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Using Low Density, Small Footprint LIDAR in Forest Inventory Applications in the Southeastern U.S.

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USING LOW DENSITY, SMALL FOOTPRINT LIDAR IN FOREST INVENTORY APPLICATIONS IN THE SOUTHEASTERN U.S.

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ABSTRACT

Light Detection and Ranging (LIDAR) is becoming a widely used tool in forestry and natural resource fields. The availability of free and low cost datasets gives LIDAR the ability to save time and money over traditional forest inventory practices. In this study, the effectiveness of low density, small footprint LIDAR compared to forest field inventory measurements from the Clemson Experimental Forest was determined. LIDAR based estimates were analyzed to determine if LIDAR is a viable tool for estimating particular forest inventory features in the Southeastern U.S. and whether a transition could be made to a more GIS based analysis. Standard field inventory methods were used to assess forest stand measurements throughout the Clemson Experimental Forest. Processed LIDAR data was used in conjunction with Treevaw, a LIDAR software application, to extract forest inventory features at the individual tree level. Statistical correlation and regression comparisons were made between the data at the plot level. Comparisons were also made between stand types to determine the type of effects that leaf-off conditions could have on the LIDAR data analysis. Overall, results of the entire sample comparing tree heights, diameter at breast height, and above ground biomass were varied. Correlations between inventory and LIDAR measurements were high, with a minimum value of 0.70. Dividing the plots by stand cover type showed variations in the dataset. Pine plantation plots achieved the best overall results, followed by pine-hardwood plots. Natural pine, upland hardwood, and cove hardwood plots each produced similar results, but were not as accurate as the stands mentioned previously. Results show that low density, small footprint LIDAR can be used to accurately estimate certain features of individual trees in particular forest stand types. The use of higher density LIDAR would most likely provide a more accurate analysis across a broader range of forest types.

Keywords: LIDAR, Low density, Tree height, Treevaw

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CHAPTER ONE

INTRODUCTION

Statement of the Problem

Forestry is a business that requires the continuous up-to-date inventory of forest resources. Timber cruising is the preferred method used by foresters to achieve forest inventory estimates (Brooks, Wiant 2004). Timber cruising costs in the southern U.S. were estimated at $3.45 per acre in the year 2000. Although this was a decrease from the 1998 $4.10 per acre, overall, timber cruising costs have generally increased since they were first documented in 1952 (Dubois 2003). Depending on the acreage of a forested area, timber cruising can be an expensive process. This high cost has caused many foresters to seek out a more cost effective alternative to field surveying (Suarez et al. 2005). As technology has advanced, new remote sensing techniques have been developed to alleviate these problems. Aerial photography and satellite imagery allow foresters to survey and analyze large areas without having to enter the field. Multispectral imagery is able to provide a wealth of information including stand delineation, segmentation, and change detection (Warner et al. 2006). Presently, Light Detection and Ranging (LIDAR) is becoming a more common practice for forest inventory analysis (Magnusson et al. 2007).

LIDAR is a collection of points of the earth's surface. Each point contains three dimensional X, Y and Z values, where they represent latitude, longitude, and elevation respectively. LIDAR data is collected by a sensor which is mounted to the underside of an airplane or other low flying aircraft. A global positioning system (GPS) receiver and inertial measurement unit (IMU) located within the aircraft is linked with the sensor which allows it to collect location and elevation simultaneously (Fugro Horizons, Inc.). The sensor emits light pulses towards the ground and receives them back as they are reflected by the earth's surface. The elevation of each pulse is determined by the altitude of the plane and the return time of the pulse to the sensor. Using the laser light equivalent of radar, LIDAR accurately estimates such important forest structural characteristics as canopy heights, stand volume, basal area, and above ground biomass (Dubayah, Drake 2000).

One of the biggest drawbacks to LIDAR has been cost. A study by Tilley et al. (2005) showed that the cost of collecting and processing high and low density LIDAR over a 1,200 acre area was [$16,200] and [$15,000] respectively. Even at a contemporary level of 70 to 80 cents per acre for large projects, LIDAR can still prove too costly for forestry needs (Carson et al. 2004). However, as with most technology, as time has passed cost has begun to decrease. Presently there are efforts in progress to provide free LIDAR datasets for the purposes of floodplain mapping, coastal erosion detection, and topographic mapping.

The State of South Carolina in conjunction with the South Carolina Department of Natural Resources (SCDNR), the U.S. Geological Survey (USGS), and several other public and private agencies, is currently in the process of collecting leaf-off LIDAR data for the entire state. Over the next few years this project will provide LIDAR datasets for each county. This data can be freely downloaded by the general public from the SCDNR website (www.dnr.sc.gov).

The state of North Carolina, with the help of the Federal Emergency Management Agency (FEMA), has recently completed a statewide mapping program. LIDAR data was collected in three phases over the past 7 years for the purposes of floodplain mapping. This data is readily available to the general public free of charge (www.fema.gov).

The USGS currently allows the downloading of a select group of datasets in certain areas of the U.S. There is a possibility that the number of areas available by the USGS could increase in the future (www.usgs.gov). The National Oceanic and Atmospheric Association (NOAA), National Aeronautics and Space Administration (NASA), and USGS partnered to collect LIDAR data along the sandy beaches of the U.S. between 1996 and 2000. This beach change detection is important when monitoring water flow, beach volume changes, and shoreline changes (www.noaa.gov). With the availability of low cost or no cost data, LIDAR has the power and ability to change forestry data collection techniques for years to come.

Literature Review

The majority of commercial LIDAR systems are low flying, small footprint systems. Small footprint scanners, like the one used to collect data for this project, have high pulse rates (1,000 to 10,000 Hz) and emit beams between 5 and 30 centimeters in diameter (Dubayah, Drake 2000). Collected by low flying aircraft, small footprint scanners shower the earth with thousands of laser pulses. Small diameter beams pick up on tree canopies, but are also able to penetrate gaps in the canopy to the understory and forest floor. LIDAR points in close proximity to one another can be used to recreate ground and canopy surfaces (Dubayah, Drake 2000). However, particularly dense tree canopies with fewer gaps can cause problems when trying to obtain understory data using a small footprint scanner. The returned data may only show a dense canopy with minimal or no understory, even though a dense understory exists (Maltamo et al. 2005). In this instance it has been suggested by Hirata et al. (2003) that two different analyses should be performed using data from both leaf-on and leaf-off conditions. Leaf-on data provides information about the first and second canopy as well as the forest gaps. Leaf-off data is better for determining understory and ground features assuming that the area is primarily deciduous.

Deriving outputs directly from raw data is nearly impossible, which is why the data must be extracted and separated as a preliminary step. Before canopies or topography can be determined, the raw data must be separated by geographic information or returns (Filin 2004). Returns refer to the time difference between when a laser pulse emission and when it is received back by the sensor. First returns, or the first pulses to be received, are generally the highest points on the Earth’s surface. These returns can include tree canopies and roofs of buildings. As pulses penetrate closer to the ground, they require more time to return to the sensor. The return number increases as pulses continually move closer to the ground. The last return is the lowest point recorded by the laser pulse, which is usually the ground or low lying vegetation. Once the data has been separated, it is ready for analysis.

Several spatial interpolation techniques, such as inverse distance weighted (IDW), spline, and kriging methods, can be used to model terrain (Suarez et al. 2005). These types of analysis, in conjunction with field measurements and other remote sensing tools, are needed for the validation of LIDAR results (Lee et al. 2004). In this way, the major strength of LIDAR is that it can directly measure forest structure. Being able to directly obtain canopy height, understory, and surface topography provides a vast amount of data that can be used to improve forest management procedures (Dubayah, Drake 2000).

Different scanners and sensors have the ability to collect LIDAR data at various densities. To reduce costs over large areas, flight speed or flight altitude can be increased, resulting in lower density LIDAR data (Magnusson et al. 2007). A general assumption is that higher density LIDAR data would yield greater accuracy. In most cases, this is true, but it also depends on the manner in which the data is going to be used. Lower density LIDAR used in the right situation can still yield positive results and has been shown in certain cases to produce better results than high density.

Parker and Glass (2004) compared high and low density LIDAR in identifying tree heights in a sample forest inventory. Low density LIDAR had a posting space of 1 meter, with a footprint diameter of 0.213 meters. A posting density of 1 meter is equivalent to a single laser pulse per square meter. High density LIDAR had a posting space of 0.5 meters, with a footprint diameter of 0.112 meters. A posting density of 0.5 meters is equal to 4 laser pulses per square meter. In both cases, pine tree heights were underestimated, while hardwood heights were overestimated. The underestimation of pine tree height is due to the fact that the probability of a laser pulse hitting the crown apex is low. The conical shape of a pine tree crown provides a small area for a LIDAR pulse to reflect off its true apex. The more conical and narrow a crown becomes, the greater the chance its height will be underestimated. The overestimation of hardwood heights is less documented, however, Brandtberg et al. (2003) describes that it could be related to field measurement errors. Due to the fact that many hardwoods have a large rounded crown, it can be difficult for a ground observer to locate a true crown apex.

The comparison between low and high density LIDAR data showed that, in general, the heights produced by low density LIDAR had a stronger relationship and less estimation error compared to ground height measurements. It is perceived that the smaller footprint size of the high density LIDAR caused more pulses to pass though the canopy, while the larger footprint of the low density LIDAR increased its likelihood of being intercepted by crown foliage

(Parker, Glass 2004). A similar study, conducted by Magnusson et al. (2007), compared LIDAR pulse densities and showed that low density LIDAR could be effective for the estimation of forest variables at stand level. By decreasing the density from 25,000 to 40 returns per hectare, an increased error was seen in the estimation accuracy of tree heights and stem volume. However, the estimation accuracies were equal or better than estimates commonly obtained using a conventional forest inventory practice such as aerial photo interpretation.

Leaf-on and leaf-off LIDAR data collection both have distinct advantages that cater towards specific collection results. Leaf-on data provides good canopy coverage for deciduous trees, while leaf-off data allows pulses to penetrate through limbs to achieve increased ground coverage. In the past, LIDAR studies measuring tree height have almost exclusively concentrated on coniferous stands. This is partly due to lack of detail of past data and the expense of small footprint LIDAR datasets (Popescu et al. 2004). As technology has advanced, LIDAR sensor scanning rates have increased. This produces greater point densities and allows aircrafts to fly at higher altitudes to collect the same amount of data in a shorter period of time. The decrease in cost and increase in point density are allowing for the detection and analysis of individual trees under leaf-off conditions.

Brandtberg et al. (2003) achieved success by analyzing individual tree crowns in leaf-off conditions, as well as classifying individual tree species. The common theme shared by both these analyses was the use of high density

LIDAR datasets. Sampling density for both procedures was approximately 12 returns per square meter (Brandtberg 2007, Brandtberg et al. 2003). Low density LIDAR would most likely be ineffective since there would not be enough concentrated returns to reflect the structure of a deciduous tree.

Much is known about LIDAR and its capabilities, as extensive analysis using elevation is well documented. Another aspect of LIDAR data that is less documented, but can be equally important, is intensity. Intensity is defined as the ratio of the strength of reflected light to that of emitted light (Song et al. 2002). Similar to satellite imagery, LIDAR intensity is primarily influenced by the light reflectance of an object. LIDAR elevation values can help predict several forest inventory attributes including stand height, crown width, and volume.

Intensity values are expected to show characteristics of forest composition and structure. This could include species type, moisture content, leaf display, arrangement, and density (Langford 2006). LIDAR intensity values also have the unique ability of measuring only the light reflectance from a forest canopy. Therefore, intensity can be separated by return number to eliminate understory and ground surface features that are often associated with error when trying to classify canopy features (Donoghue et al. 2007). This is a feature that cannot be duplicated with airborne or satellite optical sensors, since they lack the ability to separate these influences when trying to delineate species using near infrared reflectance (Ripple 1986). In addition to forestry applications, intensity has be proven effective in road delineation in urban areas (Yu et al. 2002), as well as glacial surface classification (Lutz et al. 2003). However, LIDAR intensity data tends to incorporate noise and can have low separability depending on the wavelength of the laser used. The variability of intensity values creates fine scale speckling in the imagery, which can make interpretation difficult (Langford 2006). The main source of noise is due to the angle of reflection. Some materials exhibit different intensity values depending on the angle at which they are reflected. Using a kriging interpolation, as opposed to an IDW, will help remove noise and smooth the image (Song et al. 2002).

The measurement of forest biomass gives an indication of carbon sequestration in trees and also provides an estimate of material that could be a potential source of renewable energy (Popescu 2007). Biomass measurements cannot be directly derived from LIDAR data, but can be estimated from other information gathered using LIDAR. Individual tree measurements such as tree height and crown diameter can be obtained from LIDAR data and can be placed into algorithms to estimate other forest features including above ground biomass and diameter at breast height (dbh).

Popescu (2007) used individual tree height and crown width measurements, calculated in Treevaw, to estimate diameter at breast height (dbh) and above ground biomass. Results showed that LIDAR data can be used to accurately estimate individual tree parameters like dbh, which is the most reliable variable for estimating above ground biomass. Biomass was estimated from previously created equations (Jenkins et al. 2003) developed for individual trees in forests in the U.S.

The backbone of the LIDAR analysis for this project was performed using the program called Treevaw (Kini, Popescu 2004). Treevaw is a LIDAR processing software application created by Dr. Sorin Popescu, that supports individual tree location, canopy height, and crown width measurements. Treevaw uses an interpolated surface of the forest canopy, referred to as a canopy height model (CHM), and variable windows, to accomplish this task. Variable windows refer to a circular buffer that is applied around a local maximum (LM), based off of a specified algorithm. A LM is the highest point in a particular area within the CHM. The algorithms were calculated from stand composition equations (Kini, Popescu 2004):

Deciduous: $\textit{Crown width (m)} = 3.09632 + 0.00895\, H^2$ (1)

Pines: $\textit{Crown width (m)} = 3.75105 - 0.17919\, H + 0.01241\, H^2$ (2)

Combined: $\textit{Crown width (m)} = 2.51503 + 0.00901\, H^2$ (3)

where H represents of the height of the LM. The algorithm applied is determined by the user. In essence, the taller the tree, the greater its crown width. Deciduous crowns are assumed to be larger than those of coniferous trees and mixed stands are a compromise between the two. Treevaw applies a variable window around each LM and then scans each cell within the window to determine total tree height. If the LM is the highest cell within the window, it is flagged as a tree top. If another cell is found to have a greater height value within the window, the original LM is eliminated. This process continues throughout the entire CHM until all possible locations have been identified.

Treevaw's procedure for calculating crown width is a slightly more complicated. Once all tree locations and heights have been identified their crown widths can be measured. A 3x3 median filter is applied to the CHM to eliminate some of the noise associated with the image. This filter serves a dual purpose: it suppresses noise while maintaining original cell values and acts as an edge preserving filter. Therefore, it is better suited to delineate adjacent tree crowns. At each tree location two perpendicular profiles of the CHM are extracted on the center of the tree top. A fourth degree polynomial is fit along each profile which aids in finding critical points of the fitted function around tree tops. Crown width is calculated along each profile and is eventually determined by taking the average of the two profiles (Kini, Popescu 2004). Models for location of individual trees and calculation of height and crown width are shown in Appendix A.

Regression analysis by Popescu (2007) revealed that Treevaw less accurately estimated the average crown width versus the average tree height. In high density stands canopies tend to overlap. Therefore, crown width cannot always be calculated for trees with overlapping canopies. The algorithm used by Treevaw seems appropriate to measure crown width for dominant and co-dominant trees with individualized canopies within the CHM (Kini, Popescu 2004).

Research Objectives

The overall objective of this project was to evaluate the effectiveness of low density, small footprint LIDAR, and compare it to field measurements collected in a forest inventory. Tree height, dbh, and above ground biomass values derived from LIDAR were compared with values obtained through forest inventory. Estimation accuracy will be assessed to determine the ability of LIDAR in predicting forest ground measurements. In addition, an overall cost analysis estimation will be presented comparing the two sampling procedures.   It will be determined if there is a great enough economic impact and estimation accuracy to begin moving away from field work and more towards a GIS based analysis approach. Also, further recommendations will be made that could potentially result in improved accuracy.

CHAPTER TWO

MATERIALS AND METHODS

Project Study Area

The study area chosen for this study was the Clemson University Experimental Forest, located in and around the city of Clemson, South Carolina. The experimental forest is nearly 18,000 acres in size, with 11,000 acres in the south forest and 7,000 in the north forest. Although centrally located in Pickens County, the forest spreads to the surrounding counties of Anderson and Oconee (Figure 1). It is one of the largest un-fragmented plots of Piedmont land remaining in South Carolina (CEF 2008). Its location at the base of the Blue Ridge Mountains provides a generally mild climate with four distinct seasons. Summers tend to be very warm with temperatures ranging from 80 to 90 degrees Fahrenheit and winters are cold with temperatures often reaching freezing. Annual rainfall averages approximately 50 inches. There are typically 226 days of sun (IDcide 2008). The topography of this area is similar to that of the rest of the upper piedmont of South Carolina: a landscape characterized primarily by gently rolling hills with low to medium slopes, although sections of the north forest have steep ridges with greater slopes. Elevation within the forest ranges from 650 feet to just over 1,000 feet above sea level.

The Clemson University Experimental Forest is divided into 15 divisions, which are sub-divided by compartment and then broken down to stand level. In total, the forest has more than 2,000 stands. The data for our study area was limited to Oconee County, with some overlap into Pickens and Anderson Counties. Particular attention was paid to stands that are natural pine or planted pine. These stands were more recognizable because of the leaf-off conditions of the aerial photos and LIDAR data.

