – Vol2	74	-2.48	0.0152*	4	-4.78	0.0088*	36	-1.76	0.0875

* denotes significant difference, Vol1 = volume derived from the height given by hypsometer 1, Vol2 = volume derived from the height given by hypsometer 2, Avg = volume derived from the averaged heights of both hypsometers at $\alpha = 0.05$

immature pine. In mature pine plots the comparison between NS-EW was significantly different but all other comparisons were not. In hardwood plots EW volume measurements were significantly different from volume based on height measurements from hypsometers 1 and 2 and volume from the average of hypsometers 1 and 2(Table 3.13).

In the no edge plots there was only one mature pine plot, and it could not be analyzed using a paired t-test. Immature pine plots showed significant differences between NS volume measurements and volume based on height measurements from hypsometers 1 and 2. In hardwood plots, no tested estimates were significantly different from each other (Table 3.14).

Table 3.13 Paired Student's t test values for comparisons of mean volume differences of plots by forest type of all plots in east-central Mississippi.

	Immature Pine:			Mature Pine:			Hardwood:		
Difference	df	t Value	Pr > |t|	df	t Value	Pr > |t|	df	t Value	Pr > |t|
NS - EW	15	-2.98	0.0093*	15	-3.61	0.0025*	14	-1.82	0.0895
Vol1 – Vol2	15	-0.25	0.804	15	-0.65	0.5252	14	-1.07	0.3035
NS – Avg	15	-4.3	0.0006*	15	-0.81	0.4291	14	1.49	0.1571
EW - Avg	15	-1.73	0.1042	15	1.28	0.2206	14	2.84	0.0131*
NS – Vol1	15	-4.24	0.0007*	15	-0.79	0.444	14	1.57	0.1384
NS – Vol2	15	-4.36	0.0006*	15	-0.84	0.4153	14	1.42	0.1773
EW – Vol1	15	-1.69	0.1113	15	1.3	0.2123	14	2.99	0.0098*
EW – Vol2	15	-1.77	0.0978	15	1.25	0.2295	14	2.7	0.0173*

* denotes significant difference, Vol1 = volume derived from the height given by hypsometer 1, Vol2 = volume derived from the height given by hypsometer 2, Avg = volume derived from the averaged heights of both hypsometers at $\alpha = 0.05$

Table 3.14 Paired Student's t test values for comparisons of mean volume differences of plots by forest type of no edge plots in east-central Mississippi.

	Immature Pine:			Hardwood:		
Difference	df	t Value	Pr > |t|	df	t Value	Pr > |t|
NS - EW	7	-1.92	0.0963	3	-1.8	0.1701
Vol1 – Vol2	7	-2.23	0.0609	3	-0.71	0.5309
NS – Avg	7	-3.34	0.0124	3	-0.65	0.5593
EW - Avg	7	-1.23	0.2598	3	-0.09	0.9304
NS – Vol1	7	-3.16	0.0160*	3	-0.65	0.5618
NS – Vol2	7	-3.53	0.0096*	3	-0.66	0.5572
EW – Vol1	7	-1.12	0.3006	3	-0.06	0.9544
EW – Vol2	7	-1.34	0.2220	3	-0.12	0.9088

* denotes significant difference, Vol1 = volume derived from the height given by hypsometer 1, Vol2 = volume derived from the height given by hypsometer 2, Avg = volume derived from the averaged heights of both hypsometers at $\alpha = 0.05$

CHAPTER IV

DISCUSSION

Edge Plot Distortion

LiDAR data collected at the edge of the scan are less likely to capture the true shape of the targets trees due to returns from the crown edges being stacked on top of each other and increased canopy penetration by the laser on the scanner side. The canopy surface generated from these stacked returns tends to have linear inconsistencies of high and adjacent lower values on the edges of tree crowns (Figure 4.1). These inconsistencies made data analysis more difficult because they interfered with the tree finding models by giving false tree locations which in turn skewed the tree finding accuracies and height analysis. The lack of returns from part of the crown opposite of the scanner was smoothed over with the surfacing algorithm.

