DERIVING A FRAMEWORK FOR ESTIMATING INDIVIDUAL TREE MEASUREMENTS WITH LIDAR FOR USE IN THE TAMBEETLE SOUTHERN PINE BEETLE INFESTATION GROWTH MODEL

A Thesis

by

JARED DEE STUKEY

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2009

Major Subject: Forestry

DERIVING A FRAMEWORK FOR ESTIMATING INDIVIDUAL TREE MEASUREMENTS WITH LIDAR FOR USE IN THE TAMBEETLE SOUTHERN PINE BEETLE INFESTATION GROWTH MODEL

A Thesis

by

JARED DEE STUKEY

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Approved by:

Chair of Committee,	Sorin C. Popescu
Committee Members,	Robert N. Coulson
	Andrew Millington
Head of Department,	Steven G. Whisenant

December, 2009

Major Subject: Forestry

ABSTRACT

Deriving a Framework for Estimating Individual Tree Measurements with Lidar for Use in the TAMBEETLE Southern Pine Beetle Infestation Growth Model. (December 2009)

Jared Dee Stukey, B.S., Texas A&M University

Chair of Advisory Committee: Dr. Sorin C. Popescu

The overall goal of this study was to develop a framework for using airborne lidar to derive inputs for the SPB infestation growth model TAMBEETLE. The specific objectives were (1) to estimate individual tree characteristics of XY location, individual bole height (IBH), diameter at breast height (DBH), length of crown (CrHT), and age for use in TAMBEETLE; (2) to estimate individual tree age using lidar-estimated height and site index provided by the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) Soil Survey Geographic Database (SSURGO); and (3) to compare TAMBEETLE simulation results using field measurements and lidar-derived measurements as inputs. Diameter at breast height, individual bole height, and crown length were estimated using lidar with an error for mean measurements at plot level of 0.16cm, 0.19m, and 1.07m, respectively. These errors were within root mean square error (RMSE) for other studies at the study site. Age was estimated using the site index provided by SSURGO and the site index curves created for the study area with an RMSE of 4.8 years for mean plot age. Underestimation of tree height by lidar and error in the site index curve explained 91% of the error in mean plot age. TAMBEETLE was used to compare spot growth between a lidar-derived forest map and a forest map generated by TAMBEETLE, based on sample plot characteristics. The lidar-derived forest performed comparably to the TAMBEETLE generated forest. Using lidar to map forests can provide the large spatial extents of the TAMBEETLE generated forest while maintaining the spatially explicit forest characteristics, which were previously only available through field measurements.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1 Background

The Southern Pine Beetle (SPB), *Dendroctonus frontalis* Zimmermann (Coleoptera: Scolytidae), is the most destructive pest to the logging industry, causing $2.5 billion in pine timber loss every year (Coulson et al., 2004). The SPB targets loblolly (*Pinus taeda*), shortleaf (*Pinus echinata*), and slash (*Pinus elliottii*) pine species, which are the dominant species for logging in the southern United States. Loblolly, the SPB's preferred host, dominates 45% (13.4 million ha) of the commercial forest land in the southern United States (Schultz, 1999). The forestry industry is a large portion of the southeastern region's economy. In 1996, the southern forestry industry directly employed more than 550,000 people and had product shipments exceeding $100 billion. Another SPB epidemic outbreak could stifle the region's economy.

In response to overwhelming losses from SPB outbreaks in the early 1970s, the U.S. Department of Agriculture (USDA) began the Expanded Southern Pine Beetle Research and Applications Program (ESPBRAP) in 1975, as a well-funded, five year initiative (Clarke, 2003). The Integrated Pest Management (IPM) for Bark Beetles of Southern Pines followed ESPBRAP as another five year initiative (Clarke, 2003). ESPBRAP and IPM generated several models for predicting SPB outbreaks and their impacts, with the majority of SPB models used today linked to this time period.

This thesis follows the style of *Remote Sensing of Environment.*

The models developed under ESPBRAP and IPM can be generally grouped into five categories (Turnbow et al., 1983; as cited by Saterlee, 2002):

1. Stand Hazard Models – to predict the likelihood of SPB outbreak in a stand.
2. Stand Risk Models – to predict the likelihood of an existing infestation to spread.
3. Spot Growth Models – to predict the development and spread of an existing infestation over time.
4. Stand Growth and Yield Models – to predict timber yield at rotation age, accounting for expected SPB damage.
5. Economic Models – to predict economic gains or losses from salvage or other treatment.

When considering SPB impacts on forests, research usually focuses on modeling infestation growth (category 3) (Feldman et al., 1980; Satterlee, 2002) or rating the hazard/risk of stands to infestation (categories 1 and 2) (Hicks, 1980; Lorio et al., 1982; Mason & Bryant, 1984; Billings et al., 1985). This research focuses on spot growth.

Spot growth models are either regression-based or mechanistic biophysical models. Regression-based models used correlations to predict number of trees killed. For example, Hedden and Billings (1979) used the ratio of the basal area of new trees killed per day to the basal area of active trees at initial visit or the basal area of active trees at day 30 to the basal area of active trees at initial visit to predict loss. TAMBEETLE and SPBMODEL are two examples of mechanistic models. TAMBEETLE uses individual tree characteristics as input whereas SPBMODEL uses stand conditions. The use of individual tree characteristics by TAMBEETLE allows it to represent infestation growth spatially. This study focuses on the mechanistic spot growth model TAMBEETLE because it is able to use individual tree characteristics as inputs and is a spatial model.

Coulson et al. (1989) describe TAMBEETLE, created by Feldman et al. (1980), as "a mechanistic model of population dynamics of *D. frontalis* occurring in forest stands." Mechanistic models are sometimes viewed as overly complex because they require an intensive knowledge of SPB ecology; however, if the postulations behind the model are accurate, the model can be viable outside of the original data (Hain, 1980). Along with the SPB ecology, TAMBEETLE needs the forest stand conditions to model infestation growth. The required forest structure inputs are individual tree characteristics of XY location, diameter at breast height (DBH), length of crown (CrHT), individual bole height (IBH), and tree age. Although TAMBEETLE was included as a component of the model base for the Southern Pine Beetle Decision Support System (SPBDSS) (Saunders et al., 1985), the extensive data requirements needed to initialize TAMBEETLE limit its utility in forest management practices (Coulson et al., 1989).

Technological advances since the creation of TAMBEETLE, specifically in Light Detection and Ranging (lidar) sensors, could expand its utility in forest management practices by estimating individual tree characteristics more efficiently than field measurements, while maintaining comparable accuracy. Lidar is a relatively new remote sensing tool that measures distance from the sensor by taking the product of the speed of light and the time required for an emitted laser pulse to travel to a target object and return to the sensor (Lim et al., 2003). The ability to estimate individual tree characteristics with lidar could make it an indispensible tool for deriving inputs for SPB models.

Lidar has been used to estimate most of the individual tree measurements needed for TAMBEETLE. Popescu et al. (2002) created a software package, TreeVaW, which uses a varying local maxima filter on lidar data to automatically identify individual trees and their height and crown diameter. A more detailed description of TreeVaW can be found in Popescu and Wynne (2004) and Popescu et al. (2004). Popescu and Zhao (2008) used TreeVaW to identify individual tree heights and crown diameters for 94 pine trees with a root mean square error (RMSE) of 1.38 and 1.68 meters, respectively. Aside from tree height, DBH is the most common tree measurement used to calculate potential growth, volume, and yield of stands. With the knowledge that DBH is highly correlated with tree height and crown diameter, Popescu (2007) obtained DBH through regression of TreeVaW derived tree height and crown diameter, resulting in a small RMSE of 4.9 cm (approximately 18% of the DBH for all measured trees).

Crown base height (CBH) is another measurement successfully estimated with lidar. Holmgren and Persson (2004) used 0.5m height bins (vertical "slices" of the canopy space above ground) and defined the CBH as the point above the highest height bin with less than 1% of non-ground points. Popescu and Zhao (2008) also used height bins to define CBH. A pseudo waveform, as defined by Blair and Hofton (1999), was created by placing a cylinder, with a radius defined by TreeVaW, around the tree and plotting the frequency of lidar points in each height bin. Popescu and Zhao defined CBH at an inflection point in the pseudo waveform curve, resulting in an RMSE of 2.0m.