Sampling Procedures

Grid networks of points were generated using ArcGIS 9.2 (ESRI) software which provided field sampling locations throughout the school forest. Each point was approximately 85 meters in distance from each of its surrounding points and incorporated over one hundred randomly selected stands (Figure 2). The sampling process involved navigating to each plot location using a Trimble Geo XT GPS unit and recording a variety of data including: plot number, cover type, topography, regeneration growth, tree species, dbh, merchantable height, and total height.

Using the GPS unit, the plot center was determined by navigating as close as possible to the pre-selected point target. Once the plot center had been determined sampling could begin. The first step was determining cover type and topography. Visually assessing the terrain for species composition and slope allowed for the selection of cover types and topography on the sampling collection sheet (Appendix B).

Next, the amount of regeneration growth was determined. Beginning from the plot center and working outward in a 4 foot radius, the amount of pine, oak, yellow poplar, and other species regeneration growth was recorded. The next step was to determine which trees would be included in the sample plot. Since this was a variable radius plot, a 10-factor wedge prism was used to determine which trees were “in” and which were “out.” A wedge prism is a small piece of glass that has been ground at a particular angle to refract light and create an optical illusion. The 10-factor, most commonly used in eastern forests, refers to the amount of basal area the prism represents. This means that a tree that is tallied is approximately equal to 10 square feet of basal area. The optical illusion the wedge prism creates appears to offset a portion of a tree’s trunk. If the offset portion is connected to the trunk, the tree is countable or is “in.” If the offset portion is completely separated from the trunk, it is “out” or not countable (FOREST 2008). Trees that are border-line require extra steps to determine their status. A Haglöf DME 201 Cruiser (LandMark Systems) measuring instrument placed at the plot center allowed dbh to be calculated digitally. This reading was compared with an actual measurement to determine the tree’s status. If the measured dbh is greater than the digital reading, the tree can be counted. If it is less, it cannot.

Once all trees in the plot were determined and marked, they were measured. Beginning by facing north and working clockwise, each tree is numbered and identified by species and measured for dbh, merchantable height, and total height. Diameter at breast height was obtained using a measuring tape. Both height measurements were calculated using a clinometer.

Laboratory Analysis

LIDAR data from Oconee County, South Carolina provided the basis for the laboratory analysis. The county was flown by Kucera International Inc. on April 17th and 18th of 2005. A Leica ALS50 Phase I+ laser altimeter attached to a Piper Navajo Chieftan aircraft was used for data collection. The aircraft maintained a flight speed of 140 knots and its altitude varied between 9,900 and 10,200 feet. The sensor employed a field of view of 55 degrees, a scan rate of 17 Hz, and a pulse rate of 36 KHz (Kucera International, Inc.). Average raw post spacing was approximately 3 meters, but sometimes slightly less. Vertical accuracy met National Map Accuracy Standards of 4 foot contour requirements, which was Oconee County's intended purpose for the data. However, a point density this low is generally less than optimal for forest analysis.

The raw data was obtained in LAS file format and was classified before analysis. Using the program LASEdit, developed by Cloud Peak Software (Fugro Horizons, Inc.), the raw data was classified by returns. These return classifications separated the raw data into sets of ground and non-ground data. The newly classified data was exported to an ESRI shapefile format for further analysis in ArcGIS 9.2 (ESRI). The new shapefiles were in the NAD 1983 StatePlane South Carolina (feet) coordinate system. Steps further along in the analysis required the data be in meters, so each shapefile was re-projected to NAD 1983 UTM 17N.

Varying interpolation methods allow a surface to be created from a set of points. In the case of the LIDAR data, it is the ability to generate high resolution digital elevation models (DEM) and digital surface models (DSM). The inverse distance weighted (IDW) interpolation was chosen for this analysis, but there are other interpolation methods for creating a surface. Spline and Kriging tools can also be used to accomplish the same task with slightly different results. Spline estimates values, while minimizing surface curvature. It produces a smooth surface that passes directly through the input points. Sometimes referred to as rubber sheeting, the Spline interpolation is useful in predicting peaks and valleys and best represents smoothly varying surfaces, such as temperature (Childs 2004).

Inverse distance weighted (IDW) determines cell values using a linear-weighted approach. Unmeasured areas are assigned values based off the measured points that surround that area. The weighting that is assigned is a function of distance: whereas the further a point is from an unmeasured cell, the less input it has on the output value (Childs 2004). Kriging is a set of linear regression routines which minimize estimation variance from a predefined covariance model (Song et al. 2002). Kriging is similar to IDW in the fact that it uses measured values to create a prediction for unmeasured areas. The main difference is the Kriging tool's use of semivariograms, which can be described as the statistical relationship among the measured points. Instead of using only the surrounding points to predict unmeasured areas, it incorporates a network of points to create an accurate detailed surface (McCoy, Johnston 2001). However, the added intricacies in this procedure can cause an increase in processing times, especially when dealing with large numbers of points. Results by Anderson et al. (2005) indicated that simple interpolation techniques like IDW maintained accuracy for elevation predictions and were sufficient for interpolating irregularly spaced LIDAR datasets.

A model was created using ArcGIS ModelBuilder to perform the IDW interpolations for the point shapefiles. For each input feature, the Z value field was set to the elevation column and the output cell size was specified as 0.3048 meters (1 foot). The model was run with both ground and non-ground LIDAR shapefiles and produced high resolution DEM and DSM for the study area portion of the Clemson Experimental Forest.

At this point, the newly created rasters contained elevation values that represented height above sea level. By utilizing the raster calculator under the spatial analyst toolbar, the ground values could be subtracted from the non-ground values yielding a new raster containing heights above the earth's surface. Referred to as CHM, these rasters have the ability to differentiate features within a forest such as stand type, cuttings, disturbance, and forest gaps. After each CHM was created, it was converted back to points by using the raster to point tool in ArcToolbox. This procedure assigned a point to each cell center accompanied by a height value. The dense collection of points generated would have been too great to process together, so they were separated by forest stands. Stand boundary shapefiles for the randomly selected field sampling stands were used to select plots that were located within each stand. Using the "select by location" option under the selection dropdown menu, the criteria was set to select points that "are completely within" the selected stand boundary. This process highlighted the proper points to be exported to new shapefiles for each selected forest stand. Using LASEdit, the new point shapefiles were imported back into LAS files to be used in Environment for Visualizing Images (ENVI).

ENVI is an image analysis software product created by ITT Visual Information Solutions and is required to create an input that can be used in Treevaw; the next step in this process. The newly created LAS files were converted to ENVI format using specified parameters. The output format was an ENVI raster file with a model type that included the full feature. The output image was created based on elevation values using a linear interpolation. Each pixel was set to a size of 0.3048 meters and used a floating point output data type. The resulting output yields a CHM with two files, a flat binary file which contains the image itself and a header text file which contains the image's metadata.

Treevaw is a LIDAR processing software application that uses variable windows to locate individual trees and measure their heights and crown widths (Kini, Popescu 2004). It is dependent on ENVI raster images as input files and does not support any other file type. The resulting output produced by Treevaw is a numbered text list of X and Y coordinates (height and crown width measurements) for each tree. In order to display these locations visually, each text file was to be converted to a dbf file using Microsoft Excel. Column cells were formatted according to type (number with two decimal places) and were saved to a DBF 4 table (dBASE IV). The newly created dbf files were then added into ArcMap and displayed using the "display X Y data" option. This provided point shapefiles that showed tree locations accompanied by height and crown with measurements in the attribute table. Some stands contained outlying points that extended past stand boundaries. Using the editor tool these points were selected and removed from all affected shapefiles.

Each field inventory site utilized a variable radius plot as a way of characterizing and quantifying trees in the forest. This type of inventory, often associated with timber cruising, is effective, but yields no standard or uniform plot size. However, for the purposes of statistical analysis, a plot radius was determined for each site. Radius was determined by averaging the dbh for all trees within the plot and multiplying that number by 33. Dividing by 12 yields plot radius in feet, since dbh is measured in inches. A 10-factor wedge prism has a 1:33 ratio. Therefore, any tree located 33 times farther than their diameter cannot be tallied in a variable radius plot. This concept was used as the basis for creating plot buffers. Using the buffer tool in ArcGIS a unique radius was created for each plot based on its average dbh. Treevaw generated trees that fell within each buffer. These trees were selected and exported as a basis for comparison to the field measured plots (Figure 3).

Datasets were created using Microsoft Excel for both forest field inventory and Treevaw derived inventory. Diameter at breast height cannot be directly derived from LIDAR, so values were only present in the field inventory measurements. Diameter at breast height was estimated from the Treevaw data using an equation created by Popescu (2007):

$$dbh = -0.16 + \mathrm{CD} + 1.22H \tag{4}$$

where *dbh* is calculated in centimeters (cm); CD represents crown diameter and *H* represents the LIDAR derived height. Once dbh was calculated, above ground biomass could be estimated, because dbh is the most reliable variable for estimating biomass (Popescu 2007). The equation used for this calculation came from Jenkins et al. (2003):

$$BM = \mathrm{Exp}\ (\beta_0 + \beta_1 \ \mathrm{ln}\ dbh) \tag{5}$$

where BM is the total aboveground biomass in kilometers (km), *dbh* is again in cm, *exp* is the exponential function, *ln* is the log base e, and β_0 and β_1 (Table 1) are parameters for tree species groups (Jenkins et al. 2003). Each of these spreadsheets were imported into SAS 9.1 (SAS Institute, Inc.) and was used to compare different forest features. Total tree height, dbh, and above ground biomass were averaged for each plot in both datasets. Correlation and linear regression analyses were conducted to analyze mean tree height, dbh, and above ground biomass for the inventory and Treevaw derived plots. Paired t-tests were used to test for differences in the means of measurements using the two techniques. The data was then evaluated by stand cover type to determine how leaf-off conditions may have affected the analysis. All hypothesis tests were performed using a significance level of 0.05.

CHAPTER THREE

RESULTS AND DISCUSSION

Trees Identified per Plot

The greatest weakness encountered using low density LIDAR was found to be its inability to accurately and consistently identify the correct number of trees within a sample plot. Looking at an average of the entire sample (Table 2), we find that the number of forest inventory trees and LIDAR derived trees share similar means and total trees identified. However, looking at the same values separated by cover type shows the error associated with tree identification. Figure 4 shows the relationship between inventory measured trees and LIDAR derived trees. All cover types had a low or negative correlation, with p-values greater than 0.05.

Data was collected for 269 forest inventory plots, but only 259 LIDAR derived plots because Treevaw failed to identify trees in 10 of the sample plots. All unidentified plots shared three common themes; a small plot radius, low average field tree height, and dbh measurements. Plot radius ranged from a high of 4.7 m down to a low of 2.5 m in the smallest plots. In some cases, this was smaller than the average posting density of the LIDAR. A small plot radius combined with low density LIDAR only produced a few points per plot. When interpolated, there was not enough point coverage to accurately identify a canopy. Tree heights and dbh also had an effect on identification. The highest mean height for the 10 plots was 5.6 m and the largest mean dbh was 14.4 cm. The small stature of trees in these plots had a greater chance of being missed because of their size (in Appendix C).

Tree Heights

Total tree heights are measurements that can be made directly from LIDAR data (Dubayah, Drake 2000). Although low density LIDAR struggled in locating individual trees, it proved to have good vertical accuracy in estimating tree heights. Figure 5 investigates the relationship between mean inventory measured tree height per plot and mean LIDAR derived tree height per plot. Mean tree heights and standard deviation for all plots (Table 3) between inventory and LIDAR data were similar. LIDAR derived mean height was slightly higher due to the overestimation of hardwood species. The two height measurements had a moderate correlation coefficient, root mean squared error (RMSE), and R^2 (Table 4). It could be possible to estimate inventory height measurements from LIDAR if some of the outlying data were removed.

Diameter at Breast Height

Diameter at breast height is the most common tree measurement made by foresters. Although it cannot be directly derived from LIDAR, it correlates well with LIDAR derived measurements (Popescu 2007). Diameter at breast height was calculated using the heights and crown widths generated by Treevaw. Means and standard deviations (Table 3) were again similar over the entire sample. Diameter at breast height comparisons showed a moderate correlation coefficient, RMSE, and R^2 (Table 4). Comparisons in the data can be seen in figure 6. Much like estimating tree heights, dbh could possibly be estimated by the elimination of outlying data.

Above Ground Biomass

Above ground biomass is a forest feature that is not directly identifiable from LIDAR. Equations put in place by Jenkins et al. (2003) allow biomass to be estimated for different stand types in both inventories. Biomass was not actually measured in the field. Both inventory and LIDAR measurements were estimated from dbh. Above ground biomass means and standard deviations (Table 3) were nearly identical among both sampling procedures. A strong correlation coefficient and low RMSE (Table 4) make LIDAR derived biomass a good indicator of forest ground biomass. Figure 7 shows the strong correlation between inventory measured and LIDAR derived above ground biomass.

Variation in Stand Types

The LIDAR data for this project was collected in mid-April of 2005; when deciduous trees are just starting to bloom, but have not fully developed their leaves. This causes many pulses to pass through the canopy and reflect off of lower limbs or the ground resulting in incorrect heights or missing the tree completely. Data was grouped into the five most common forest cover types in the Clemson Experimental Forest (cove hardwood, natural pine, pine-hardwood, pine plantation, and upland hardwood) to determine the affects of leaf-off analysis between groups. The lack of fully emergent leaves in hardwood species creates a sparse area for LIDAR pulses to reflect off of. For this reason it can be assumed that there could be more error associated with LIDAR data from hardwood and mixed stands. The best results were achieved in the pine plantation and pine-hardwood stands, with the other groups producing moderate results.

Cove hardwood stands represent the majority of hardwood stands on the Clemson Experimental Forest. They are dominated by various species of oak (*Quercus spp.*), hickory (*Carya spp.*), and yellow poplar (*Liriodendron tulipifera*). Nineteen cove hardwood plots were analyzed by comparing average tree height, dbh, and above ground biomass. Mean height plot values varied between inventory and LIDAR derived plots for cove hardwoods. However, dbh and biomass values were very similar (Table 5). The overestimation of hardwood heights has been documented by Brandtberg et al. (2003), however with differing mean heights and similar dbh it could be assumed that the equation used to calculate dbh (Popescu 2007) slightly underestimates dbh in hardwood species.

Cove hardwood plots had the greatest height correlation of any other cover type, but had low dbh and biomass correlations (Table 6). R^2 height values were high enough to be able to estimate inventory height from LIDAR derived height. Figure 8 shows the LIDAR derived height vs. the inventory measured height, which contains the prediction equation. Figures 9 and 10 show comparisons for dbh and biomass respectively. They were not useful in predicting forest ground measurements, however, due to their low R^2.

Natural pine stands are those that are allowed to grow and regenerate naturally after some type of disturbance. The stands are composed primarily of Virginia pine (*Pinus virginiana*) and some shortleaf pine (*Pinus echinata*). In some of the older natural pine stands, traces of hardwoods have begun to emerge. Thirty-four inventory and LIDAR plots were compared in this category. This cover type produced the worst and most unexpected results of all cover types. Mean height, dbh, and biomass comparisons (Table 5) were similar, with LIDAR derived dbh being slightly underestimated. However, correlation coefficients and RMSE (Table 6) were among the worst in natural pine stands. R^2 values for all variables were too low to accurately estimate forest inventory as shown in figures 11, 12, and 13.

Pine-hardwood stands are mixtures of several species of coniferous and deciduous trees. These plots unexpectedly produced good results with the greatest consistency. Table 5 show that means and standard deviations are similar in nature to cove hardwood plots. Mean heights are slightly overestimated, mean dbh is slightly underestimated, and biomass values are similar. Correlation values were good and nearly identical for all variables (Table 6). RMSE and R^2 values are good enough to estimate forest ground measurements for tree height, dbh, and biomass in pine-hardwood stands. Figures 14, 15, and 16 show plot distributions and equations for estimating inventory measurements.

Pine plantation stands are even-aged planted areas dominated primarily by loblolly pine (*Pinus taeda*) and some shortleaf pine (*Pinus echinata*). These stands represent the majority on the Clemson Experimental Forest and achieved the greatest results. Mean tree height, dbh, and biomass were compared for 20 pine plantation plots. Inventory measured mean height, dbh, and biomass were very similar to values derived through LIDAR (Table 5). Pine plantation plots had the second highest height correlations behind cove hardwoods and had the highest dbh and biomass correlation coefficients (Table 6). Low RMSE and good R^2 values allow forest inventory measurements to be estimated using LIDAR derived data in pine plantation stands. Figures 17, 18, and 19 show comparisons of tree heights, dbh, and biomass; as well as linear regression equations for predicting forest ground measurements.

Upland hardwood stands are characterized by various hardwood species, including white oak (*Quercus alba*) and southern red oak (*Quercus falcata*), hickory (*Carya spp.*), and yellow poplar (*Liriodendron tulipifera*). This cover type represented the majority of plots in the study site at 133 plots. Upland hardwood plots showed moderate correlations for all measured forest features. Table 5 shows that upland hardwood plot means followed the same pattern as other hardwood stands. Tree heights were overestimated, dbh was underestimated, and biomass means were similar. Upland hardwood plots achieved moderate results (Table 6). Low R^2 values did not allow inventory to be estimated from the upland hardwood plots. A comparison of plot height, dbh, and biomass values are shown in figures 20, 21, and 22 respectively.