LiDAR Tree Finding Accuracy

The analysis for all plots and no edge plots showed that mature pine plots in both NS and EW directions appeared to have a better overall tree identification accuracy than immature pine or hardwood plots (Table 3.1 and

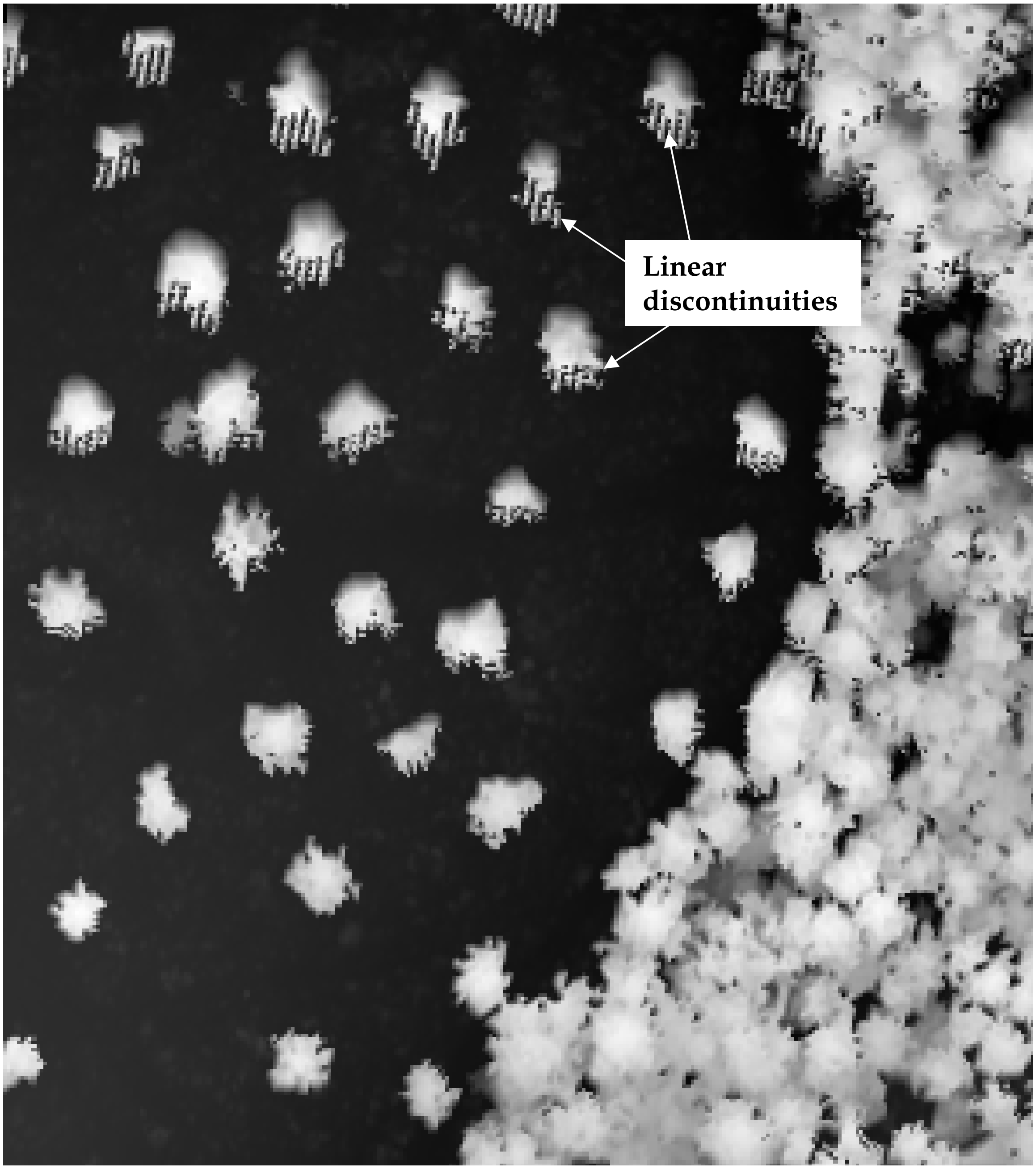


Figure 4.1 Canopy surface of the northern portion of an EW flightline showing linear discontinuities pointing toward nadir (bottom of image). Area being viewed is isolated seed trees on left and closed canopy on the right. The gray tones in this response surface represent relative heights of the vegetation.

3.2). Tree spacing in mature timber is wider than immature timber due to mortality of less vigorous trees during stand development, so they are more easily distinguishable. Immature conifers have a higher density of stems per acre, and the crowns are in some cases too close to differentiate using LiDAR data. The individual crowns of mature conifers have less crown engagement because they have self-pruned as they grew. Lower branches have died back because of light deficiencies, and as trees become taller they sway in the wind more and interlaced branches are broken off. "This results in crown shyness, a phenomenon which leaves spaces between the crowns of adjacent trees" Smith *et al*. (1997). This allows them to be identified as separate clumps in the tree canopy surface that is easily discernible in the tree finding model. By comparison, older hardwoods that have large spreading crowns were identified as multiple tree tops which resulted in the hardwood plots having high commission errors. The high commission errors found in this study could potentially overestimate volume assessments on the plot level. These findings are similar to those reported by Koch *et al.* (2006) where, in a Douglas fir stand, they found 87.3 percent of the trees with LiDAR, but in a broad-leaved stand they only found 50 percent of the trees successfully.