Age is most often determined through either plot planting data or a time series of aerial imagery (Moan, 2008). Heo et al. (2006) used image differencing techniques on a time series of satellite images to validate age in an inventory geographic information system (GIS) database. While this was not a complete solution for inventory verification, Heo et al. were able to offer a list of tracts with potential age-discrepancy to be field verified. Lefsky et al. (2005) also used historical satellite imagery to determine stand age by detecting stand replacement through image processing techniques developed and verified by Cohen et al. (1998; 2002). Sivanpillai et al. (2006) estimated managed loblolly pine stand age through multivariate regression of Landsat ETM+ reflectance values with an R^2-value of 0.78 and RMSE of 2.89 years. The stands in the Sivanpillai et al. study ranged from 2 to 26 years of age.

Using lidar is not the most obvious method of determining tree age. Farid et al. (2006) used lidar to differentiate three age classes of individual cottonwood trees (young, mature, and old) in a riparian area. Differences in tree structure (height, crown diameter, and canopy cover) measured with lidar allowed Farid et al. to differentiate between age classes.

Although a search of literature did not reveal any studies estimating age through the use of lidar-derived height, in theory it is possible to use height to estimate age through the combined use of lidar and auxiliary data. Age can be related to height through site index, the most common measure of forest site quality. Site index is a relative measure of site quality based on the height of dominant trees at a specific age. The United States Department of Agriculture (USDA) Natural Resources Conservation

Service (NRCS) Soil Survey Geographic (SSURGO) Database provides site index as an attribute of each soil type. Estimating individual tree age using the SSURGO site index and lidar-estimated tree height could prove more useful than estimating stand age through historical satellite imagery for calculating forest growth and yield.

1.2 Objectives

The overall goal of this study was to develop a framework for using airborne lidar to derive inputs for the SPB infestation growth model TAMBEETLE. More specific objectives were to:

1. Derive input layers for TAMBEETLE with lidar, including: tree location, individual bole height (IBH), diameter at breast height (DBH), length of crown (CrHT), and age;
2. Use lidar-estimated height and SSURGO site index to estimate individual tree age; and
3. Compare TAMBEETLE simulation results using field measurements and lidar-derived measurements as inputs.

2. MATERIALS AND METHODS

2.1 Study Area

Because it is an excellent example of SPB habitat, an area east of Huntsville, TX, USA was chosen as the study site. In addition to its representation of SPB habitat, an abundance of research has been conducted on the site, providing lidar data, QuickBird multispectral imagery, and in situ data (Mutlu et al., 2007; Popescu, 2007; Zhao and Popescu, 2007; Griffin et al., 2008; Popescu and Zhao 2008; Zhao et al., 2009). The study area is 47.15 square kilometers, within latitude of 30° 39’ 36” and 30° 44’ 12” N and longitude of 95° 24’ 57’’ and 95° 21’ 33” W. It contains pine stands, pine-hardwood mixed stands, and hardwood stands, all in various stages of development. The study area consists of both private land and the Sam Houston National Forest, representing a full range of management intensities. Along with forests, an urban interface and open fields are also present in the study area. The topography is characterized by gentle slopes with a mean elevation of 85m, with a minimum of 62m, and a maximum of 105m. The study area is shown in Figure 1.

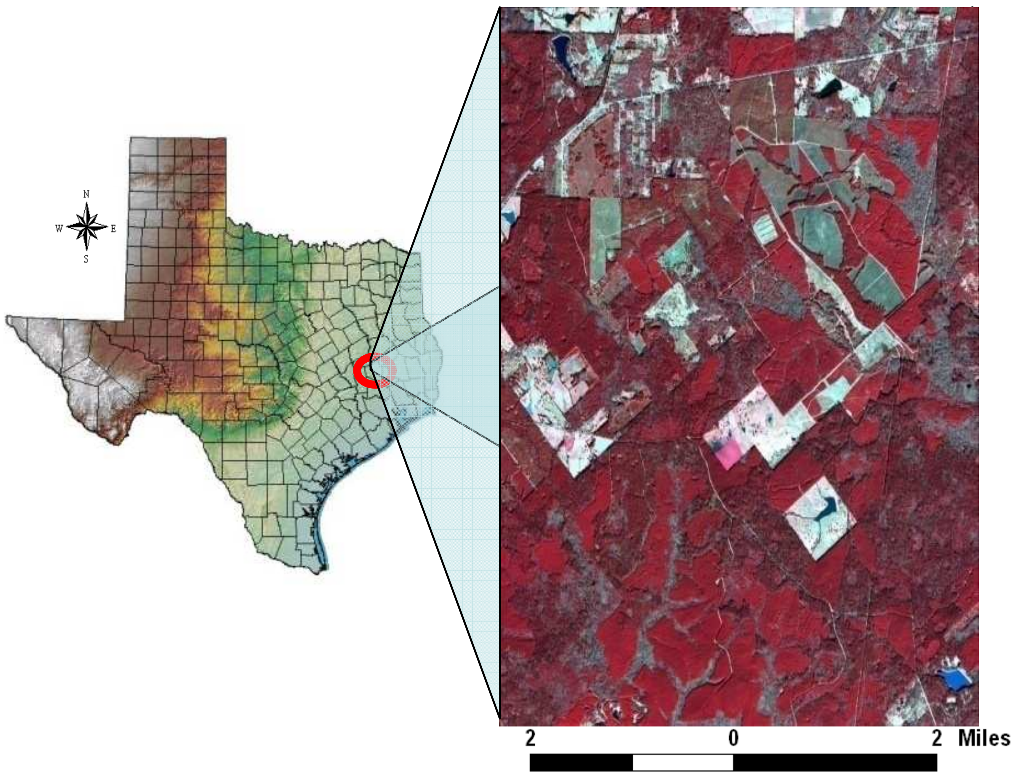

Figure 1. The study area is located in east Texas and is shown in the false color composite of a QuickBird (DigitalGlobe, Inc.) image.

2.2 Lidar Data and Multispectral Imagery

Lidar data were collected in March 2004 (leaf-off) by M7 Visual Intelligence of Houston, Texas, with a Leica-Geosystems ALS40 lidar sensor. The system recorded first and last return per pulse, with a reported accuracy of 20-30cm horizontal and 15cm vertical. Nineteen north-south flight lines and twenty-eight east-west flight lines were flown at a mean altitude of 1000m above ground level using a ±10° swath from nadir, resulting in an average swath width of 350m, with an average of 2.6 laser hits per m^2.

M7 Visual Intelligence also provided a digital elevation model (DEM) derived from the lidar data using a proprietary package. A digital surface model (DSM) was created by using the highest laser hits per 0.5m x 0.5m cell and interpolating to characterize the top surface, using techniques described by Popescu and Wynne (2004). Before any calculations were performed, a canopy height model (CHM) was created by subtracting the DEM from the DSM and then interpolated to 2.5m.

QuickBird (DigitalGlobe, Inc.) orthorectified, multispectral imagery of the study area was acquired during the 2004 leaf-off season with a spatial resolution of 2.5m. The imagery was used to differentiate between pine and other land cover types (deciduous trees, fields, and urban).

2.3 Ground Reference and Soil Data

Two sets of field data were collected. The first set of field data was collected between May and July 2004 on randomly selected 0.004ha (0.01 acre) plots and 0.04ha (0.1 acre) circular plots. Height, crown width, IBH, DBH, species, and Kraft crown class were measured for each tree. Tree height and crown base height (CBH) (defined as the lowest live branch) were measured using a Vertex Forester hypsometer. Crown width was calculated by averaging the radii measured from the bole of a tree in each cardinal direction. DBH was measured using a diameter tape. Crown class was determined as one of four Kraft classes, i.e., dominant, co-dominant, intermediate, and overtopped (USDA Forest Service FIA National Core Field Guide, 2005, p. 78).