CHAPTER FOUR

CONCLUSIONS

The main objective of this research was to explore the feasibility of using low density, small footprint LIDAR for the purposes of estimating forest inventory measurements. Results show that this type of LIDAR can be used to accurately estimate certain features of individual trees in particular forest stand types. Individual tree height and crown width measurements derived using Treevaw proved important in the estimation of dbh and biomass. As expected, the best results were achieved in the pine plantation stands. Their year round leaf-on conditions of even age, height, and spacing make them easily identifiable with this type of data.

The overall cost of LIDAR analysis was low. However, this assumes that the software needed to process the data is already available to the user and in situations where data can be acquired free of charge, like in this study. Therefore, it provides the advantage of analyzing an area quickly and cost effectively. Traditional forest inventories can be expensive and time consuming. Inventory costs for this study were $23 per plot. Overall, there were nearly 2,000 sample plots to be measured, which totaled roughly $46,000 to collect the entire forest inventory. In addition to cost, traditional forest inventory can also require several months to complete. With the steadily increasing quality of LIDAR data it has the ability to be a cost effective alternative to traditional forest inventory.

The quality of results achieved are only going to be as good as the input data used for the analysis. Although this study produced encouraging results, the accuracy was not high enough to estimate forest inventory in most cases. An average posting density of 3 meters is satisfactory for DEM creation, but not ideal for estimating forest inventory. Higher density LIDAR data with a posting space of 1 meter or less would be better suited for this task. Higher density data would allow more pulses to be reflected from the canopy, creating a more accurate interpolated canopy surface. It also allows analysis to be taken down to the individual tree level.

In recent years, the increasing knowledge and advances in technology have allowed LIDAR to become a more integral part of forestry practices. With an increase in LIDAR collection systems capabilities and a decrease in data acquisition costs, the potential for cost effective and accurate GIS based analysis is possible. The results of this study demonstrate the usefulness of LIDAR, even at low densities, for forest inventory practices.

Table 1. Parameters for estimating total aboveground biomass for hardwood and softwood species in the U.S.

Species Group	B_0	β_1
Mixed (Pine-Hardwood)	-2.4800	2.4835
Hardwood	-2.0127	2.4342
Pine	-2.5356	2.4349

Table 2. Forest inventory vs. LIDAR derived inventory: Mean number of trees identified per plot, standard deviation, and summed total.

	Inventory n=269			*LIDAR n=259*		
	Mean	Std. Dev.	Sum	Mean	Std. Dev.	Sum
Entire Sample	9.96	3.53	2679	9.73	5.94	2520
Cove Hardwood	10.37	3.34	197	7.89	4.38	150
Natural Pine	8.26	3.60	289	13.94	8.28	474
Pine-Hardwood	10.22	3.62	562	12.32	6.04	653
Pine Plantation	12.95	3.44	259	10.70	4.84	214
Upland Hardwood	9.80	3.26	1372	7.74	4.42	1029

Table 3. Forest inventory vs. LIDAR derived inventory: Average plot means and standard deviations for the entire sample.

	Inventory n=269		*LIDAR n=259*	
	Mean	Std. Dev.	Mean	Std. Dev.
Height (m)	18.64	4.67	21.91	5.16
Dbh (cm)	32.73	9.43	31.94	7.99
Biomass (kg)	4.34	1.17	4.44	1.18

Table 4. Forest inventory vs. LIDAR derived inventory: Correlation coefficients, RMSE, and R^2 for the entire sample.

	Correlation	*RMSE*	R^2
Height (m)	0.70	2.72	0.49
Dbh (cm)	0.70	6.13	0.48
Biomass (kg)	0.97	0.30	0.93

Table 5. Forest inventory vs. LIDAR derived inventory: Average plot means and standard deviations separated by cover type.

		Inventory		*LIDAR*		
		Mean	Std. Dev.	Mean	Std. Dev.	P-Value
Cove Hardwood	Height (m)	21.00*	3.66	25.77*	3.77	<0.0001
n_i=19	dbh (cm)	38.41	5.99	37.82	5.30	0.69
n_l=19	Biomass (kg)	5.37	0.29	5.50	0.22	0.05
Natural Pine	Height (m)	15.49	4.44	15.79	3.64	0.91
n_i=35	dbh (cm)	25.99*	8.37	22.17*	4.99	0.001
n_l=34	Biomass (kg)	2.79	0.31	2.76	0.21	0.21
Pine-Hardwood	Height (m)	18.54*	4.79	21.58*	4.05	<0.0001
n_i=55	dbh (cm)	33.01*	9.53	31.30*	6.19	0.004
n_l=53	Biomass (kg)	3.34	0.39	3.42	0.22	0.18
Pine Plantation	Height (m)	17.52	3.63	18.03	5.31	0.52
n_i=20	dbh (cm)	24.69	7.42	25.47	7.86	0.31
n_l=20	Biomass (kg)	2.80*	0.26	2.88*	0.27	0.03
Upland Hardwood	Height (m)	19.30*	4.60	23.64*	4.38	<0.0001
n_i=140	dbh (cm)	34.68	8.83	34.82	6.80	0.05
n_i=133	Biomass (kg)	5.20*	0.54	5.36*	0.35	0.02

n_i indicates the number of plots in the sample forest inventory and n_l represents the number of plots in the LIDAR derived inventory and * represents means that are significantly different from paired t-tests.

Table 6. Forest inventory vs. LIDAR derived inventory: Correlation coefficients, RMSE, and R^2 by cover type.

		Correlation	*RMSE*	R^2
Cove	Height (m)	0.79	2.29	0.63
Hardwood	dbh (cm)	0.40	5.65	0.16
	Biomass (kg)	0.48	0.26	0.23
Natural	Height (m)	0.64	3.06	0.41
Pine	dbh (cm)	0.44	7.30	0.20
	Biomass (kg)	0.47	0.26	0.22
Pine-	Height (m)	0.71	2.63	0.50
Hardwood	dbh (cm)	0.70	6.22	0.49
	Biomass (kg)	0.73	0.23	0.52
Pine	Height (m)	0.76	2.41	0.58
Plantation	dbh (cm)	0.91	3.23	0.82
	Biomass (kg)	0.85	0.14	0.72
Upland	Height (m)	0.55	2.72	0.30
Hardwood	dbh (cm)	0.55	5.88	0.30
	Biomass (kg)	0.53	0.31	0.28

Figure 1

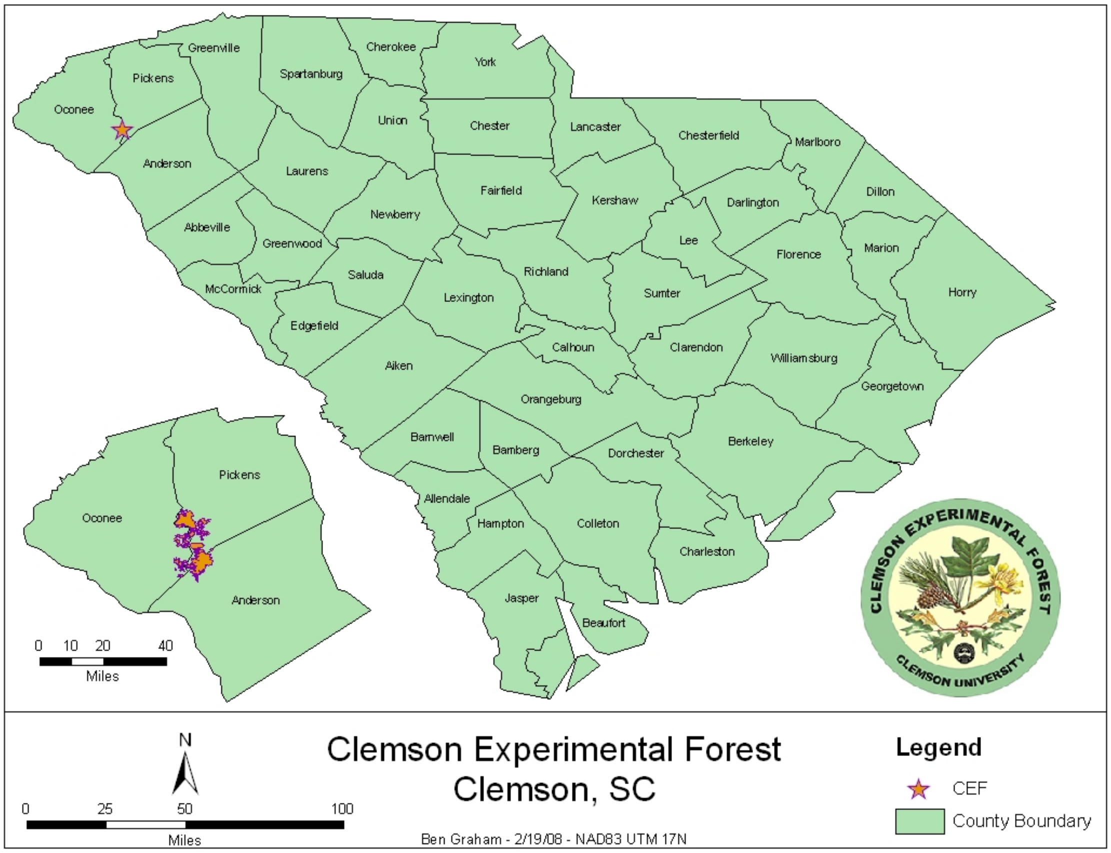

Greenville
Pickens
Oconee
Spartanburg
Cherokee
York
Union
Chester
Lancaster
Chesterfield
Marlboro
Anderson
Laurens
Fairfield
Kershaw
Darlington
Dillon
Newberry
Abbeville
Greenwood
Lee
Marion
Florence
Saluda
Richland
McCormick
Lexington
Sumter
Horry
Edgefield
Calhoun
Clarendon
Aiken
Williamsburg
Georgetown
Orangeburg
Barnwell
Bamberg
Dorchester
Berkeley
Allendale
Hampton
Colleton
Charleston
Jasper
Beaufort
Pickens
Oconee
Anderson
0 10 20 40
Miles
CLEMSON EXPERIMENTAL FOREST
CLEMSON UNIVERSITY
N
0 25 50 100
Miles
Clemson Experimental Forest
Clemson, SC
Ben Graham - 2/19/08 - NAD83 UTM 17N
Legend
CEF
County Boundary

Figure 2

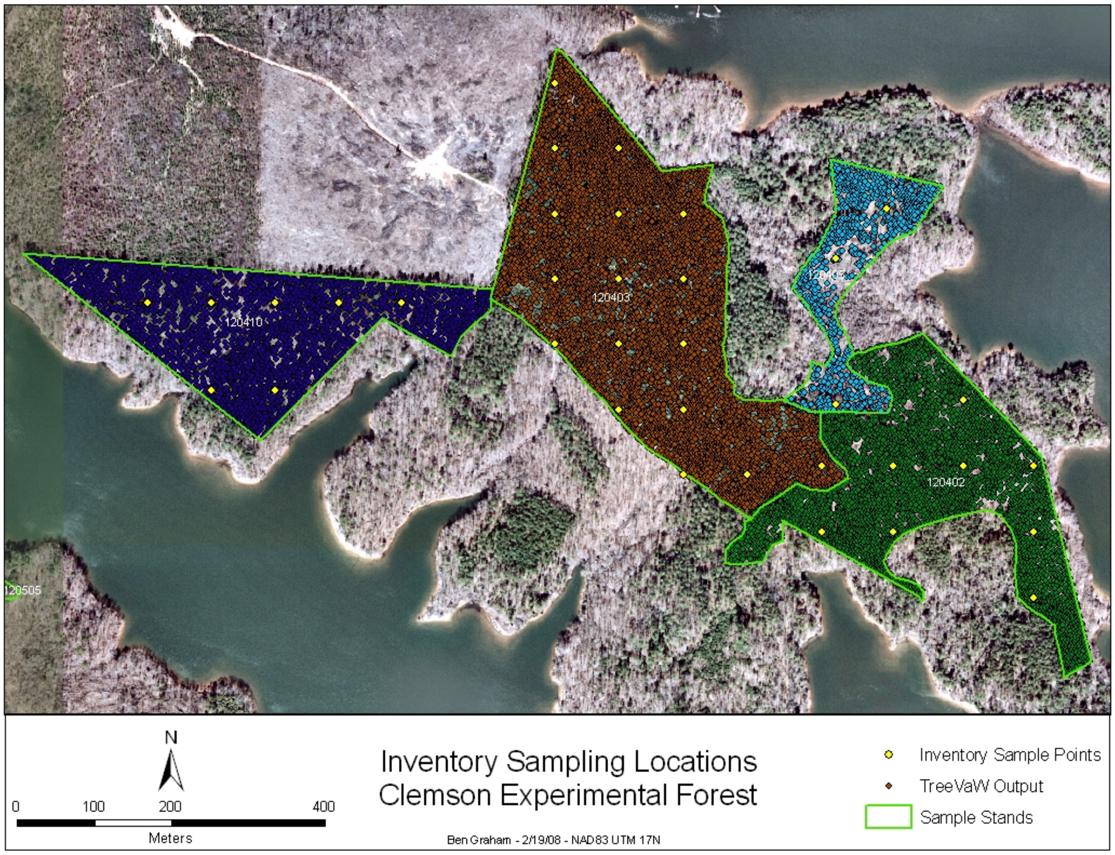

120410
120403
120402
120505
N
0
100
200
400
Meters
Inventory Sampling Locations
Clemson Experimental Forest
Ben Graham - 2/19/08 - NAD83 UTM 17N
Inventory Sample Points
TreeVaW Output
Sample Stands

Figure 3

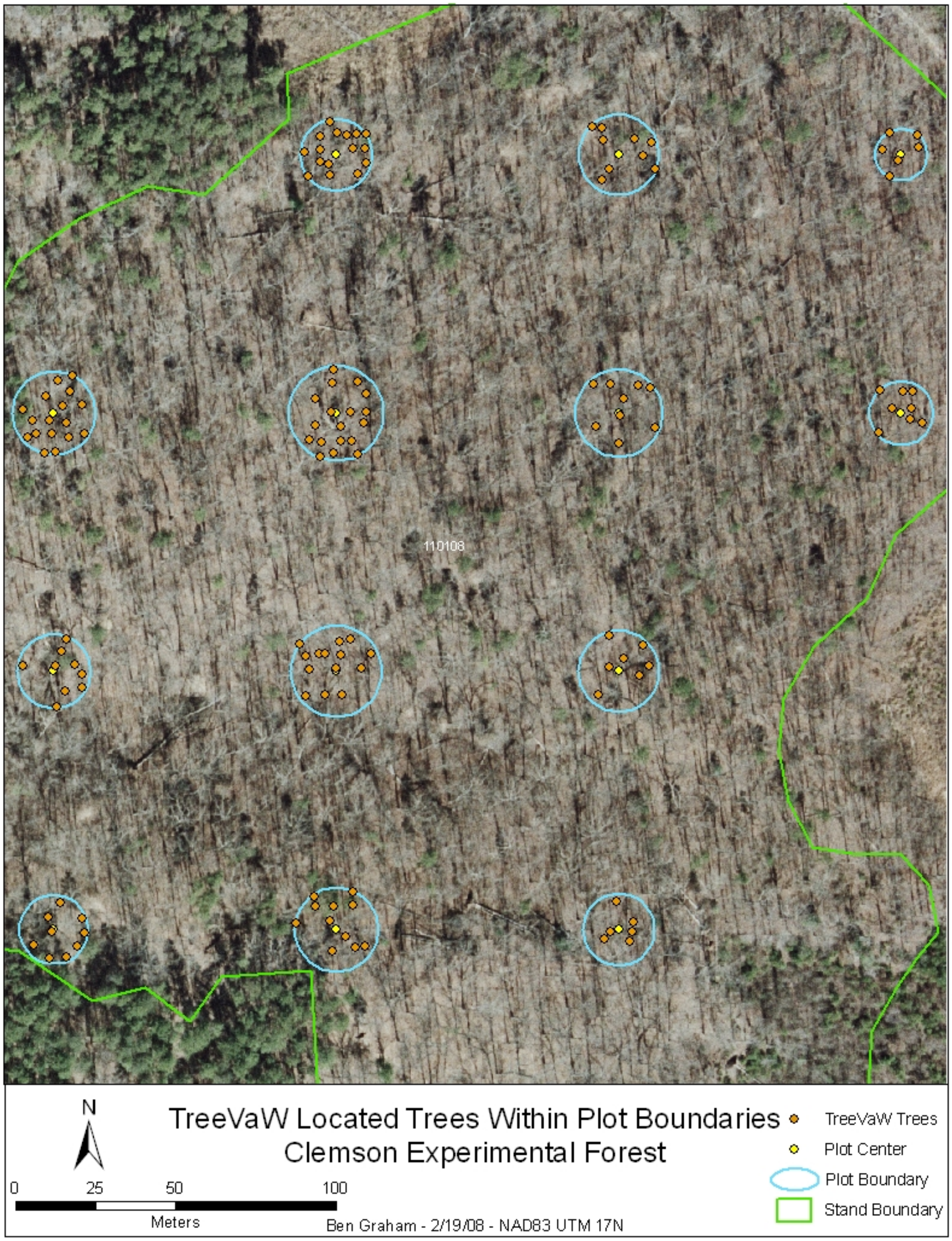
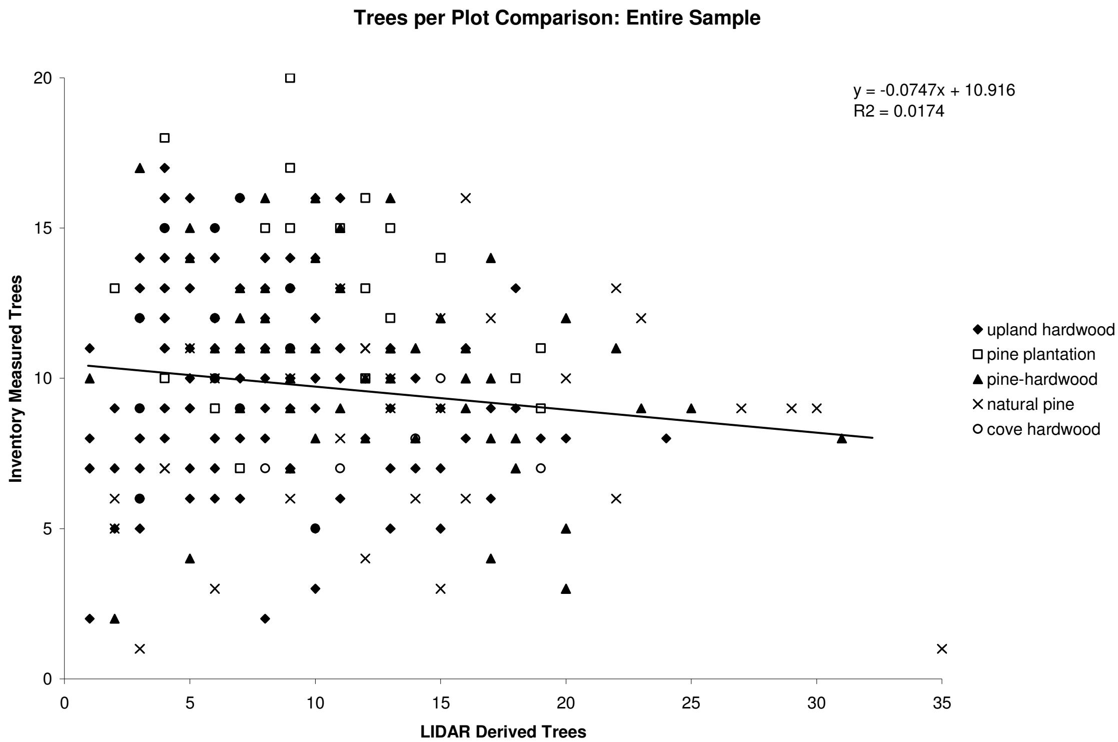