Tree Finding Accuracy Comparison

The EW flight line appeared to have a higher tree finding accuracy than the NS flight line. But this apparent difference was only significantly different for all plots within the immature pine plot type. The no edge plots had no significant differences for immature pine, mature pine, or hardwoods plots within plot types according to the Chi-squared test (Table 3.3 and 3.4). This finding is noteworthy because LiDAR missions are expensive, and if one direction is not better than the other then is it less complicated for the mission planner. For example, if the target area has a orientation that is longer in one direction than another, then flight lines parallel to the long axis of the area would mean fewer turns and lower overall costs for the data provider to pass on to the user. Also, if there are any restrictive characteristics (example Military Operations Area [MOA]) these can be better avoided at lower costs if flight line orientation is not an issue.

Crown Class

As expected, in all plot types, dominant trees had the highest percentage of trees found, codominant the second highest, and intermediate the lowest percentage of trees found (Table 3.5). Koch *et al.* (2006) note that problems occur with detecting very small or suppressed trees, and Hyyppä and Inkinen (1999) indicated that only crowns in the top layer can be detected so the smaller trees underneath are undetected. Therefore, LiDAR cannot be readily used for complete forest structure detection. It would be useful for inventory compilation in both a plantation setting as well as an uneven aged stand, although it would not be helpful in predicting future growth of an uneven aged stand.

Height Analysis

When looking at all plots in all plot types, the two field recorded heights were not significantly different; also the two LiDAR derived heights were not significantly different for mature pine and hardwood plots. Immature pine plots were the only plot type that had significantly different LiDAR-derived heights (Table 3.6). When testing no edge plots, hypsometer 1-hypsometer 2 for all plot types and NS-EW for mature pine were not statistically different. Significant differences for mature pine are NS-hypsometer 2 and EW-hypsometer 2, and for hardwood EW-hypsometer 2. This could be an indication that hypsometer 2 was not being operated as precisely as hypsometer 1. Hypsometer 1 was mainly used by a single graduate student, but hypsometer 2 was used by used by 4 workers on separate occasions. So, each person had a different skill/experience level and may not have measured trees to exactly the same point. Additionally, for immature pine, the only comparison that was not statistically different was hypsometer 1-hypsometer 2 (Table 3.7). Immature pine and hardwood plots had significantly different LiDAR-derived heights. Immature pine tree crowns are sharply conical, and as pointed out by Parker and Mitchell (2005), the top of the sharply conical crown has a high probability of being missed. Also, the laser had to travel into the crown a distance in order to hit foliage dense enough to reflect the beam. These distances into the crown were, in all probability, different depending on where the laser hit, so this could be the reason immature pine trees had different LiDAR derived heights.

Height Discrepancies

Only using unadjusted predicted LiDAR tree heights would distort the predicted DBH by either over- or under-estimating it depending on if the LiDAR height was predicted at taller or shorter than field measurements. While it is physically impossible for LiDAR to measure tree heights taller than they actually are, it is possible to over predict the heights through the ground and height modeling process. Consequently, volume, site index, and any other predicted stand characteristics would also be skewed. For example, a predicted height that was too high would accordingly give a volume that was also too high, and extrapolating this error to stand level would overestimate what is actually there. To correct these errors the LiDAR derived heights were adjusted using ground tree heights in a SLR model. This should have improved the relationship between predicted LiDAR heights and ground heights which should improve the relationship between volume calculated from ground measurements and volume calculated from predicted LiDAR measurements.