Individual tree coordinates were calculated according to trigonometric relations using the geographic coordinates of plot centers and the azimuth and distance of tree boles relative to the plot center. These were measured with a Differential GPS, a Suunto compass (KB-14), and the vertex hypsometer, respectively. The mapped tree locations refer to boles, not treetops, which may deviate from tree boles.

The second set of field data was collected in October 2009 in order to assess tree age. Previous plots were revisited to measure height, DBH, and take core samples. Core samples were taken at breast height with an increment borer for 3 trees per plot. A total of 30 trees were cored, 22 trees in plots with a site index of 21.3 and 8 trees in plots with a site index of 24.4. The trees selected were of average height for the dominant and co-dominant trees in the plot. Annual rings were counted in each core sample to determine tree age at breast height. Age at breast height was converted to total age by adding years according to the SSURGO site index reference curve (Coile and Schumacher, 1953), as seen in Table 1.

Table 1

Number of years added to age at breast height to account for the time it took the tree to reach breast height for each site index

Site Index	Age-to-Breast-Height Factor
15.2	6
21.3	4
24.4	3
25.6	3
27.4	3

SSURGO data for the study area was obtained from the Soil Data Mart on the USDA NRCS website (http://soildatamart.nrcs.usda.gov, accessed on September 5, 2009). Spatial and tabular data were downloaded and queried for the site index. Site indices for the study area were used to create a vector dataset and then converted to raster at 2.5m resolution. The base age for the site index is twenty-five years. The SSURGO site index was created using soil properties outlined in Coile and Schumacher (1953), which are based on the site index curves in USDA Miscellaneous Publication 50 (Anonymous, 1929).

2.4 Pine Classification

To differentiate pines from other land use and land cover, a rule-based classification was performed on a fused QuickBird and lidar dataset. The fused dataset consisted of six bands: blue, green, red, and near-infrared reflectance bands from the QuickBird image; normalized difference vegetation index (NDVI) was calculated from the QuickBird image; and the lidar CHM. NDVI was calculated as defined by Baret and Guyot (1991):

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{1}$$

where *NIR* is the near-infrared reflectance value and *R* is the red reflectance value for a given pixel.

The classification was created using two rules. The first rule separates trees from non-trees by setting a minimum height requirement of 3.0m. This minimum height requirement was adjusted down from 5.0m (minimum height needed to be classified as a tree according to the United States Environmental Protection Agency (EPA) Multi-Resolution Land Characteristics Consortium (MRLC) National Land Cover Data 2001 (NLCD 2001) class definitions (http://www.epa.gov/mrlc/definitions.html#2001, accessed October 20, 2009), to allow for the underestimation of tree height due to lidar not intercepting the exact treetop, based on RMSE of 1.38m as reported by Popescu and Zhao (2008). The second rule separates pines from hardwoods (and any urban structures over 3.0m) by setting a minimum NDVI value of 0.35 to be considered a pine tree. The threshold for NDVI was determined through trial and error to achieve the greatest separability between pines and other land cover for the study area. In summary, this classification defines pine trees as being over 3.0m and having an NDVI value of 0.35.

2.5 Tree Location, Height, and DBH

To start TAMBEETLE an input text file with tree location, IBH, DBH, CrHT, and tree age is needed. TreeVaW allows the user to define the relationship of height to crown radii based on field data if available. Equation (2) illustrates the relationship between crown diameter and height achieved through regression of the field-measured pine trees in the study area:

$$CD = -0.033 + H(0.301) \tag{2}$$

where CD is crown diameter and H is height.

TreeVaW was run on the CHM to generate a list of trees with their location, height, and crown radii. TreeVaW identified 976,064 pine trees after non-pines had been removed. This satisfied the first need of TAMBEETLE, tree location. Figure 2 illustrates the identification of individual trees in TreeVaW.

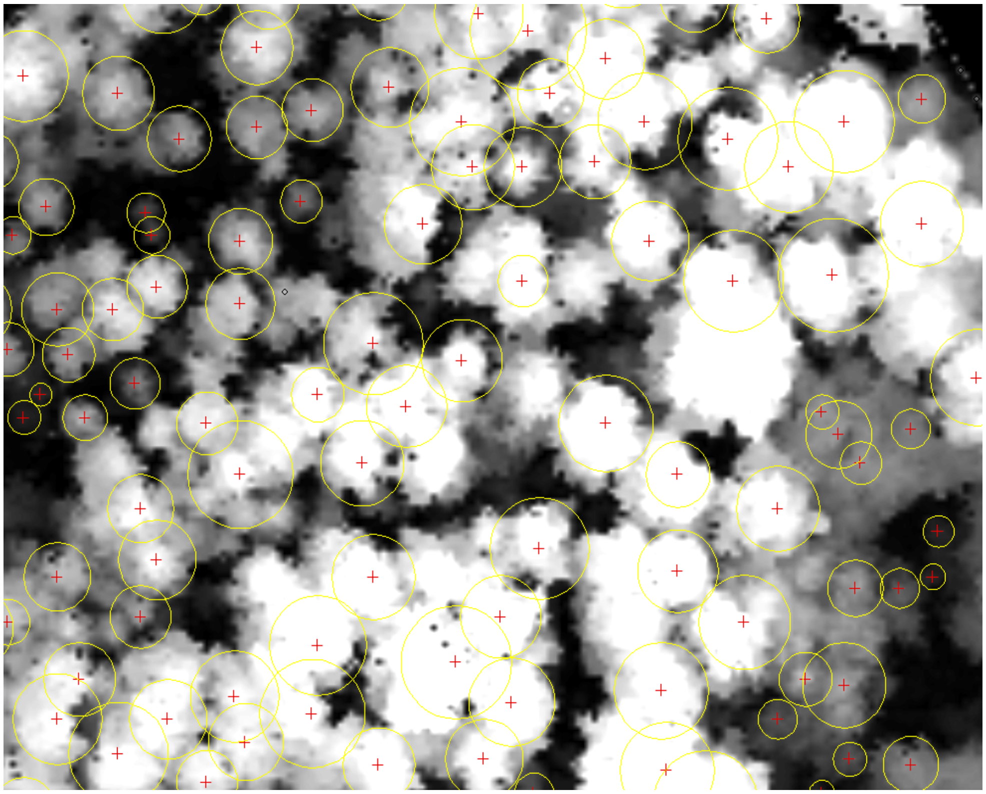

Figure 2. Subset of the CHM with the location of TreeVaW identified trees (shown with pink crosses) and crown diameter (yellow circle).

DBH is highly correlated with tree height and crown diameter. Through regression, Popescu (2007) was able to estimate individual tree DBH with a small RMSE of 4.9cm, approximately 18% of the average DBH for this study area. DBH was calculated using the line of best fit reported in Popescu (2007):

$$DBH = -0.16 + CD + 1.22H \tag{3}$$

where *CD* is crown diameter and *H* is lidar-derived height.

2.6 Individual Bole Height and Length of Crown

Total tree height is equal to the sum of IBH and CrHT. IBH is the length of the tree stem to crown base, while CrHT is from crown base to the top of the tree. Therefore, CBH had to be estimated before IBH and CrHT could be calculated.

Crown base height was determined by creating a vertical profile for each tree and was defined at the height where a sudden drop in frequency of lidar hits occurred, as outlined by Popescu and Zhao (2008). The vertical frequency profile was created by dropping a cylinder with a radius defined by TreeVaW over each identified tree. CBH was defined at the height corresponding to the first inflection point after the frequency curve reaches its maximum, as shown in Figure 3.