110108
N
TreeVaW Located Trees Within Plot Boundaries
Clemson Experimental Forest
0
25
50
100
Meters
Ben Graham - 2/19/08 - NAD83 UTM 17N
TreeVaW Trees
Plot Center
Plot Boundary
Stand Boundary

Figure 4



Trees per Plot Comparison: Entire Sample
y = -0.0747x + 10.916
R2 = 0.0174
Inventory Measured Trees
LIDAR Derived Trees
0
5
10
15
20
25
30
35
upland hardwood
pine plantation
pine-hardwood
natural pine
cove hardwood

Figure 5

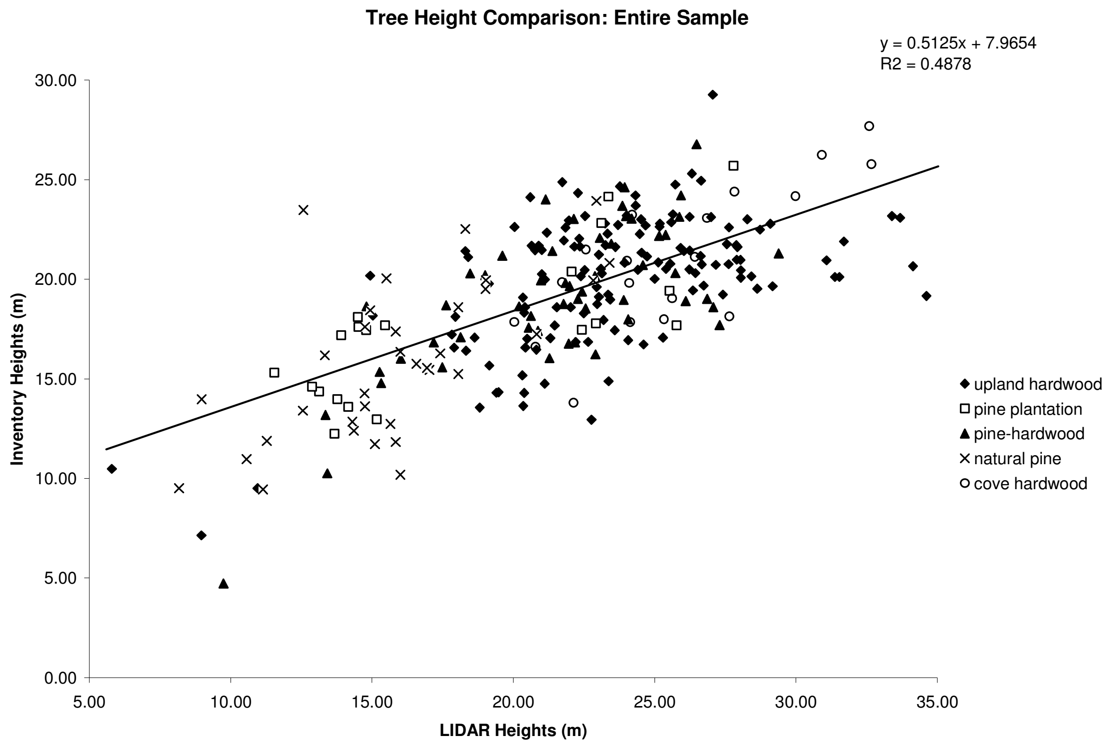

Tree Height Comparison: Entire Sample
y = 0.5125x + 7.9654
R2 = 0.4878
30.00
25.00
20.00
15.00
10.00
5.00
0.00
Inventory Heights (m)
5.00
10.00
15.00
20.00
25.00
30.00
35.00
LIDAR Heights (m)
upland hardwood
pine plantation
pine-hardwood
natural pine
cove hardwood

Figure 6

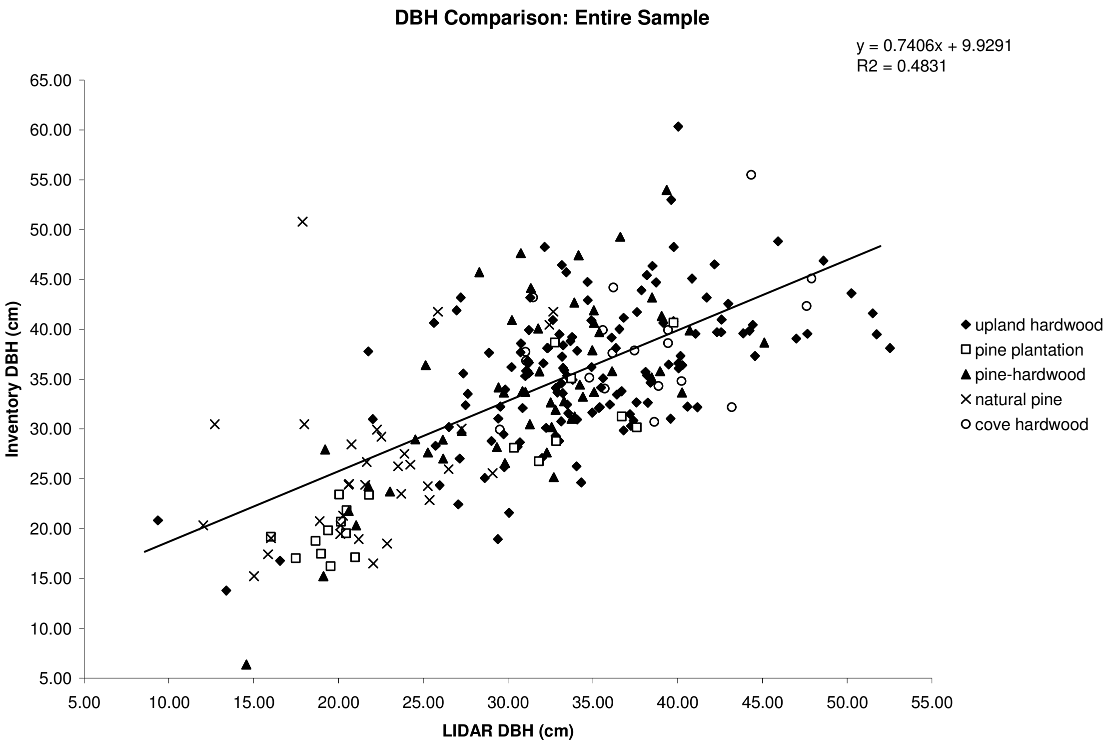

DBH Comparison: Entire Sample
y = 0.7406x + 9.9291
R2 = 0.4831
65.00
60.00
55.00
50.00
45.00
40.00
35.00
30.00
25.00
20.00
15.00
10.00
5.00
Inventory DBH (cm)
5.00
10.00
15.00
20.00
25.00
30.00
35.00
40.00
45.00
50.00
55.00
LIDAR DBH (cm)
upland hardwood
pine plantation
pine-hardwood
natural pine
cove hardwood

Figure 7

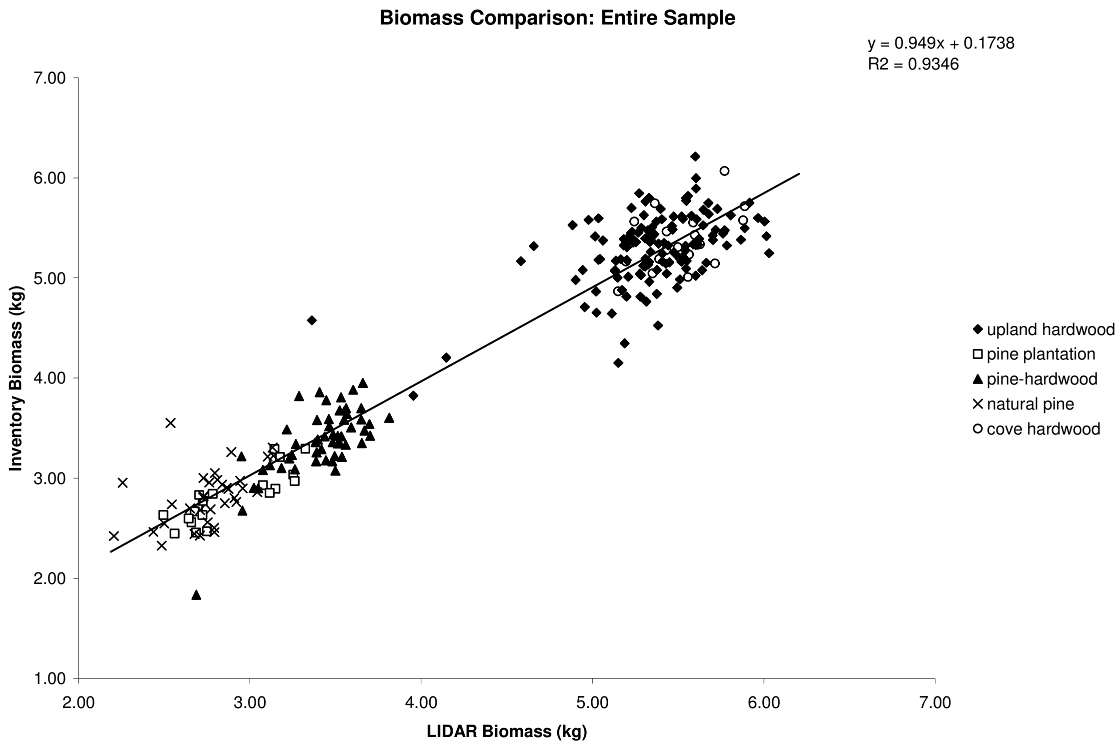

Biomass Comparison: Entire Sample
y = 0.949x + 0.1738
R2 = 0.9346
7.00
6.00
5.00
4.00
3.00
2.00
1.00
2.00
3.00
4.00
5.00
6.00
7.00
Inventory Biomass (kg)
LIDAR Biomass (kg)
upland hardwood
pine plantation
pine-hardwood
natural pine
cove hardwood

Figure 8

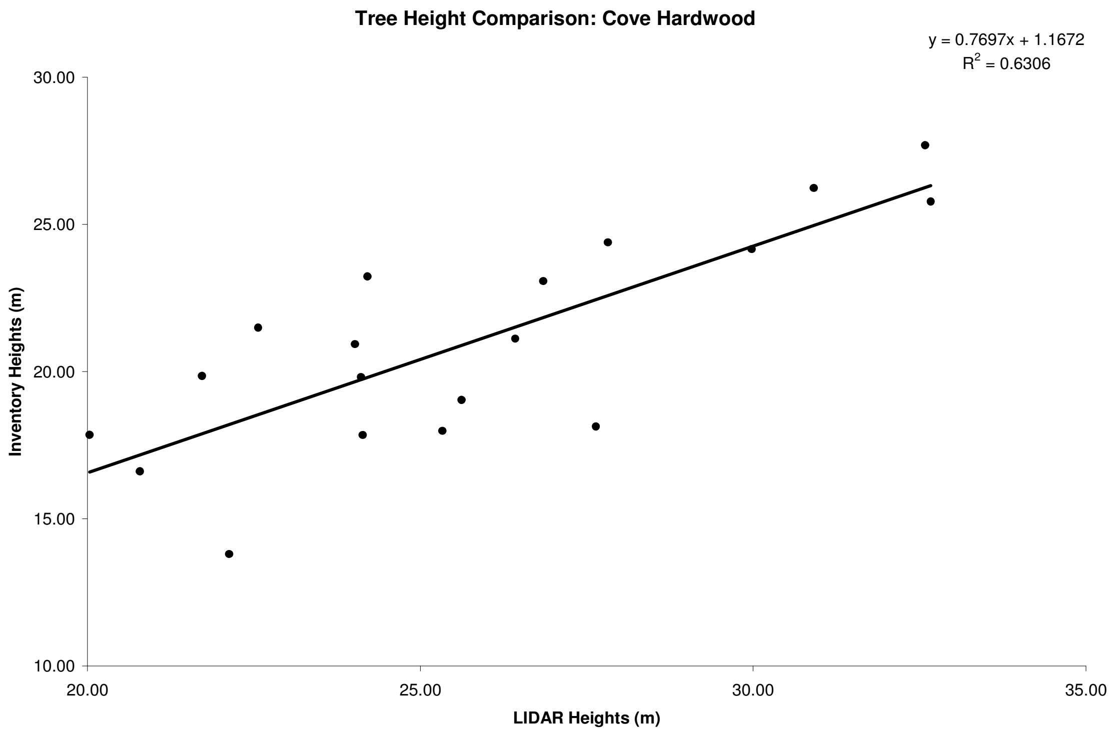

Tree Height Comparison: Cove Hardwood
y = 0.7697x + 1.1672
R2 = 0.6306
30.00
25.00
20.00
15.00
10.00
Inventory Heights (m)
20.00
25.00
30.00
35.00
LIDAR Heights (m)

Figure 9

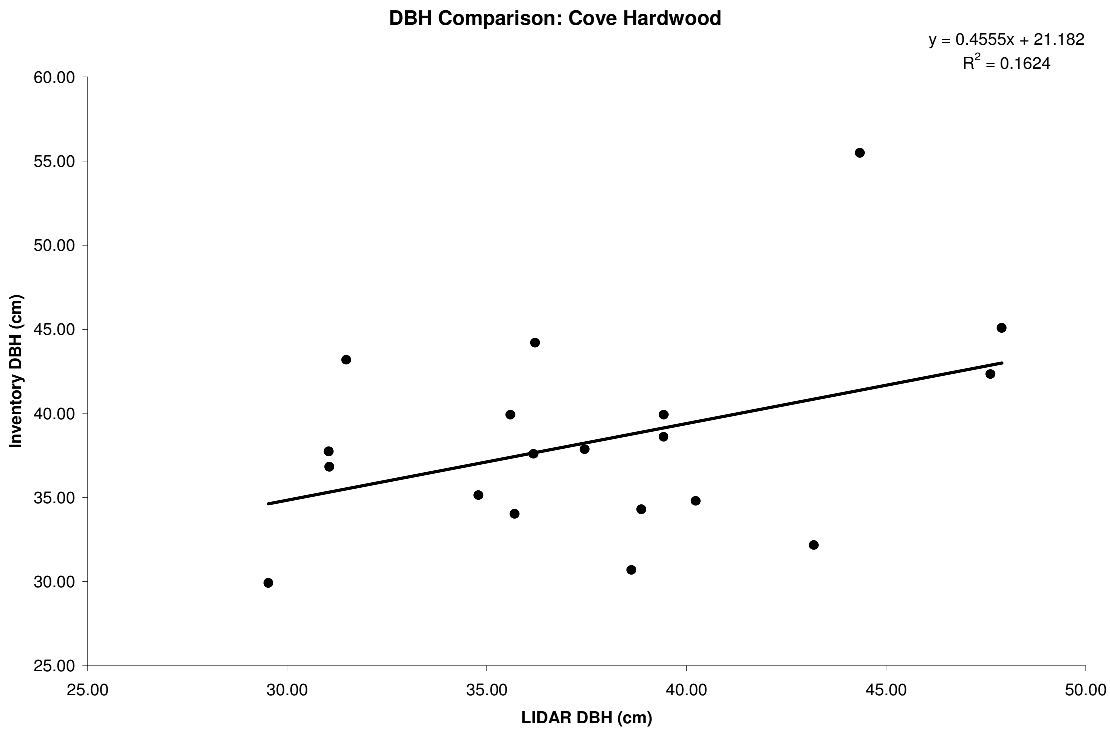

DBH Comparison: Cove Hardwood
y = 0.4555x + 21.182
R2 = 0.1624
60.00
55.00
50.00
45.00
40.00
35.00
30.00
25.00
Inventory DBH (cm)
25.00
30.00
35.00
40.00
45.00
50.00
LIDAR DBH (cm)