Volume Analysis

Volume Analysis by Individual Matched Trees

Results of the paired t-tests for volume were expected to closely resemble the paired t-tests results for heights (either both were significantly different or both were not significantly different). In some cases this was true; but not in every case. Volume comparisons that did resemble their corresponding paired t-tests for heights for all plots were the mean volume differences between volume predicted from the adjusted heights for the NS and EW flightlines (NS-EW) and the mean volume predicted by the heights measured by hypsometers 1 and 2 (Vol1-Vol2) for mature pine and hardwood. Also, for immature pine, volume comparisons that resembled the corresponding paired t-test results for heights were the mean volume predicted from the heights measured by hypsometers 1 and 2 (Vol1-Vol2), NS volume measurements and volume based on height measurements from hypsometers 1 and 2 (NS-Vol1 and NS-Vol2), and EW volume measurements and volume based on height measurements from hypsometers 1 and 2 (EW-Vol1 and EW-Vol2). For no edge plots, volume comparisons that did resemble their corresponding paired t-tests results for heights were the mean volume differences between volume predicted from the adjusted heights for the NS and EW flightlines (NS-EW), NS volume measurements and volume based on height measurements from hypsometer 2 (NS-Vol2), and EW volume measurements and volume based on height measurements from hypsometer 2 (EW-Vol2) for mature pine and hardwood. Other volume comparisons that resembled their corresponding paired t-tests results for heights were the mean volume predicted from the heights measured by hypsometers 1 and 2 (Vol1-Vol2) for immature pine and hardwood, NS volume measurements and volume based on height measurements from hypsometer 1 (NS-Vol1) for hardwood, and EW volume measurements and volume based on height measurements from hypsometer 2 (EW-Vol2) for immature pine.

Some reasons the heights and volumes were not as correlated as expected are that before deriving volume, the LiDAR heights of trees had to be adjusted through regression to the field data, and the DBHs were predicted. Errors are associated with each equation and these errors could be either additive or compensating. Also, the residuals for the regression equations that were derived from the field heights and DBHs using NLREG (Sherrod, 2001) were not uniform. Both of these calculations added error into the volume prediction; additionally, the volume equation used did not adequately represent the stands. It was created using pine pulpwood stands in southeastern Louisiana and was meant to be used on trees with a form class of 82 (Merrifield and Foil, 1967). Another point to consider is that the potential for error in measurement of tall trees is high because of several factors. It is hard to see the top of a tall tree from the ground because limbs of other trees are sometimes in the way and because the exact terminal is indiscernible from the ground. So, the different measurers of the trees probably shot different points as the terminal. Additionally, heights need to be shot at angles not exceeding 45 degrees due to inherent instrument error. For every degree above 45 degrees, the height error increases 3.49 percent, and for every degree above 60 degrees, the height error increases 6.987 percent[2]. To avoid these extreme angles, the heights must be taken from greater distances for taller trees, and taking tree heights from greater distances is more difficult due to sight obscuration of the tree tops.

Volume Analysis by Plot

The tree finding model accuracies were statistically different within plot types for immature pines according to the Chi-squared test results (Table 3.3). Additionally, the NS commission errors were larger and the omission errors were smaller than the EW errors. This is probably why the NS mean plot volumes were statistically different from every other volume estimate they were compared against with the paired t-test. Commission and omission errors could

[2] Personal communication with Thomas G. Matney, Professor, Mississippi State Univesity on January 27, 2009.

have a big influence on overall volume, but there are ways to compensate for these errors. One technique might be to relate back to previously collected ground data from the same area to get relative trees per acre. Parker and Evans (2004) demonstrate a method of utilizing ground data where they adjust for LiDAR volume through a double-sample regression estimator.

CHAPTER V

CONCLUSIONS

LiDAR flown at 0.75m posting spacing can find 86-100% of mature pine trees, 64-81% of immature pine trees, and 63-72% of mature hardwood trees in southeastern forest types examined in this study. Immature pine trees were the only plot type that had statistically different tree finding accuracies between NS and EW flightlines. Dominant trees were found better than lower crown classes and pines were generally easier to identify than hardwoods.

For all plots, the height error for hardwood measured on EW plots was significantly larger than all other plot types except hardwood on NS plots. For no edge plots, the regression coefficients of error used to adjust heights for immature pine on NS plots were better than the regression coefficients of error used to adjust heights for both hardwood NS and EW plots.

Individual tree volumes for immature pines and hardwoods cannot be predicted using the criteria used in this study. However, individual tree volumes for mature pines for both the NS and EW flightlines were accurately predicted, and individual tree volumes for mature pines had high precision between the NS and EW flightlines. Plot volumes for immature pine were accurately predicted for the EW flightlines but not the NS flightlines; precision between the NS and EW flightlines was low because of the variability in omission errors and percent correct trees. Contradictorily, plot volumes for hardwood were predicted accurately for NS flightlines, but not for the EW flightlines because of the higher commission errors. The plot volumes for mature pines were predicted accurately for both NS and EW flightlines, and plot volumes for mature pines had high precision between the NS and EW flightlines.

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