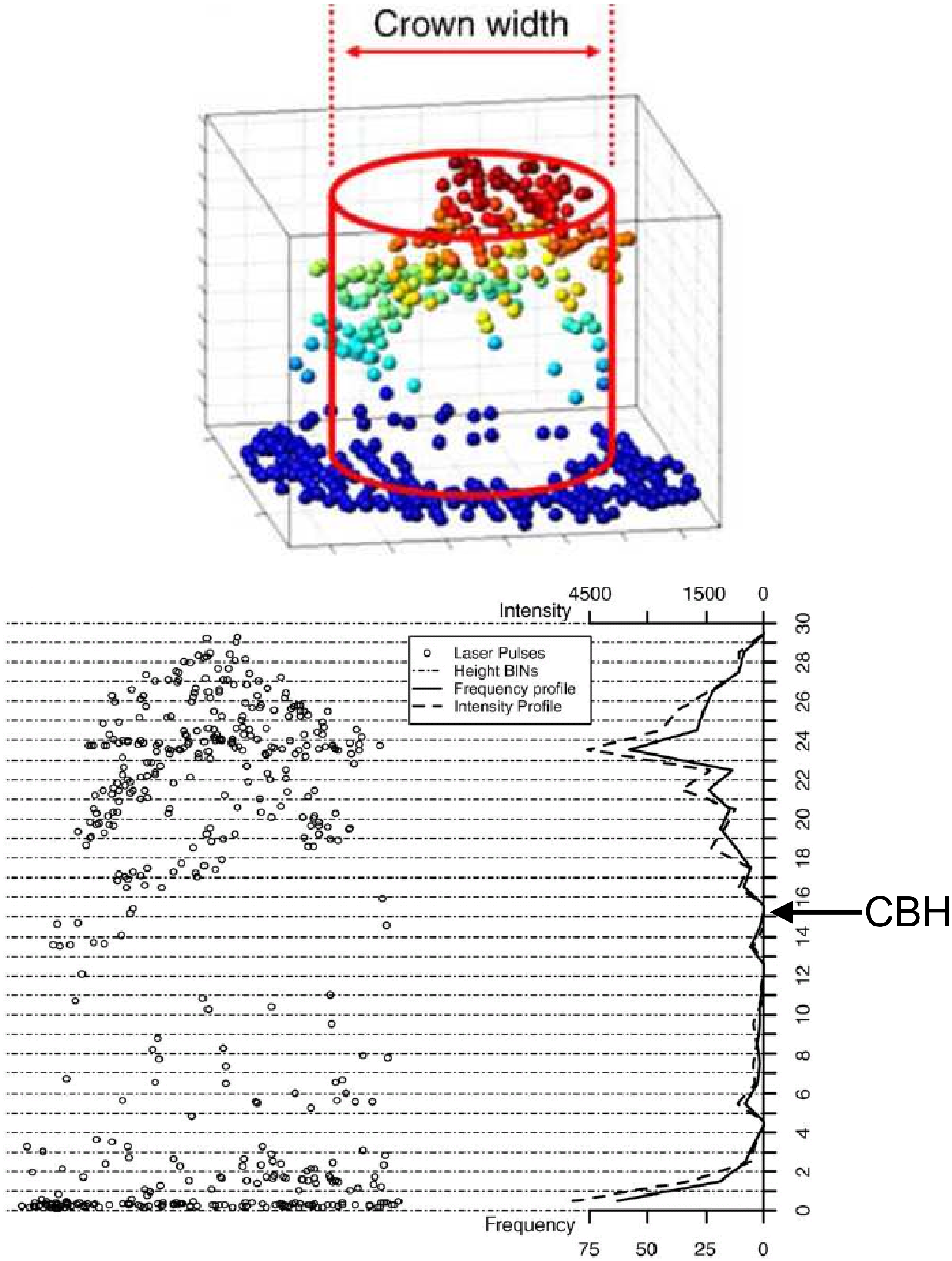

Figure 3. (top) 3D representation of lidar points for a single tree(Popescu and Zhao, 2009) (bottom) and pseudo waveform used to delineate crown base height (CBH).

CBH was used as the value for IBH. CrHT was calculated by subtracting CBH from total tree height as illustrated in the following equation:

$$CrHT = H - CBH \tag{4}$$

where H is total tree height and CBH is crown base height.

2.7 Tree Age

Tree age was determined using the site index provided by SSURGO data. SSURGO's site index is based on Coile and Schumacher's (1953) methods for estimating site quality of land based on soil characteristics alone. Their methods use the site index curves outlined in the USDA Miscellaneous Publication 50 (Anonymous, 1929).

A site index guide curve (Figure 4) was created from the trees located in plots with a site index of 21.3 meters (70 feet) at 25 years as outlined in Avery and Burkhart (2002). The resulting site index curve had an R^2 of 0.94 with an RMSE of 1.3m (approximately 6.3% of field measured height) following the line of best fit:

$$\hat{y} = 10.788 Ln(x) - 15.924 \tag{5}$$

where $\hat{y}$ is height in meters and x is age in years.

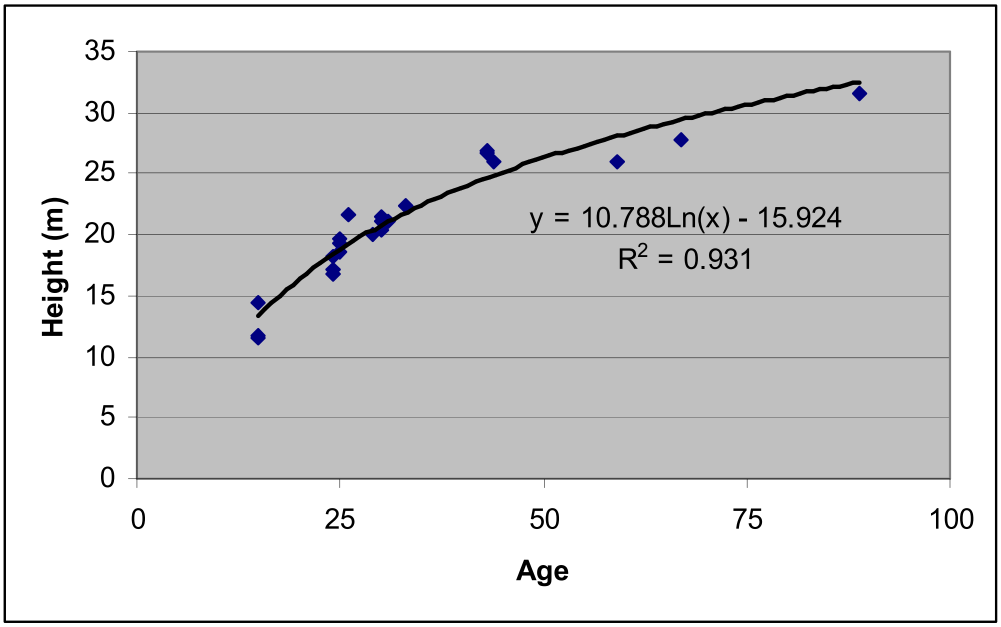

Figure 4. Site index guide curve of site index of 21.3 meters with base age of 25 years derived from field measured height and age.

An anamorphic family of curves was created by transforming the guide curve for each site index (Figure 5.). The study area contained site indices of 15.2, 21.3, 24.4, 25.6, and 27.4 meters (50, 70, 80, 84, and 90 feet, respectively). Equation (6) shows the transformation of the guide curve for each site index:

$$\hat{y} = SI((\frac{10.788}{21.3})Ln(x) - \frac{15.924}{21.3}) \qquad (6)$$

where *SI* is site index.