Figure 10

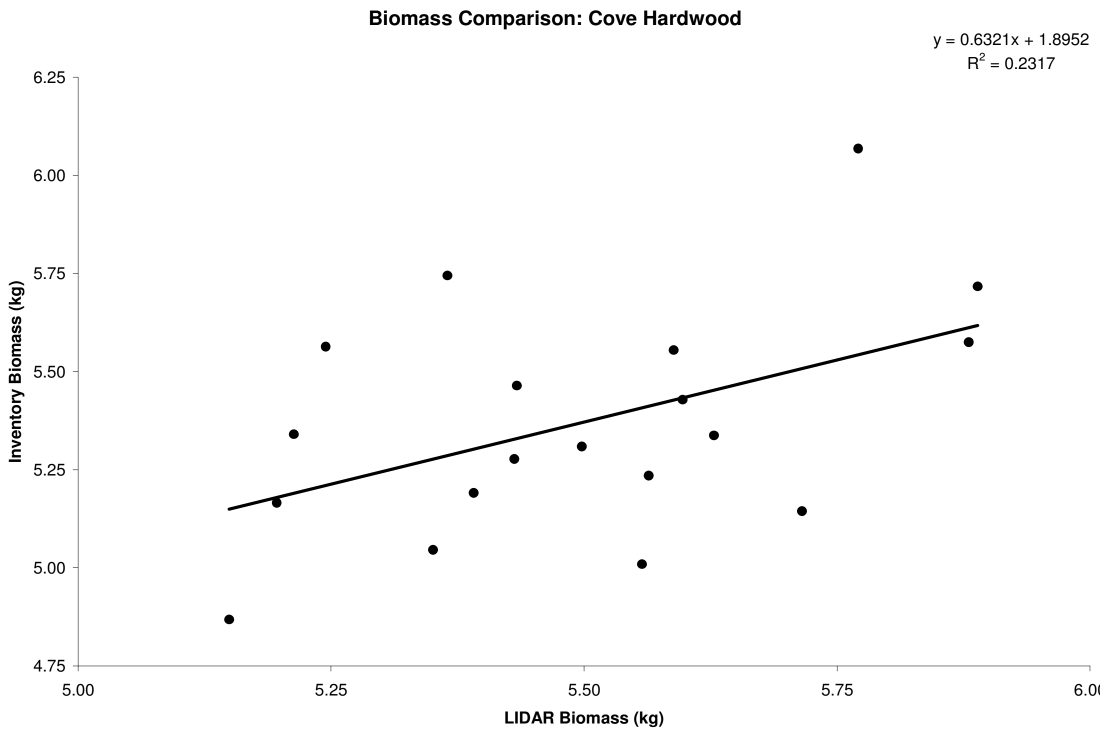

Biomass Comparison: Cove Hardwood
y = 0.6321x + 1.8952
R2 = 0.2317
6.25
6.00
5.75
5.50
5.25
5.00
4.75
Inventory Biomass (kg)
5.00
5.25
5.50
5.75
6.00
LIDAR Biomass (kg)

Figure 11

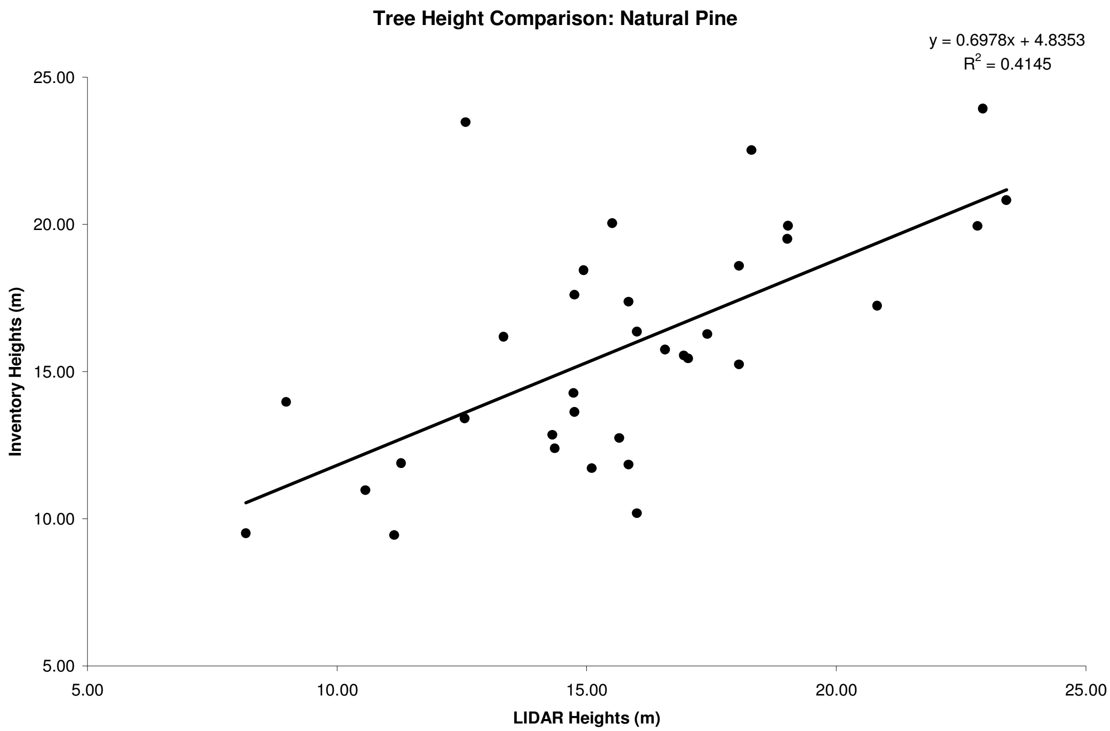

Tree Height Comparison: Natural Pine
y = 0.6978x + 4.8353
R2 = 0.4145
25.00
20.00
15.00
10.00
5.00
Inventory Heights (m)
5.00
10.00
15.00
20.00
25.00
LIDAR Heights (m)

Figure 12

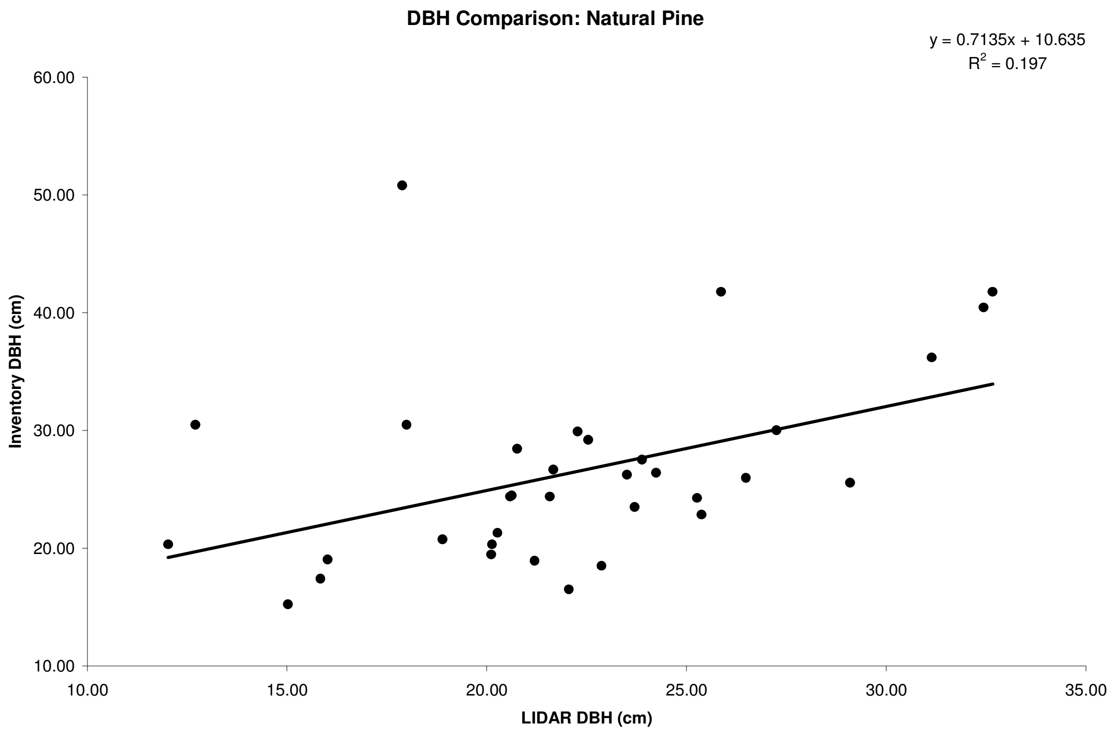

DBH Comparison: Natural Pine
y = 0.7135x + 10.635
R2 = 0.197
60.00
50.00
40.00
30.00
20.00
10.00
Inventory DBH (cm)
10.00
15.00
20.00
25.00
30.00
35.00
LIDAR DBH (cm)

Figure 13

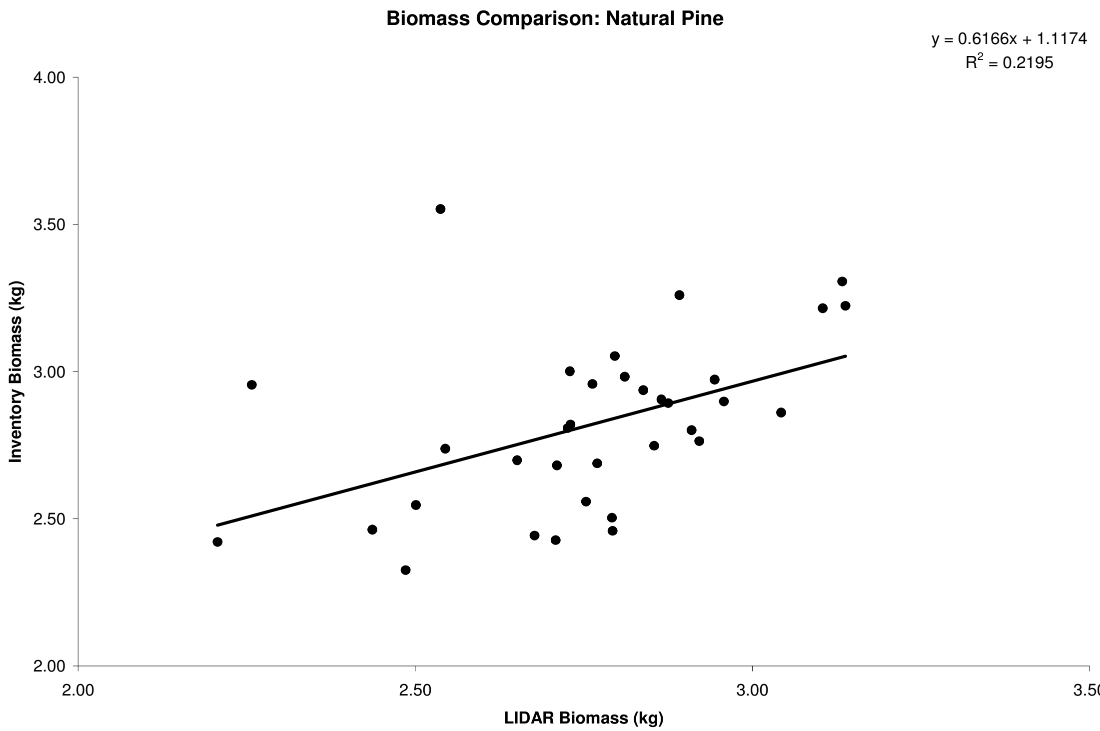
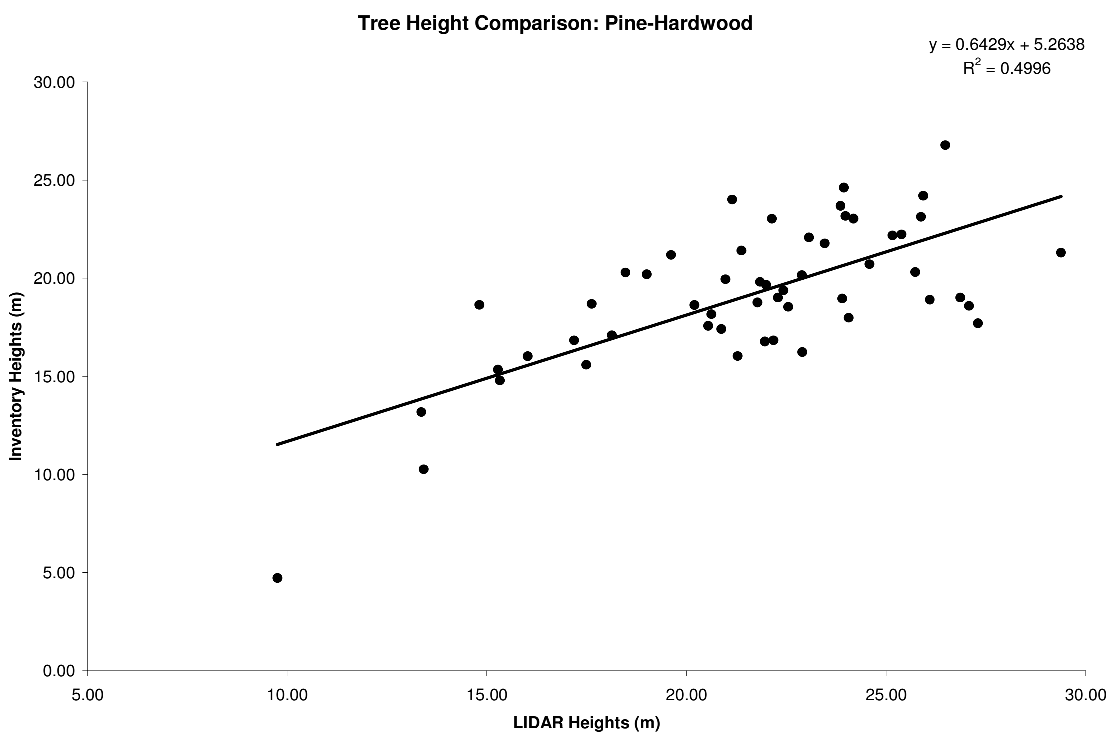

Biomass Comparison: Natural Pine
y = 0.6166x + 1.1174
R2 = 0.2195
4.00
3.50
3.00
2.50
2.00
Inventory Biomass (kg)
2.00
2.50
3.00
3.50
LIDAR Biomass (kg)

Figure 14



Tree Height Comparison: Pine-Hardwood
y = 0.6429x + 5.2638
R2 = 0.4996
30.00
25.00
20.00
15.00
10.00
5.00
0.00
Inventory Heights (m)
5.00
10.00
15.00
20.00
25.00
30.00
LIDAR Heights (m)

Figure 15

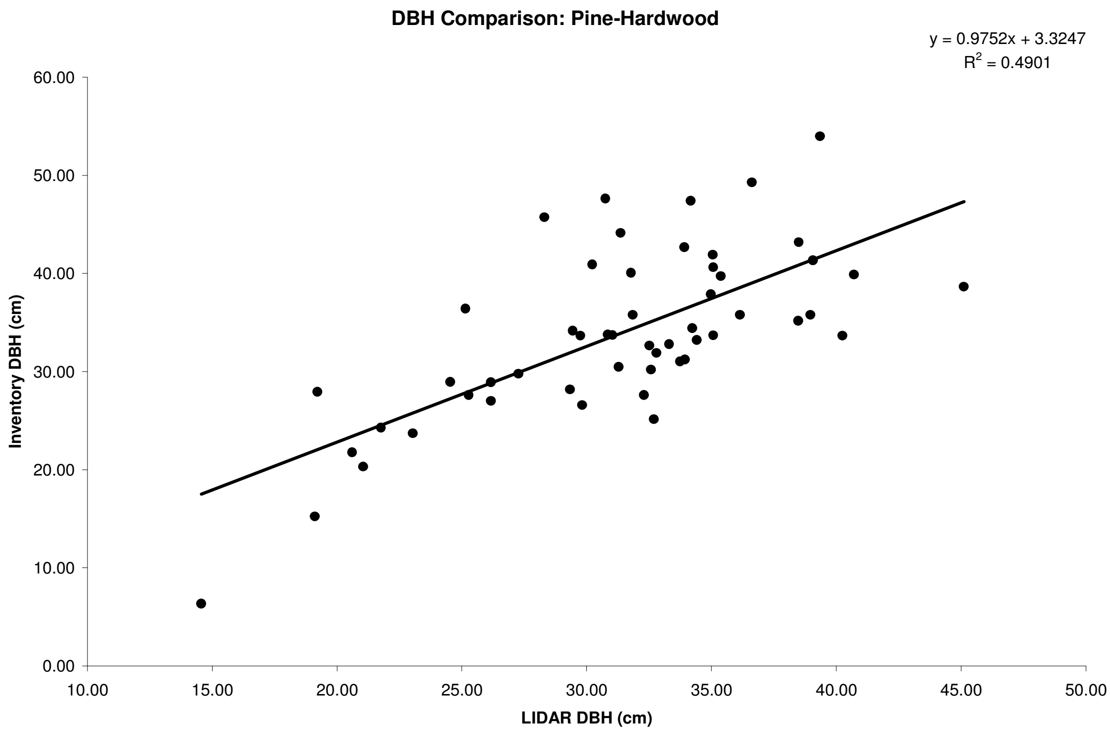

DBH Comparison: Pine-Hardwood
y = 0.9752x + 3.3247
R2 = 0.4901
60.00
50.00
40.00
30.00
20.00
10.00
0.00
Inventory DBH (cm)
10.00
15.00
20.00
25.00
30.00
35.00
40.00
45.00
50.00
LIDAR DBH (cm)