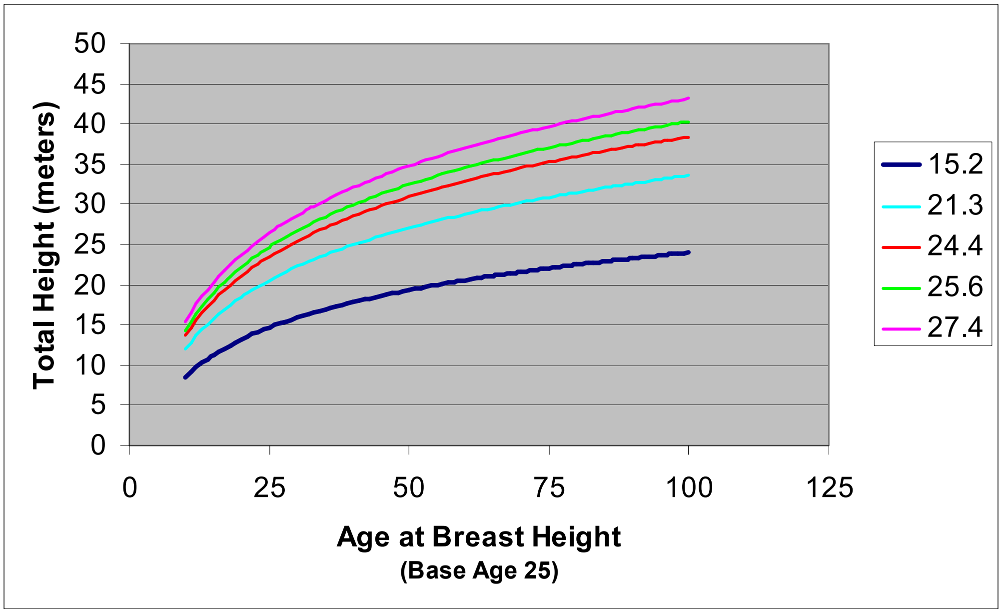

Figure 5. Anamorphic site index family of curves for the study area.

To estimate age from height, Equation (6) must be algebraically rearranged:

$$x = e^{\left(\frac{y+\left(\left(\frac{15.924}{21.3}\right)*SI\right)}{\left(\frac{10.788}{21.3}\right)*SI}\right)} \qquad (7)$$

where *e* is the base of the natural logarithm, 2.71828182845904.

The prediction performance of Equation (7) was assessed using the field measured age corrected for age-to-breast height and age predicted using field measured height. Equation (7) was also tested using average plot age using lidar-derived heights against average plot age from the field measurements.

Two tree age datasets were created using Equation (7). Individual tree age was determined by using the equation with each tree's lidar-derived height and corresponding SSURGO site index. Equation (7) is only considered valid for trees up to an age of 100 years. Trees that received an age over 100 from the equation were set to 100 years.

2.8 TAMBEETLE

Two TAMBEETLE simulations were performed on four stands (Figure 6), for a total of eight simulations. One set of simulations was run using a forest generated by TAMBEETLE using field-measured plot characteristics of pine BA and the means and standard deviations of DBH and IBH. The other set of simulations were run using the lidar-derived forest. Aside from forest structure measurements, TAMBEETLE needs information on attack date (day of year 1-365), attack stage, attack end date, and day of year reemergence ended for previously infested trees. Simulations began on day 151 (May 31) with 15 trees under active attack, 5 trees in brood stage, and 3 trees already dead. This ensured a successful infestation was established in the plot during the peak season for SPB infestation. The simulations were run for 30 days and daily records were kept for number of trees actively under attack, in brood, and a cumulative total of dead trees.

Figure 6. The location of the four zones in which TAMBEETLE spot growth simulations were run to assess the performance of lidar-derived forest attributes when compared to TAMBEETLE-generated forest.

3. RESULTS AND DISCUSSION

3.1 Diameter at Breast Height

DBH is the most frequently used tree measurement used to predict growth, volume, yield, and forest potential. While DBH is not able to be directly measured with lidar as height is, lidar-derived estimates correlated well with field-measured DBH. Popescu (2007) reported a small RMSE of 4.9cm, approximately 18% of the average DBH of all measured trees. The estimates of DBH for this study area are not unexpected. Persson et al. (2002) also used lidar-estimated height and crown diameter of Norway spruce and Scots pine to estimate DBH, resulting in an RMSE of 3.8cm.

3.2 Individual Bole Height and Length of Crown

IBH and CrHT measurements depend on accurate estimates of CBH. Popescu and Zhao (2008) estimated CBH for the study area with an RMSE of 2.0m. Along with other studies (Holmgren & Persson, 2004; Riano et al., 2004; Andersen et al., 2005), Popescu and Zhao (2008) overestimated CBH. An overestimated CBH and underestimated tree height leads to a smaller CrHT. These estimation errors make IBH proportionally larger to total tree height.

3.3 Age

Age for pine trees in the study area was calculated using Equation (7) with lidar-estimated height and SSURGO site index. Figure 7 illustrates individual tree age derived from lidar-estimated height for the entire study area.

Linear regression analysis demonstrated a good fit for predicting individual tree age based on tree height for field measured trees with Equation (7). The transformed logarithmic regression model resulted in RMSE of 5.8 years (approximately 16.5% of mean age for field measured trees) with R^2 of 0.9168 (Figure 8.). The RMSE resulting from predicting age from height is much greater than that of predicting height from age. Transformation of the nonlinear logarithmic regression model for predicting height from age to predicting age from height introduced bias, as outlined in Sprugel (1983). The bias introduced caused an overestimation of age.

Average lidar-derived plot age was then compared to average field plot age. Five years was subtracted from the age corrected to include age-to-breast-height so that age in 2004 could be compared. Again, linear regression showed high correlation between predicted age and field age, this time predicting age with lidar-estimated height. The linear regression model resulted in an R^2 of 0.9873 (Figure 9) and an RMSE of 4.8 years (approximately 15.3% of the field measured age). Predicted age using lidar-estimated height tended to underestimate height. This is expected with the noted underestimation of tree height with lidar data; however, this underestimation also overpowers the bias created when transforming Equation (6) to predict age based on height.

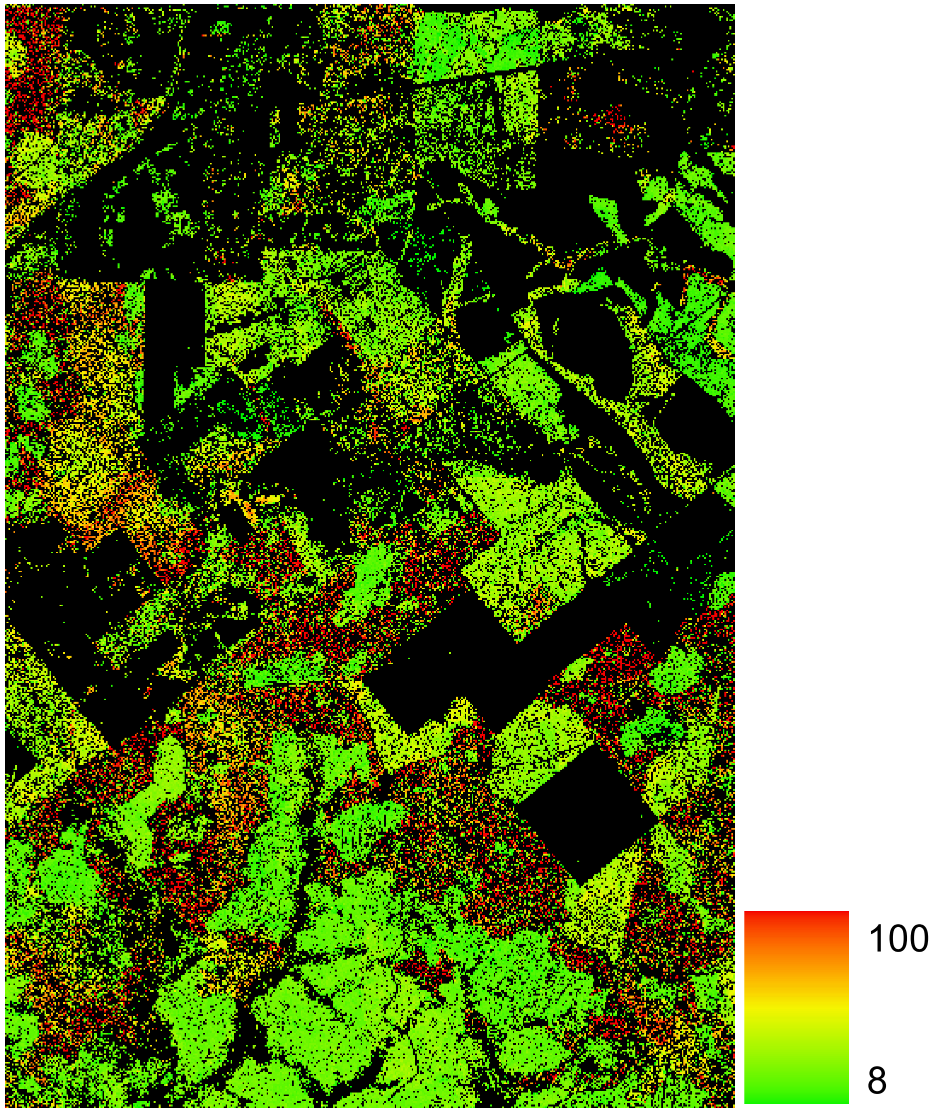

Figure 7. A 5x5m resolution image of tree age derived using site index curves and lidar-derived height. Areas in black were not classified as pine trees.

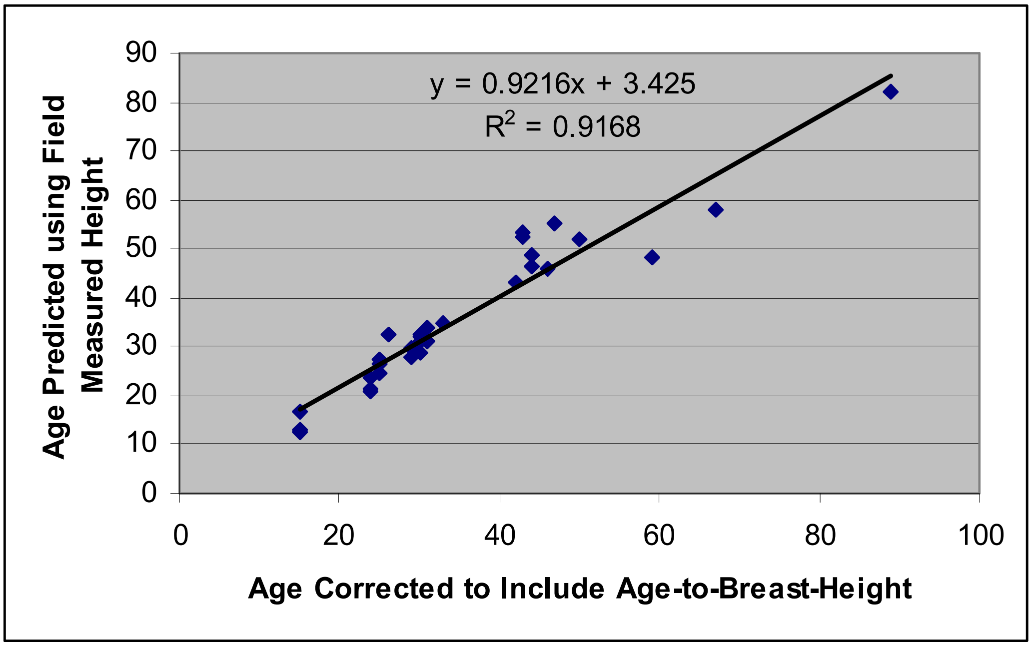

Figure 8. Field measured age corrected to include age-to-breast height vs. age predicted from field measured height.

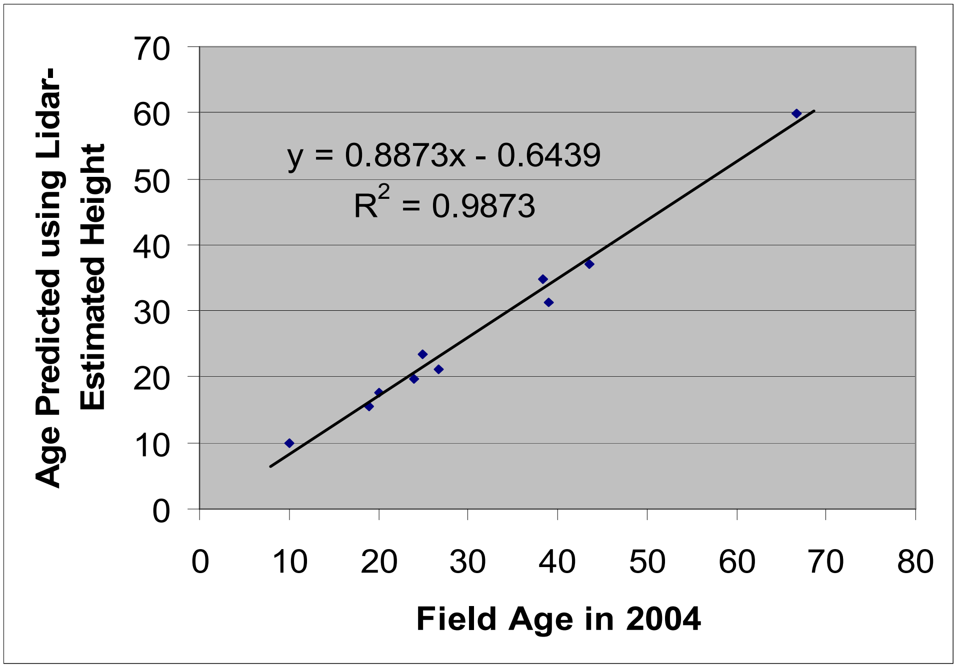

Figure 9. Linear regression of average age predicted using lidar-estimated height vs. average field age in 2004 for ten plots.

When the RMSE of 1.38m for lidar derived tree height for the study area is considered, RMSE for age predicted using lidar-estimated height decreases to 1.93 years (6.2% of average field measured age). Lidar-estimated height only explains some of the error. The error in the original logarithmic regression model used as the site index curve (RMSE of 1.3m) also contributes to the underestimation of tree height. When the error in both the lidar-estimated height and original site index curve are considered, RMSE is 4.2 years, explaining 91% of the error.

Another source of error is the way site index curves are created. Average site quality in the sample data needs to be the same for all age classes for the guide curve to be reliable. The guide curve in this study was created using trees from within the

SSURGO site index of 21.3 to limit this error. While this error was controlled as much as possible, the nature of anamorphic curves (common shape across all site indices) is a weakness in itself. The shape of a site index curve can vary with site quality, with higher-quality lands generally exhibiting more pronounced sigmoid shapes and lower-quality lands producing height-growth patterns that are "flatter" (Avery and Burkhart, 2002).

Using a time series of satellite imagery to determine stand age through disturbance detection (Lefsky et al., 2005; Heo et al., 2006) is the most popular remote sensing technique to determine stand age. This technique can be employed for even aged stands, but is not effective in uneven aged stands or stands older than the satellite imagery available. Using lidar-estimated tree height and SSURGO site index allows age to be estimated for individual trees in an uneven aged stand and stands that have not had a disturbance during the time period satellite imagery is available.

In contrast to Farid et al. (2006), which grouped 84 individual cottonwood trees into three age classes through statistical analysis of tree height and crown diameter, this study estimated individual tree age based on lidar-estimated tree height and SSURGO site index for close to 1 million pine trees. Aside from tree height, Farid et al. (2006) benefited from the significant differences in crown shape, canopy cover, and stand characteristics among age classes. As pine trees age, crown shape, canopy cover, and stand characteristics do not change significantly enough to be used to help determine age. Also, age varies greatly for trees of the same height in different site indices, which is important to note in large study areas. Using lidar-estimated tree height and SSURGO site index can provide a more exact individual tree age than just age class and is also viable for larger study areas.

3.4 Plot Characteristics

The ability to estimate tree characteristics with lidar is illustrated in Table 2. Overestimation of minimums can be attributed to lidar only detecting dominant and co-dominant trees while field measurements included intermediate and overtopped trees. Mean and median IBH are underestimated, which is unexpected due to the consistent overestimation of CBH in previous studies. Although there is some overestimation of IBH, it well within RMSE of 2.0m of CBH for the study area. All of the mean, max, and median statistics fall within the expected RMSE for that variable. Age for both the field-measured and lidar-estimated pine trees was estimated with Equation (7), attributing differences in age to height discrepancies between the lidar-estimated and field-measured heights.