Figure 16

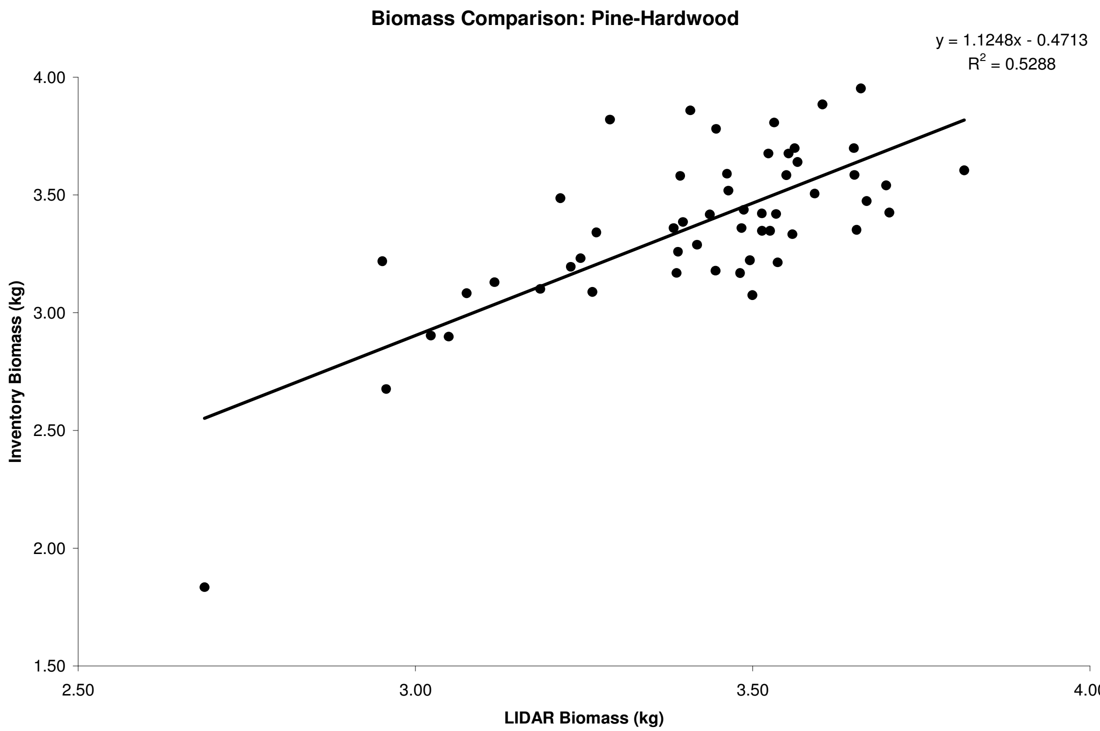

Biomass Comparison: Pine-Hardwood
y = 1.1248x - 0.4713
R2 = 0.5288
Inventory Biomass (kg)
4.00
3.50
3.00
2.50
2.00
1.50
2.50
3.00
3.50
4.00
LIDAR Biomass (kg)

Figure 17

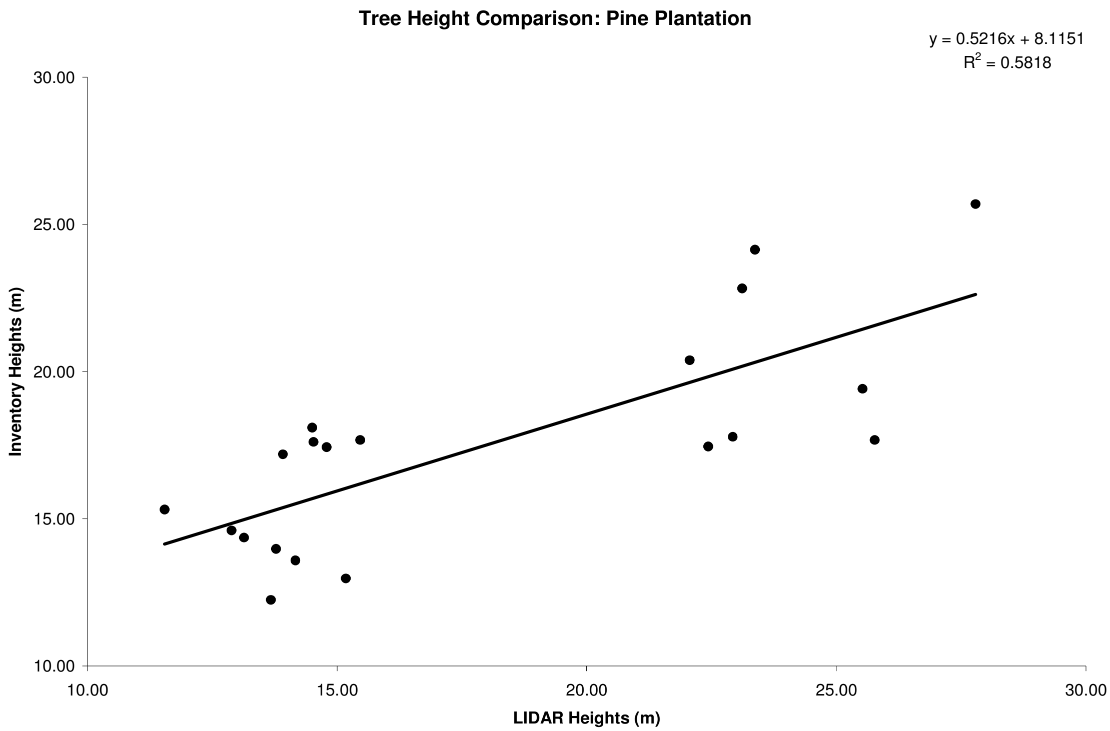
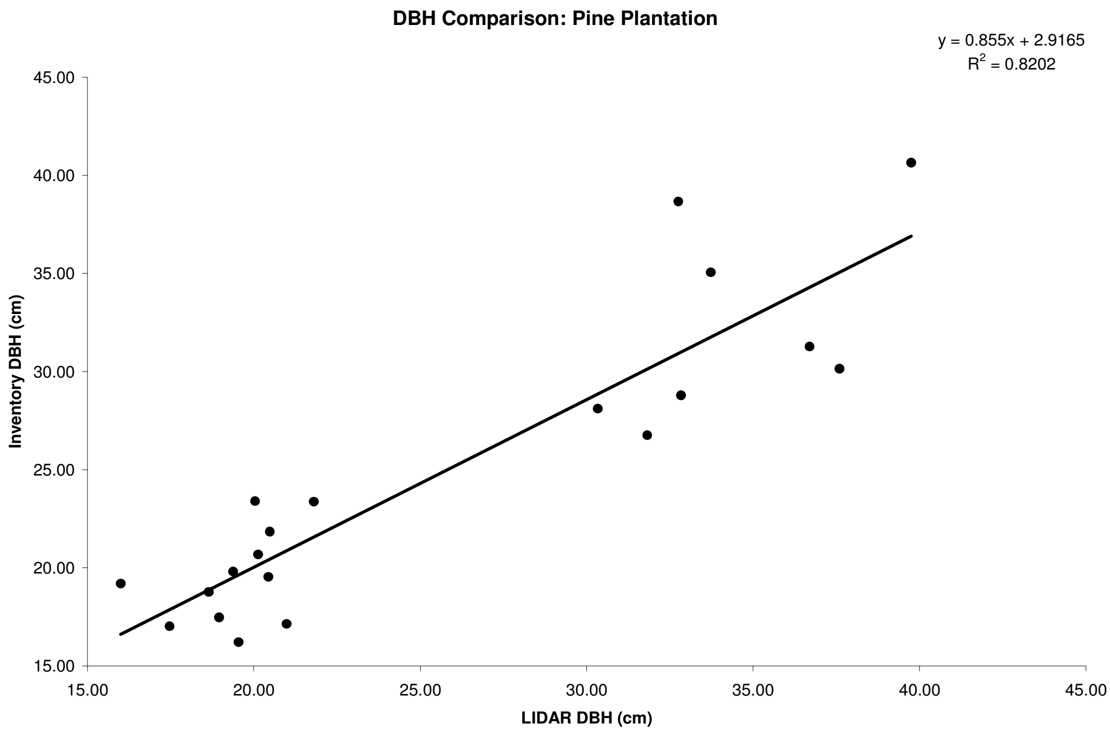
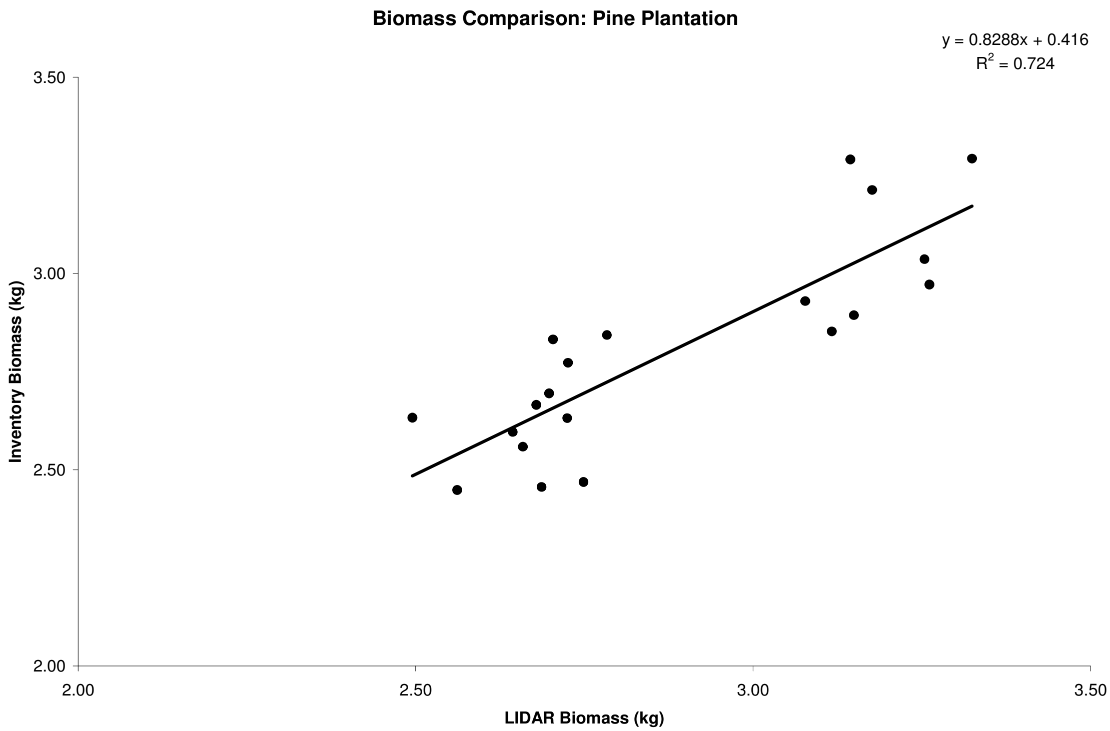

Tree Height Comparison: Pine Plantation
y = 0.5216x + 8.1151
R^2 = 0.5818
30.00
25.00
20.00
15.00
10.00
Inventory Heights (m)
10.00
15.00
20.00
25.00
30.00
LIDAR Heights (m)

Figure 18



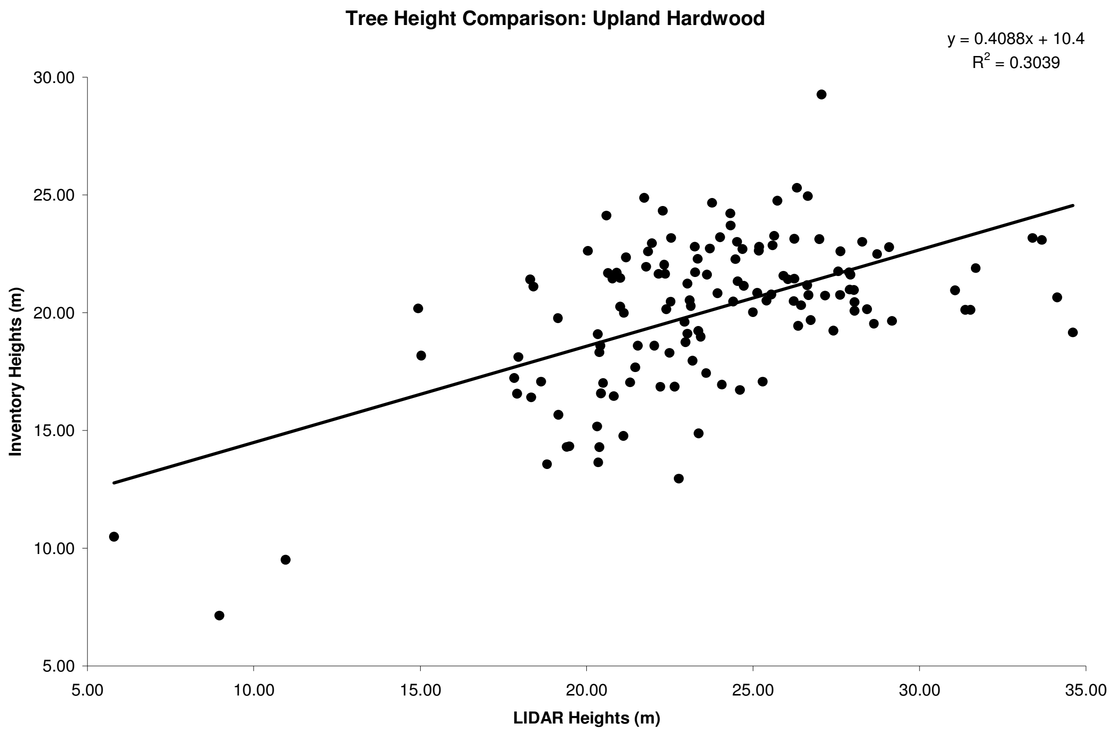
DBH Comparison: Pine Plantation
y = 0.855x + 2.9165
R2 = 0.8202
45.00
40.00
35.00
30.00
25.00
20.00
15.00
Inventory DBH (cm)
15.00
20.00
25.00
30.00
35.00
40.00
45.00
LIDAR DBH (cm)

Figure 19



Biomass Comparison: Pine Plantation
y = 0.8288x + 0.416
R2 = 0.724
3.50
3.00
2.50
2.00
Inventory Biomass (kg)
2.00
2.50
3.00
3.50
LIDAR Biomass (kg)

Figure 20



Tree Height Comparison: Upland Hardwood
y = 0.4088x + 10.4
R2 = 0.3039
30.00
25.00
20.00
15.00
10.00
5.00
Inventory Heights (m)
5.00
10.00
15.00
20.00
25.00
30.00
35.00
LIDAR Heights (m)