Table 2

Descriptive statistics of field inventory data and lidar-derived inventory data for pine trees on a plot

	2004 Field-Measured Pine Trees				Lidar-Measured Trees			
	DBH (cm)	CrHT (m)	IBH (m)	Age	DBH (cm)	CrHT (m)	IBH (m)	Age
Mean	24.22	5.24	11.30	20	24.38	5.43	10.23	19
Max	28.20	6.83	13.11	24	29.90	8.70	13.28	21
Min	15.00	2.68	9.75	16	20.17	2.00	7.50	16
Median	24.90	5.64	11.16	21	24.47	4.95	10.50	19

3.5 TAMBEETLE Simulations

TAMBEETLE simulations were run on 4 zones, each having a different forest structure. Zone West is unmanaged, having many stands of differing tree densities, height, DBH, and age. It also has a small percentage of hardwoods concentrated along a creek bed that passes through the zone. Zone Central is a young, even aged, pure pine stand with a high tree density. Zone Southeast is a pine dominated, yet mixed forest, composed of older, larger pine trees and hardwoods. Zone Thinned is an intensely managed pre-commercial aged forest that has had row thinning performed on it.

Two simulations were run per stand, one using a TAMBEETLE randomly generated forest using field plot measurements as inputs and another using individual tree measurements derived from lidar as inputs. The TAMBEETLE randomly generated forest was used because in situ plots were too small to get useful information from

TAMBEETLE simulations. TAMBEETLE can use pine BA, mean DBH, standard deviation of DBH, mean IBH, and standard deviation of IBH from field data to generate a forest for spot growth simulations. Table 3 shows the field-measured plot characteristics used by TAMBEETLE to generate the random forests.

Table 3

Field-measured plot characteristics used by TAMBEETLE to generate random forests

Zone	Pine BA m^2/ha	Mean DBH (cm)	DBH Std. Dev. (cm)	Mean IBH (m)	IBH Std. Dev. (m)
West	25.25	35.53	24.21	10.64	4.99
Central	27.16	23.13	6.32	10.31	1.7
Southeast	14.03	34.25	22.75	11.95	6.07
Thinned	27.03	26.94	4.36	10.97	1.24

Although Zone Thinned has been managed with techniques to reduce pine basal area, it has the second highest pine basal area. This can be attributed to a very dense planting strategy.

The first outcome analyzed when comparing the TAMBEETLE forests to the lidar forests was the total number of trees killed. Table 4 shows the number of trees killed during the first 30 days of an infestation per zone for the TAMBEETLE generated and lidar-derived forests, as well as the difference between the numbers of trees killed for the different forest types.

Table 4

Number of trees killed per zone for TAMBEETLE and lidar forests in the first 30 days of infestation simulations

Zone	Forest Type	Trees Killed	Difference
West	TAMBEETLE	25	-5
	Lidar	30	
Central	TAMBEETLE	23	12
	Lidar	11	
Southeast	TAMBEETLE	24	0
	Lidar	24	
Thinned	TAMBEETLE	25	17
	Lidar	8	

These statistics alone are misleading. In TAMBEETLE, trees that are in the brood and active stages are guaranteed to die. The guaranteed total number of trees killed when trees in the brood and active stages at the end of the first 30 days of infestation simulations are included is depicted in Table 5.

Table 5

Total trees killed when brood and active stage trees are added to the trees killed in the first 30 days of an infestation

Zone	Forest Type	Trees Killed	Brood	Active	Total	Difference
West	TAMBEETLE	25	4	9	38	7
	Lidar	30	0	1	31	
Central	TAMBEETLE	23	7	19	49	13
	Lidar	11	3	22	36	
Southeast	TAMBEETLE	24	0	0	24	0
	Lidar	24	0	0	24	
Thinned	TAMBEETLE	25	8	16	49	11
	Lidar	8	4	26	38	

Investigating the number of trees in each stage at the end of the first 30 days of the infestation simulation can establish a trend of whether the infestation is just starting to grow, continuing to spread rapidly, or declining. Table 5 indicates that the infestation in zone West is still active in the TAMBEETLE generated forest, while the infestation in the lidar forest has subsided. The infestation for both types of forests have quit growing in zone Southeast, killing the same number of trees. For zones Central and Thinned, the infestation grew more slowly in the lidar-derived forest than in the TAMBEETLE-generated forest.

While TAMBEETLE is able to generate a random forest that matches average plot characteristics, it cannot give a true representation of forest conditions because it does not account for non-habitat, which can slow or halt an infestation. If an infestation outgrows the original spatial extent of the TAMBEETLE-generated forest, TAMBEETLE expands the forest using the same stand characteristics, allowing the infestation to grow indefinitely. Stand characteristics can change abruptly. The next stand in the path of the infestation is accurately represented should an infestation outgrow the stand where it originated in a lidar-derived forest, instead of having a continuation of initial stand conditions used to model the infestation growth. This is possible because lidar data can be used to estimate individual tree characteristics for the entire spatial extent of the data.

4. CONCLUSIONS

The main objective of this study was to produce a lidar-derived forest consisting of individual tree attributes of location, diameter at breast height, individual bole height, length of crown, and age. Results of this study show that lidar data can be used to derive individual tree characteristics. The framework used to derive biophysical parameters for individual trees with lidar in this study can be applied to other models which are dependent on individual tree measurements.

Age was estimated using lidar with the site index provided by the SSURGO data and site index curves derived from field work. Although lidar data represents only one point in time, knowing tree age and site index allows estimates of tree height to be made for the coming years. Because tree height can be used to estimate other tree characteristics, yearly lidar data acquisitions are not needed. Using lidar data to derive age also provides the benefits of estimating age of trees in uneven aged stands and stands that have not had disturbances since satellite imagery has become available. This method of deriving age can be useful for deriving crown bulk density and growth and yield modeling, for which age is an important variable to both.

The differences between the lidar-derived forest and TAMBEETLE generated forest in the simulations can be accredited to randomness of the TAMBEETLE generated forest and spatially explicit lidar-derived forest. Lidar-derived forests can provide the large spatial extents of the TAMBEETLE generated forest while maintaining the spatially explicit forest characteristics previously only available through field measurements. The lidar-derived forest needs to be tested against large areas of field-measured stands. Although the small size of the in situ plots (0.04ha and 0.004ha) limited the testing of the lidar inputs in TAMBEETLE, the accuracy of individual tree estimations should translate into a lidar-derived forest comparable to true stand conditions.

The benefit of lidar data is the ability to derive individual tree attributes from it for the entire area covered by the data. The individual tree characteristics needed for this study were calculated for each of the 976,064 pine trees identified, which would not be possible to do with field work. The ability to derive individual tree attributes for the entire spatial extent of the data goes far beyond field observations, which merely sample a limited number of plots and extrapolate to the desired extent, and also surpasses aerial and satellite imagery in the number of forest characteristics that can be estimated from it.

REFERENCES

Andersen, H. E., McGaughey, R. J., & Reutebuch, S. E. (2005). Estimating forest canopy fuel parameters using lidar data. *Remote Sensing of Environment, 94*, 441−449.

Avery, T. E., & Burkhart, H. E. (2002). *Forest measurements. 5th edition*. New York: McGraw–Hill.

Baret, F. and Guyot, G., 1991. Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment*, *35*, 161-173.

Billings, R.F., Bryant, C.M., Wilson, K.H. (1985). Development, implementation, and validation of a large area hazard-and risk-rating system for southern pine beetle. In: Branham, S.J., Thatcher, R.C. (Eds.), *Integrated Pest Management Research Symposium Proceedings*. GTR-SO-56. U.S. Department of Agriculture, Forest Service, New Orleans, LA, 226–232.

Blair, J. B., & Hofton, M. A. (1999), Modeling laser altimeter return waveforms over complex vegetation using high-resolution elevation data. *Geophysical Research Letters, 26,* 2509–2512.

Clarke, S. (2003). Review of the operational IPM program for the southern pine beetle. *Integrated Pest Management Review, 6,* 293–301.

Cohen, W. B., Fiorella, M., Gray, J., Helmer, E., & Anderson, K. (1998). An efficient and accurate method for mapping forest clearcuts in the Pacific Northwest using Landsat imagery. *Photogrammetric Engineering and Remote Sensing, 64,* 293–300.