Figure 21

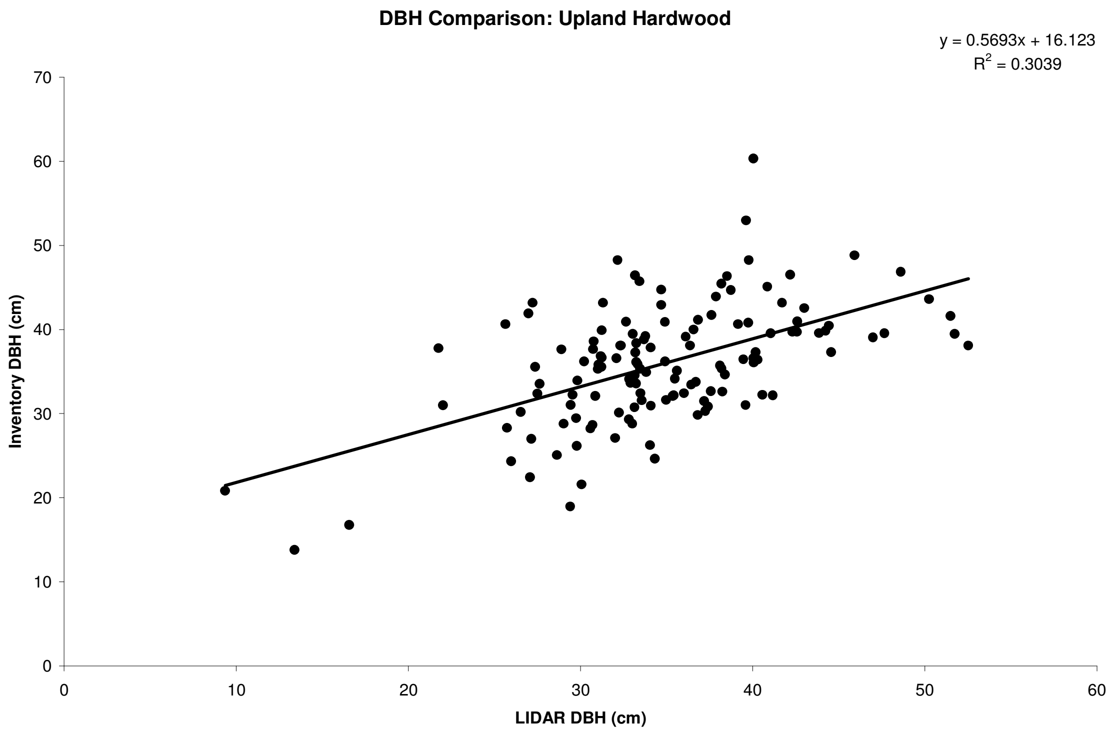
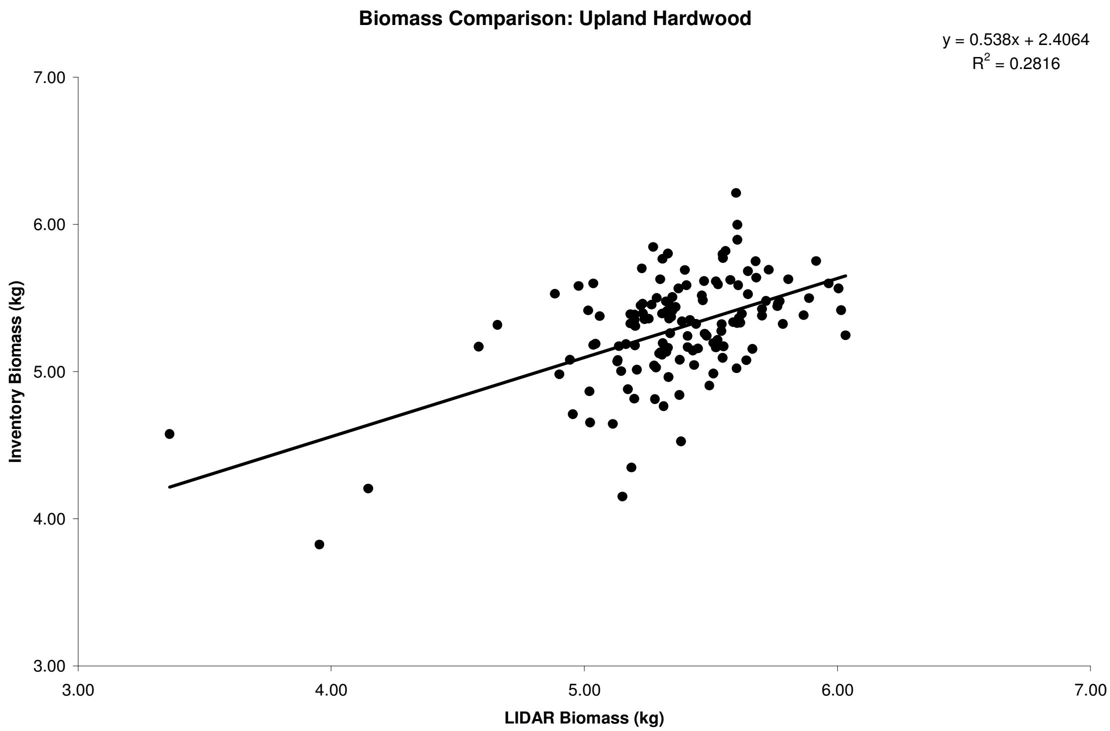

DBH Comparison: Upland Hardwood
y = 0.5693x + 16.123
R2 = 0.3039
Inventory DBH (cm)
LIDAR DBH (cm)
0
10
20
30
40
50
60
70

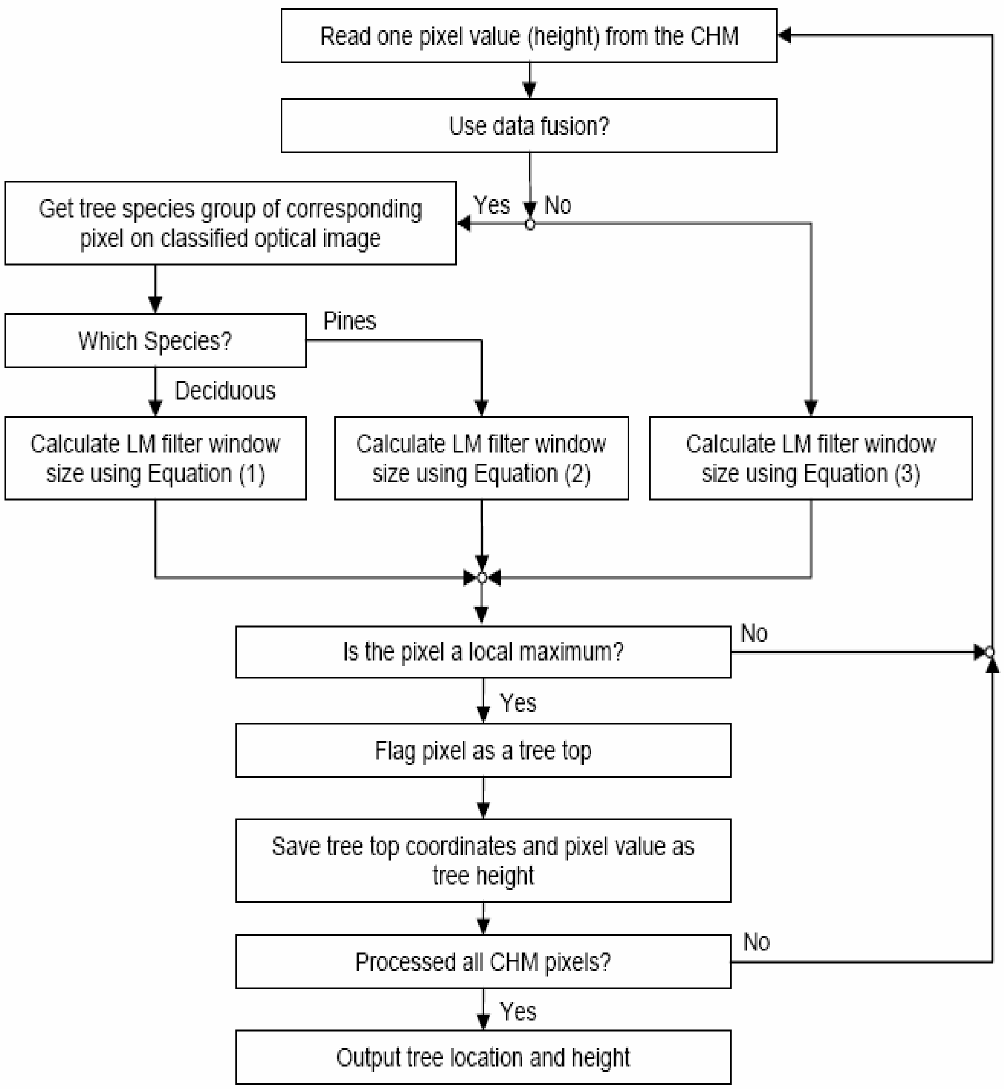
Figure 22


Biomass Comparison: Upland Hardwood
y = 0.538x + 2.4064
R^2 = 0.2816
7.00
6.00
5.00
4.00
3.00
Inventory Biomass (kg)
3.00
4.00
5.00
6.00
7.00
LIDAR Biomass (kg)

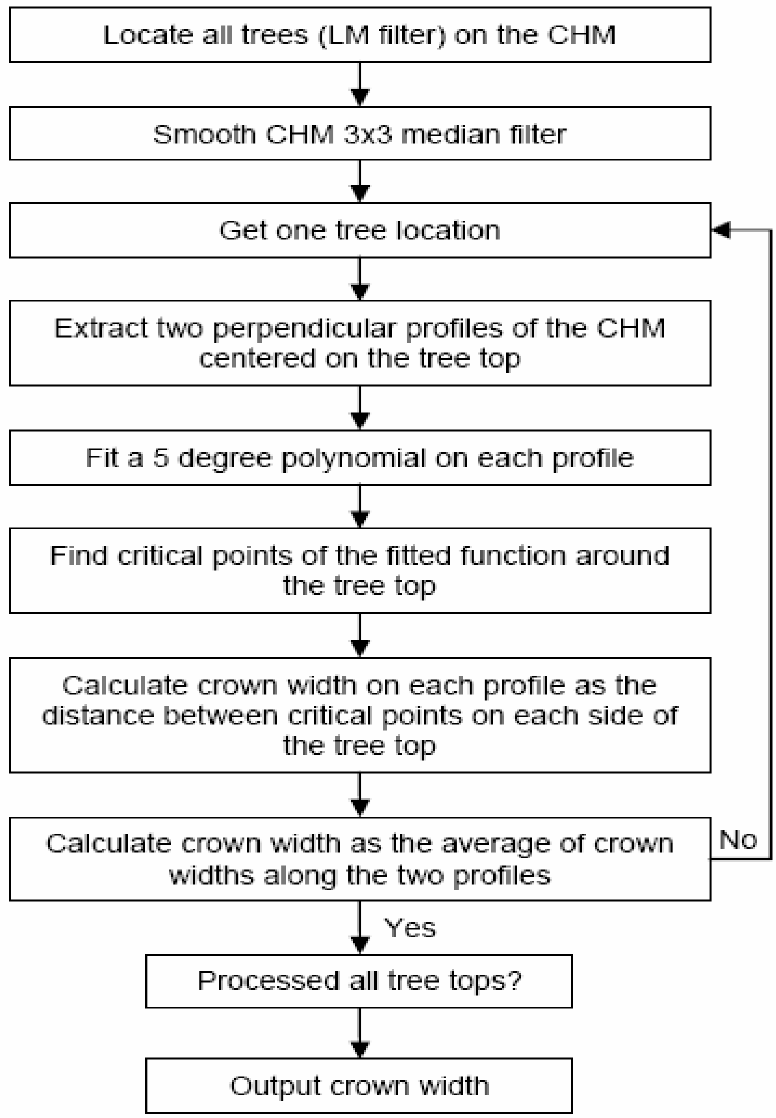
APPENDICES

Appendix A

TreeVaW Selection Process Model



Process for location of individual trees and their total heights.



Process for determining crown width of located trees.

Appendix B

Inventory Measurement Tally Sheet

Plot # ____________ **Covertype** Bottom Cove Old Field Pine Pine-Hdwd Pine Plt. Swamp Upland-Hdwd

Date ____________ **Lat** ______ **Topo:** Bottom Cove Lower middle

Cruiser ____________ **Long** ______ Upper Ridge

Reg. Pine ____________ **Reg. Oak** ______ **Regen YP** ________________ **Reg. Other** ____________________

Tree #	Species	dbh (1")	Product	Mht	TotHgt	% Defect	Comments

Appendix C

Measurement Comparisons for Each Plot

		LIDAR					**Inventory**		
Plot #	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)	Cover Type	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)
90	19	20.60	30.21	5.18	Upland HW	8	24.12	36.20	5.33
190	11	25.13	38.11	5.54	Upland HW	16	20.84	35.72	5.27
191	8	22.65	33.15	5.30	Upland HW	13	16.86	34.58	5.13
192	20	18.31	26.97	4.98	Upland HW	8	21.41	41.91	5.58
193	13	23.10	33.24	5.33	Upland HW	9	20.52	36.12	5.41
194	3	26.23	40.58	5.64	Upland HW	13	20.49	32.24	5.08
195	16	20.77	31.17	5.22	Upland HW	8	21.45	36.83	5.45
196	15	23.34	32.65	5.30	Upland HW	9	22.28	40.92	5.63
197	12	22.29	31.01	5.20	Upland HW	10	24.32	35.31	5.39
198	10	22.54	33.14	5.30	Upland HW	9	23.16	30.76	5.12
199	9	25.19	36.70	5.48	Upland HW	10	22.80	33.78	5.24
200	8	25.59	36.36	5.47	Upland HW	9	22.86	38.10	5.48
201	6	26.73	39.59	5.60	Upland HW	14	19.68	31.02	5.02
202	11	24.68	36.01	5.45	Upland HW	13	22.70	32.43	5.16
203	11	22.36	33.19	5.31	Upland HW	6	21.64	37.25	5.39
204	7	22.49	32.81	5.28	Upland HW	11	18.29	29.33	5.04
205	6	24.32	33.17	5.33	Upland HW	7	24.21	46.45	5.80
206	6	24.01	35.48	5.42	Upland HW	9	23.20	34.15	5.35
207	7	25.64	38.20	5.54	Upland HW	13	23.26	35.36	5.32
208	11	21.96	32.08	5.25	Upland HW	10	22.95	36.58	5.36
209	6	21.11	30.70	5.20	Upland HW	14	14.76	28.67	4.81
210	8	25.40	37.25	5.51	Upland HW	14	20.51	30.30	4.99
211	8	20.34	29.74	5.13	Upland HW	10	19.08	29.46	5.07
212	4	25.00	36.82	5.49	Upland HW	12	20.02	29.85	4.90

	LIDAR					Inventory			
Plot #	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)	Cover Type	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)
213	8	27.93	42.32	5.70	Upland HW	11	21.61	39.72	5.38
214	10	18.63	27.14	5.02	Upland HW	11	17.07	27.02	4.87
215	7	27.41	40.06	5.62	Upland HW	10	19.23	36.07	5.33
216	10	25.73	38.73	5.55	Upland HW	10	24.75	44.70	5.77
217	6	27.91	42.57	5.70	Upland HW	11	20.98	39.72	5.43
218	10	17.91	25.64	4.88	Upland HW	3	16.56	40.64	5.53
219	3	28.43	43.87	5.76	Upland HW	12	20.14	39.58	5.44
220	4	28.05	42.60	5.72	Upland HW	16	20.08	40.96	5.48
221	8	22.16	33.43	5.31	Upland HW	2	21.64	45.72	5.77
222	4	24.47	35.60	5.44	Upland HW	16	22.27	35.08	5.32
223	6	31.54	47.00	5.87	Upland HW	8	20.12	39.05	5.38
224	4	31.70	48.60	5.92	Upland HW	11	21.89	46.87	5.75
225	3	27.63	41.17	5.66	Upland HW	12	22.61	32.17	5.15
226	4	28.28	42.99	5.73	Upland HW	8	23.01	42.55	5.69
227	9	27.00	39.77	5.60	Upland HW	7	23.12	48.26	5.89
228	8	27.56	38.51	5.56	Upland HW	8	21.76	46.36	5.82
229	1	33.68	51.75	6.02	Upland HW	11	23.08	39.49	5.42
230	4	23.59	34.04	5.38	Upland HW	15	17.43	26.25	4.84
231	5	26.67	39.75	5.61	Upland HW	16	20.75	40.80	5.59
232	4	27.89	39.47	5.59	Upland HW	17	21.71	36.46	5.34
233	3	24.41	36.42	5.48	Upland HW	6	20.47	33.44	5.26
241	9	23.03	33.49	5.33	Upland HW	13	19.11	32.43	4.96
242	11	23.62	33.03	5.32	Upland HW	11	21.61	39.49	5.48
243	6	23.03	32.91	5.31	Upland HW	12	21.23	33.66	5.19
244	9	26.44	38.40	5.55	Upland HW	11	20.31	34.64	5.09
245	14	23.25	34.70	5.37	Upland HW	10	22.80	42.93	5.56
246	7	22.33	32.31	5.27	Upland HW	11	22.03	38.10	5.45
247	17	23.26	33.78	5.35	Upland HW	9	21.71	39.23	5.51
248	18	23.71	34.69	5.40	Upland HW	13	22.72	44.74	5.69
249	9	26.32	36.83	5.47	Upland HW	10	25.30	41.15	5.61
250	8	21.46	32.24	5.28	Upland HW	14	17.68	30.12	5.03

	LIDAR					Inventory			
Plot #	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)	Cover Type	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)
251	16	20.39	29.83	5.16	Upland HW	11	18.32	33.94	5.19
252	9	23.77	34.07	5.36	Upland HW	10	24.66	37.85	5.44
253	6	18.33	25.97	4.95	Upland HW	12	16.41	24.34	4.71
255	6	24.73	35.37	5.43	Upland HW	11	21.14	32.10	5.14
256	13	21.73	32.15	5.27	Upland HW	5	24.87	48.26	5.85
257	6	22.04	33.23	5.32	Upland HW	9	18.59	33.58	5.13
258	5	23.36	34.98	5.41	Upland HW	11	19.23	31.63	5.17
259	4	23.94	35.41	5.43	Upland HW	9	20.83	32.17	5.04
260	6	26.64	39.16	5.58	Upland HW	6	24.94	40.64	5.62
261	9	22.21	32.82	5.31	Upland HW	7	16.85	34.11	5.11
262	7	21.85	32.35	5.29	Upland HW	8	22.59	38.10	5.50
263	5	20.41	29.77	5.17	Upland HW	10	18.59	26.16	4.88
264	4	20.04	29.02	5.13	Upland HW	9	22.62	28.79	5.08
265	4	25.92	38.24	5.55	Upland HW	13	21.57	32.63	5.17
266	2	21.01	30.57	5.21	Upland HW	9	20.25	28.22	5.01
267	3	20.35	30.06	5.19	Upland HW	8	13.64	21.59	4.35
268	2	21.31	32.01	5.28	Upland HW	9	17.03	27.09	4.81
269	4	24.07	33.01	5.31	Upland HW	12	16.94	28.79	4.76
270	5	17.95	26.52	4.94	Upland HW	9	18.12	30.20	5.08
271	3	20.43	29.54	5.14	Upland HW	13	16.58	32.24	5.17
272	1	19.48	28.63	5.11	Upland HW	8	14.33	25.08	4.64
273	4	23.14	34.08	5.38	Upland HW	11	20.28	30.94	5.08
274	7	20.90	30.74	5.20	Upland HW	6	21.69	37.68	5.35
275	1	25.55	37.57	5.53	Upland HW	7	20.77	32.66	5.21
278	5	20.39	29.43	5.15	Upland HW	9	14.29	31.04	5.00
280	7	28.63	44.57	5.78	Upland HW	16	19.53	37.31	5.32
281	3	34.14	51.50	6.01	Upland HW	8	20.65	41.59	5.57
282	5	28.73	44.43	5.77	Upland HW	13	22.48	40.44	5.48
284	4	26.24	37.87	5.53	Upland HW	14	21.44	43.91	5.59
285	7	31.38	45.92	5.81	Upland HW	9	20.12	48.82	5.63
286	5	31.08	47.66	5.89	Upland HW	7	20.94	39.55	5.50

		LIDAR					Inventory		
Plot #	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)	Cover Type	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)
288	5	33.40	50.25	5.97	Upland HW	6	23.16	43.60	5.60
289	6	22.97	33.32	5.34	Upland HW	8	18.75	35.88	5.37
290	6	24.54	37.19	5.51	Upland HW	10	21.34	31.50	5.19
291	2	27.17	41.05	5.65	Upland HW	7	20.73	39.55	5.53
292	6	23.43	34.92	5.41	Upland HW	8	18.97	36.20	5.24
293	6	26.04	40.05	5.61	Upland HW	15	21.42	36.58	5.36
294	9	26.24	38.18	5.55	Upland HW	9	23.13	45.44	5.80
295	5	29.18	44.24	5.77	Upland HW	13	19.65	39.86	5.46
296	6	24.61	37.61	5.52	Upland HW	7	16.72	41.73	5.61
297	5	22.77	33.69	5.35	Upland HW	14	12.95	38.83	5.41
298	3	28.03	41.71	5.68	Upland HW	9	20.96	43.18	5.64
299	5	26.36	40.28	5.62	Upland HW	9	19.44	36.41	5.39
300	3	34.61	52.53	6.03	Upland HW	14	19.16	38.10	5.25
301	3	25.29	37.40	5.52	Upland HW	7	17.07	30.84	5.16
302	11	20.49	30.86	5.20	Upland HW	11	17.01	32.10	5.18
303	5	23.37	34.32	5.38	Upland HW	10	14.87	24.64	4.53
304	13	26.63	39.63	5.60	Upland HW	7	21.16	52.98	6.00
307	1	18.81	27.21	5.04	Upland HW	2	13.56	43.18	5.60
308	9	28.05	42.18	5.68	Upland HW	13	20.45	46.50	5.75
371	4	20.32	29.40	5.15	Upland HW	13	15.17	18.95	4.15
372	10	18.41	27.07	5.02	Upland HW	12	21.11	22.44	4.65
382	24	27.06	40.04	5.60	Upland HW	8	29.26	60.33	6.21
383	8	24.33	36.57	5.46	Upland HW	12	23.70	40.01	5.52
384	10	20.65	30.76	5.18	Upland HW	16	21.68	38.58	5.39
385	10	25.17	36.11	5.39	Upland HW	12	22.63	39.16	5.34
386	6	29.10	40.85	5.65	Upland HW	12	22.78	45.09	5.68
387	10	22.53	33.56	5.33	Upland HW	14	20.47	31.57	5.16
396	13	19.41	28.88	5.06	Upland HW	11	14.30	37.64	5.38
400	2	5.80	9.36	3.36	Upland HW	5	10.49	20.83	4.58
402	1	8.97	13.38	3.95	Upland HW	7	7.14	13.79	3.82
413	13	21.19	31.22	5.24	Upland HW	10	22.34	35.56	5.36

Plot #	LIDAR Trees per Plot	LIDAR Mean Height (m)	LIDAR Mean dbh (cm)	LIDAR Mean Biomass (kg)	Cover Type	Inventory Trees per Plot	Inventory Mean Height (m)	Inventory Mean dbh (cm)	Inventory Mean Biomass (kg)
414	6	20.82	27.49	5.04	Upland HW	12	16.46	32.39	5.18
415	14	21.12	31.23	5.23	Upland HW	7	19.99	39.91	5.46
416	12	15.03	21.76	4.66	Upland HW	8	18.17	37.78	5.32
417	10	21.54	31.06	5.20	Upland HW	10	18.59	35.81	5.31
418	9	27.62	40.17	5.60	Upland HW	13	20.75	37.32	5.33
419	15	19.14	27.37	5.02	Upland HW	7	19.77	35.56	5.42
420	17	21.79	31.31	5.23	Upland HW	6	21.95	43.18	5.70
421	9	17.82	25.73	4.90	Upland HW	14	17.22	28.30	4.98
422	12	24.52	34.91	5.40	Upland HW	10	23.01	40.89	5.59
423	15	19.15	27.63	5.04	Upland HW	5	15.67	33.53	5.19
424	18	22.95	33.25	5.33	Upland HW	9	19.61	38.38	5.47
425	9	21.01	31.23	5.23	Upland HW	7	21.47	36.65	5.40
426	10	14.94	22.02	4.58	Upland HW	5	20.18	30.99	5.17
427	8	22.39	33.47	5.34	Upland HW	11	20.14	35.33	5.36
428	10	23.19	33.82	5.34	Upland HW	12	17.96	34.93	5.26
429	3	10.96	16.56	4.15	Upland HW	5	9.51	16.76	4.20
778	13	22.07	30.34	3.08	Pine Plant	15	20.38	28.11	2.93
780	9	15.18	20.98	2.75	Pine Plant	20	12.97	17.15	2.47
781	9	13.68	18.96	2.66	Pine Plant	17	12.25	17.48	2.56
782	7	14.17	20.13	2.70	Pine Plant	7	13.59	20.68	2.69
783	2	13.78	19.54	2.69	Pine Plant	13	13.97	16.22	2.46
784	12	15.47	21.81	2.78	Pine Plant	10	17.68	23.37	2.84
785	12	14.79	20.48	2.73	Pine Plant	10	17.43	21.84	2.77
786	11	13.92	19.38	2.68	Pine Plant	15	17.19	19.81	2.67
787	15	14.50	20.04	2.70	Pine Plant	14	18.09	23.40	2.83
788	12	14.53	20.44	2.72	Pine Plant	13	17.61	19.54	2.63
789	4	13.14	18.65	2.64	Pine Plant	18	14.36	18.77	2.60
790	6	11.55	16.01	2.50	Pine Plant	9	15.31	19.19	2.63
791	4	12.89	17.47	2.56	Pine Plant	10	14.60	17.02	2.45
972	19	27.79	39.75	3.32	Pine Plant	11	25.69	40.64	3.29
973	12	25.53	36.70	3.25	Pine Plant	16	19.41	31.27	3.04

Plot #	LIDAR Trees per Plot	LIDAR Mean Height (m)	LIDAR Mean dbh (cm)	LIDAR Mean Biomass (kg)	Cover Type	Inventory Trees per Plot	Inventory Mean Height (m)	Inventory Mean dbh (cm)	Inventory Mean Biomass (kg)
974	9	25.77	37.60	3.26	Pine Plant	15	17.68	30.14	2.97
975	19	23.12	32.76	3.14	Pine Plant	9	22.83	38.66	3.29
977	18	23.37	33.73	3.18	Pine Plant	10	24.14	35.05	3.21
978	13	22.93	32.84	3.15	Pine Plant	12	17.78	28.79	2.89
979	8	22.44	31.82	3.12	Pine Plant	15	17.45	26.75	2.85
1141	11	24.59	35.07	3.56	Pine HW	15	20.71	33.70	3.33
1142	15	21.85	31.85	3.46	Pine HW	12	19.81	35.77	3.52
1143	17	22.00	32.51	3.49	Pine HW	14	19.66	32.66	3.44
1144	13	25.39	36.14	3.59	Pine HW	11	22.22	35.79	3.51
1145	7	15.28	21.05	3.05	Pine HW	12	15.34	20.32	2.90
1146	8	22.56	32.29	3.48	Pine HW	16	18.54	27.62	3.17
1147	5	20.20	29.82	3.39	Pine HW	15	18.63	26.59	3.17
1148	8	20.87	29.34	3.39	Pine HW	11	17.40	28.17	3.26
1149	9	23.91	33.94	3.51	Pine HW	10	18.96	31.24	3.35
1150	7	25.16	34.41	3.53	Pine HW	13	22.18	33.22	3.42
1151	16	22.14	31.78	3.46	Pine HW	9	23.03	40.08	3.59
1152	11	16.02	23.03	3.12	Pine HW	9	16.02	23.71	3.13
1252	20	26.48	39.35	3.66	Pine HW	12	26.77	53.98	3.95
1253	9	14.81	20.60	3.02	Pine HW	7	18.64	21.77	2.90
1254	15	23.94	34.97	3.55	Pine HW	12	24.61	37.89	3.58
1255	14	18.48	26.17	3.25	Pine HW	11	20.28	27.02	3.23
1256	10	19.01	27.27	3.27	Pine HW	11	20.20	29.79	3.34
1257	16	20.55	29.44	3.38	Pine HW	11	17.57	34.17	3.36
1258	7	22.29	33.30	3.51	Pine HW	11	19.01	32.79	3.42
1259	14	21.38	31.35	3.45	Pine HW	8	21.41	44.13	3.78
1260	17	23.86	33.91	3.52	Pine HW	10	23.68	42.67	3.68
1261	3	13.42	19.11	2.96	Pine HW	17	10.26	15.24	2.68
1262	10	15.33	21.76	3.08	Pine HW	16	14.78	24.29	3.08
1263	11	18.14	26.16	3.26	Pine HW	13	17.09	28.92	3.09
1264	12	17.49	25.27	3.23	Pine HW	8	15.58	27.62	3.19
1265	10	23.07	33.74	3.53	Pine HW	14	22.08	31.02	3.35

	LIDAR					Inventory			
Plot #	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)	Cover Type	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)
1266	23	20.98	30.22	3.39	Pine HW	9	19.95	40.92	3.58
1267	13	22.90	32.80	3.50	Pine HW	16	16.23	31.91	3.22
1268	8	20.63	29.75	3.40	Pine HW	12	18.16	33.66	3.39
1272	9	26.86	39.06	3.65	Pine HW	11	19.01	41.33	3.58
1273	22	24.06	35.38	3.57	Pine HW	11	17.98	39.72	3.64
1274	17	19.62	28.31	3.29	Pine HW	4	21.18	45.72	3.82
1275	9	22.43	32.58	3.48	Pine HW	9	19.37	30.20	3.36
1276	12	17.19	24.54	3.19	Pine HW	10	16.83	28.96	3.10
1277	10	27.30	40.25	3.70	Pine HW	16	17.70	33.66	3.42
1278	6	26.10	38.96	3.67	Pine HW	11	18.90	35.79	3.47
1279	5	29.39	45.11	3.81	Pine HW	14	21.29	38.64	3.60
1281	7	22.89	34.24	3.54	Pine HW	9	20.15	34.43	3.21
1282	25	23.47	34.17	3.53	Pine HW	9	21.78	47.41	3.81
1283	1	22.18	32.70	3.50	Pine HW	10	16.83	25.15	3.07
1285	20	17.63	25.15	3.22	Pine HW	3	18.69	36.41	3.49
1286	31	21.15	30.75	3.41	Pine HW	8	24.00	47.63	3.86
1287	5	13.36	19.22	2.95	Pine HW	4	13.18	27.94	3.22
1288	18	24.19	35.07	3.56	Pine HW	7	23.03	40.64	3.70
1289	2	9.76	14.56	2.69	Pine HW	2	4.72	6.35	1.83
1291	13	27.08	40.71	3.70	Pine HW	10	18.59	39.88	3.54
1292	18	21.96	31.28	3.45	Pine HW	8	16.76	30.48	3.18
1293	16	21.28	30.85	3.42	Pine HW	10	16.03	33.78	3.29
1294	13	21.78	31.03	3.44	Pine HW	11	18.76	33.71	3.42
1295	10	25.88	38.50	3.65	Pine HW	8	23.13	43.18	3.70
1296	17	23.99	35.06	3.55	Pine HW	8	23.16	41.91	3.68
1297	8	25.73	38.47	3.65	Pine HW	13	20.30	35.17	3.35
1298	20	25.93	36.62	3.60	Pine HW	5	24.20	49.28	3.88
1509	35	12.58	17.89	2.54	Nat Pine	1	23.47	50.80	3.55
1510	12	12.56	17.99	2.54	Nat Pine	4	13.41	30.48	2.74
1511	2	8.18	12.02	2.21	Nat Pine	5	9.51	20.32	2.42
1512	22	8.98	12.70	2.26	Nat Pine	6	13.97	30.48	2.95

	LIDAR					Inventory			
Plot #	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)	Cover Type	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)
1518	6	11.28	16.02	2.50	Nat Pine	10	11.89	19.05	2.55
1519	15	13.34	18.89	2.65	Nat Pine	12	16.18	20.74	2.70
1520	20	14.94	20.77	2.73	Nat Pine	10	18.44	28.45	3.00
1521	3	10.57	15.02	2.44	Nat Pine	1	10.97	15.24	2.46
1522	11	14.76	20.27	2.71	Nat Pine	13	17.61	21.30	2.68
1523	11	15.51	21.66	2.76	Nat Pine	8	20.04	26.67	2.96
1586	23	22.94	31.14	3.10	Nat Pine	12	23.93	36.20	3.21
1587	15	18.05	25.27	2.91	Nat Pine	9	15.24	24.27	2.80
1588	12	18.05	25.38	2.92	Nat Pine	11	18.59	22.86	2.76
1589	4	16.01	22.87	2.79	Nat Pine	7	10.19	18.51	2.50
1590	13	19.02	26.49	2.96	Nat Pine	9	19.51	25.96	2.90
1591	14	16.01	22.54	2.81	Nat Pine	6	16.36	29.21	2.98
1592	12	19.04	27.26	2.94	Nat Pine	11	19.95	30.02	2.97
1593	16	17.04	23.89	2.87	Nat Pine	6	15.44	27.52	2.90
1594	13	17.42	24.24	2.88	Nat Pine	10	16.28	26.42	2.89
1595	29	22.83	32.67	3.14	Nat Pine	9	19.95	41.77	3.22
1596	12	14.76	20.59	2.73	Nat Pine	10	13.62	24.38	2.81
1597	17	16.95	23.70	2.85	Nat Pine	12	15.54	23.50	2.75
1598	12	14.74	20.63	2.73	Nat Pine	11	14.27	24.48	2.82
1599	2	15.84	22.05	2.79	Nat Pine	6	11.84	16.51	2.46
1600	22	23.41	32.44	3.13	Nat Pine	13	20.82	40.44	3.31
1601	4	11.15	15.84	2.49	Nat Pine	7	9.45	17.42	2.33
1602	9	15.65	21.58	2.77	Nat Pine	10	12.74	24.38	2.69
1603	9	14.31	20.11	2.68	Nat Pine	6	12.85	19.47	2.44
1604	5	15.11	21.20	2.75	Nat Pine	11	11.72	18.93	2.56
1612	30	18.30	25.87	2.89	Nat Pine	9	22.52	41.77	3.26
1613	16	20.82	29.10	3.04	Nat Pine	16	17.24	25.56	2.86
1617	15	16.57	23.51	2.84	Nat Pine	3	15.75	26.25	2.94
1618	6	14.36	20.13	2.71	Nat Pine	3	12.40	20.32	2.43
1619	27	15.84	22.28	2.80	Nat Pine	9	17.37	29.92	3.05
1888	6	26.85	39.43	5.60	Cove HW	10	23.07	38.61	5.43

		LIDAR					Inventory		
Plot #	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)	Cover Type	Trees per Plot	Mean Height (m)	Mean dbh (cm)	Mean Biomass (kg)
1889	3	25.33	38.62	5.56	Cove HW	12	17.98	30.69	5.01
1890	6	27.82	40.23	5.63	Cove HW	10	24.38	34.80	5.34
1891	4	24.02	35.70	5.39	Cove HW	15	20.93	34.04	5.19
1892	9	25.62	37.45	5.50	Cove HW	11	19.04	37.87	5.31
1893	8	26.43	39.43	5.59	Cove HW	7	21.12	39.91	5.55
1894	7	27.64	38.87	5.56	Cove HW	16	18.14	34.29	5.23
1895	15	20.79	31.06	5.20	Cove HW	10	16.61	36.83	5.17
1896	11	24.11	35.59	5.43	Cove HW	7	19.81	39.91	5.46
1897	19	22.13	31.04	5.21	Cove HW	7	13.80	37.74	5.34
1908	6	24.14	36.17	5.43	Cove HW	15	17.84	37.59	5.28
1909	3	32.67	47.62	5.88	Cove HW	9	25.77	42.33	5.57
1910	3	22.57	34.79	5.35	Cove HW	6	21.49	35.14	5.05
1911	4	29.98	43.20	5.72	Cove HW	15	24.16	32.17	5.14
1913	10	24.21	36.21	5.37	Cove HW	5	23.23	44.20	5.74
1914	14	21.73	31.48	5.24	Cove HW	8	19.85	43.18	5.56
1915	7	20.03	29.53	5.15	Cove HW	9	17.85	29.92	4.87
1916	9	30.91	44.34	5.77	Cove HW	13	26.24	55.49	6.07
1917	6	32.59	47.90	5.89	Cove HW	12	27.69	45.09	5.72

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