Cohen, W. B., Spies, T. A., Alig, R. J., Oetter, D. R., Maiersperger, T. K., & Fiorella, M. (2002). Characterizing 23 years (1972–95) of stand replacement disturbance in western Oregon forests with Landsat imagery. *Ecosystems, 5*(2), 122–137.

Coile, T. S., and F. X. Schumacher.1953. Site index of young stands of loblolly and shortleaf pines in the piedmont plateau region. *Journal of Forestry* 51: 432-435.

Coulson, R. N., Feldman, R. M., Sharpe, P. J. H., Pulley, P. E., Wagner, T. L., & Payne, T. L. (1989). An overview of the TAMBEETLE model of *Dendroctonus frontalis* population dynamics. *Holarctic Ecology 12*(4), 445–450.

Coulson, R. N., Klepzig, K. D., Nebeker, T. E., Oliveria, F. L., Salom, S. M., Stephen, F. M., & Meyer, H. J. (Eds.) (2004). The research, development, and applications agenda for a southern pine beetle integrated pest management program. *Proceedings of a Facilitated Workshop, August 11-14, 2003, Mountain Lake, VA.* Southern State Agricultural Experiment Stations; U.S. Department of Agriculture Forest Service; U.S. Department of Agriculture Cooperative State Research, Education, Extension Service; and the Southern State Forestry Agencies. 3-5.

Farid, A., Goodrich, D. C., & Sorooshian. S. (2006). Using airborne lidar to discern age classes of cottonwood trees in a riparian area. *Western Journal of Applied Forestry, 21*, 149–158.

Feldman, R. M., Curry, G. L., Coulson, R. N. & Sharpe, P. J. H. (1980). The use and structure of the TAMBEETLE spot dynamics model. In F. M. Stephen, J. L. Searcy, & G. D. Hertel, (Eds), *Modeling southern pine beetle populations* (pp. 20–29). Washington, D.C.: USDA Forest Service Technical Bulletin 1630.

Griffin, A. M. R., Popescu, S. C., & Zhao, K. (2008). Using lidar and normalized difference vegetation index to remotely determine LAI and % canopy cover. *Proceedings of Silvilaser, September 17–19, 2008, Edinburgh, UK.* 446-455.

Hain, F. P. (1980). Sampling and predicting population trends. In R. C. Thatcher, J. L. Searcy, J. E. Coster, & G. D. Hertel (Eds.), *The Southern Pine Beetle* (107-135). Washington, D.C.: USDA Forest Service, Science and Education Administration Technical Bulletin 1631. 267 pp.

Hedden, R. L. & Billings, R. F. (1979). Southern pine beetle: Factors influencing the growth and decline of summer infestations in east Texas. *Forest Science, 70,* 547–566.

Heo, J., Kim, J. H., Park, J. S., & Sohn, H-G. (2006). Timber age verification using historical satellite image analysis. *Forest Ecology and Management, 236,* 315–323.

Hicks, R. R. (1980). Climatic, site, and stand factors. In R. C. Thatcher, J. L. Searcy, J. E. Coster, & G. D. Hertel (Eds.), *The Southern Pine Beetle* (pp. 55–68). Washington, D.C.: USDA Forest Service, Science and Education Administration Technical Bulletin 1631. 267 pp.

Holmgren, J., & Persson, Å. (2004). Identifying species of individual trees using airborne laser scanner. *Remote Sensing of Environment, 90,* 415–423.

Lefsky, M. A., Turner, D. P., Guzy, M., & Cohen, W. B. (2005). Combining lidar estimates of aboveground biomass and Landsat estimates of stand age for spatially extensive validation of modelled forest productivity. *Remote Sensing of Environment, 95*(4), 549–558.

Lim, K., Treitz, P., Wulder, M., St-Onge, B. & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress Physical Geography*. 27: 88-106.

Lorio, P. L., Mason, G. N., &Autry, G. L. (1982). Stand risk rating for southern pine beetle: integrating pest management with forest management. *Journal of Forestry, 80*(4), 212–214.

Mason, G. N., & Bryant, V. C. M. (1984). Establishing southern pine beetle hazard from aerial stand data and historical records. *Forest Science, 30*(2), 375–382.

Moan, J. E. (2008). *Development and assessment of remotely derived variables in current southern pine beetle (*Dendroctonus frontalis *Zimm.) hazard mapping in North Carolina, USA.* M.S. Thesis, Virginia Polytechnic Institute, Blacksburg, Va.

Mutlu, M., Popescu, S. C., Stripling, C., & Spencer, T. (2008). Assessing surface fuel models using lidar and multispectral data fusion for fire behavior. *Remote Sensing of Environment, 112*(1):274:285.

Persson, A., Holmgren, J., Söerman, U. (2002). Detecting and measuring individual trees using an airborne laser scanner. *Photogrammetric Engineering & Remote Sensing*; *68*(9):925–32.

Popescu, S. C., Wynne, R. H., & Nelson, R. F. (2002). Estimating plot-level tree heights with LIDAR: Local filtering with a canopy-height based variable window size. *Computers and Electronics in Agriculture, 37*(1-3), 71–95.

Popescu , S.C., R.H. Wynne and J.A. Scrivani. (2004). Fusion of small-footprint lidar and multispectral data to estimate plot-level volume and biomass in deciduous and pine forests in Virginia, U.S.A. *Forest Science* 50(4): 551-565.

Popescu, S.C. and R.H. Wynne. (2004). Seeing the trees in the forest: using lidar and multispectral data fusion with local filtering and variable window size for estimating tree height. *Photogrammetric Engineering & Remote Sensing* 70(5): 589-604.

Popescu, S. C., (2007). Estimating biomass of individual pine trees using airborne lidar. *Biomass & Bioenergy,* 31(9), 646–655.

Popescu, S. C., & Zhao, K. (2008). A voxel-based lidar method for estimating crown base height. *Remote Sensing of Environment 112*(3): 767-781.

Riano, D., Chuvieco, E., Condés, S., Gonzalez-Matesanz, J., & Ustin, S. L. (2004). Generation of crown bulk density for *Pinus sylvestris* L. from lidar. *Remote Sensing of Environment, 92,* 345−352.

Satterlee, S. M. (2002). *Evolution of the southern pine beetle legacy simulation model 'SPBMODEL' using genetic algorithms.* M.S. thesis, Virginia Polytechnic Institute, Blacksburg, Va.

Saunders, M. C., Loh, D. K., Rykiel, E. J., Coulson, R. N., Payne, T. L., Pulley, P. E., Sharpe, P. J. H., & Hu, L. (1985). The southern pine beetle decision support system. In J. G. Massey, B. J. Greber, & T.M. Cooney (Eds.), *Software solutions: Proceedings of a Computer Symposium, Software Fair, and Second Annual Meeting of the Forest Resources System Institute, April 21–24, 1985, Clarksville, Ind*. 92-103

Schultz, R. P. (1999). Loblolly: The pine for the twenty first century. *New Forests, 17,* 71–88.

Sivanpillai, R., Smith, C. T., Srinivasan, R., Messina, M. G., Wu, X. B. (2006). Estimation of managed loblolly pine stand age and density with Landsat ETM + data. *Forest Ecology Management, 223,* 247–254.

Sprugel, D.G. (1983). Correcting for bias in log-transformed allometric equations. *Ecology 64*(1):208-210.

Zhao K., & Popescu, S. C. (2007). Hierarchical watershed segmentation of canopy height model for multi-scale forest inventory. *International Archives of Photogrammetry and Remote Sensing (IAPRS), XXXVI,* Part 3/W52: 436–441.

Zhao, K., Popescu, S. C., & Nelson, R. F. (2009). Lidar remote sensing of forest biomass: A scale–invariant estimation approach using airborne lasers. *Remote Sensing of Environment, 113*(1), 182–196.

VITA

Name:	Jared Dee Stukey
Address:	1500 Research Pkwy, Suite B223
	College Station, TX 77843
Email Address:	jared-dee-stukey@tamu.edu
Education:	B.S., Political Science, Texas A&M University, 2004