ABSTRACT

BOST, JACOB MARK. Over and Understory Carbon Estimations Using LiDAR for the Hofmann Forest Pocosin in Eastern North Carolina. (Under the direction of Dr. Rachel Cook and Dr. Juan Jose Acosta).

The primary objective of this project was to measure both over and understory carbon with the use of airborne LiDAR remote sensing. The intent being to help the forest industry in the southeast United States quantify aboveground carbon in natural areas, such as a pocosin wetland, for carbon credits. With many companies, both small and large, attempting to be carbon neutral, the forest industry has been able to capitalize on this by selling carbon credits on the carbon sequestered by their forests. To do this, efficient measurement methods must be established. Airborne LiDAR presents a potential way to do this while also exploring a technology much of the forest industry is already exploring for forest inventory.

Quantifying forest metrics by taking ground measurements is a tried and true method that foresters are most familiar with. However, when selling carbon credits, there is typically a tighter profit margin, making it harder to justify intensive field measurements. Although LiDAR will likely not be able to replace field measurements completely, it can help cut costs and increase accuracy. LiDAR can be particularly helpful across large areas with rough terrain, such as in a pocosin, which is predominantly found in eastern Virginia, North, and South Carolina. Pocosins can range in appearance, but they are typically a wet forest ecosystem with acidic, poorly drained soils with thick, but slow-growing vegetation.

For this project, over and understory biomass were separated for individual analysis, then later converted to carbon. These were then stratified further based on the ability to process data

while still keeping the methodology simple for easier replication. Overstory carbon was separated into two classes, tall and short, using a CMH (Canopy Height Model) created from LiDAR. It was also noted after viewing the CHM, that tree canopy height was heavily influenced by horizontal tree stem density and that this change in overstory was fairly discrete, likely due to changes in the soil drainage. Field measurements were then taken in these areas and a relationship between height and diameter was calculated. LiDAR was then used to locate and measure heights for every tree. Then diameter was predicted on an individual tree basis and carbon was estimated from these values.

Understory carbon was predicted based on a relationship between LAI (Leaf Area Index) and biomass in tonnes. LAI was measured from LiDAR on a 5-meter grid across the forest. Forty-eight 1x1 meter field plots were established to measure the understory and develop a correlation. This biomass was weighed in the field, then subsamples were dried in the lab for later carbon analysis. LAI was shown to be an adequate predictor in areas with dense overstory which is likely due to the method for obtaining understory LAI with LiDAR

Using the field data collected for the overstory, a diameter prediction model was created based on height with an R^2 value of 0.557 and a p-value of <0.0001. Using R to perform a tree count with individual tree height, in conjunction with the diameter prediction model, a total of 166,631 metric tonnes of carbon was measured in the overstory. For the understory, the analysis was not sufficient to provide an estimate of carbon in the short overstory area, however for the tall overstory area, a linear model to predict green weight was calculated with an R^2 of 0.293 and a p-value of 0.008. After drying samples and converting to carbon using lab results specific to this area, the R^2 increased to 0.54. This gave an estimated 44,753 metric tonnes of carbon in the tall overstory area.

Over and Understory Carbon Estimations Using LiDAR for the Hofmann Forest Pocosin in Eastern North Carolina

by
Jacob Mark Bost

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APPROVED BY:

Dr. Juan Jose Acosta Committee Co-Chair	Dr. Rachel Cook Committee Co-Chair
Dr. Gary Hodge Member	Dr. Matthew Sumnall External

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CHAPTER ONE: INTRODUCTION

The southeast United States is considered to be one of the world's largest wood-producing areas. While this is mainly due to managed loblolly pine (*Pinus taeda*) plantations, the ecosystem naturally reverts to forests when left alone. Most areas are influenced by anthropogenic change, such as urbanization, agriculture, or by managing natural forests. Some areas remain truly or very close to a natural state, i.e., where anthropogenic influence is minimal. This project looks at one such area, a pocosin wetland, to calculate aboveground carbon to help generate revenue in an area that has not yet been turned into production.

Carbon credits are a topic of debate amongst forest professionals. The general concept is that carbon sequestered by trees can be sold as an offset credit for carbon emissions such as burning fossil fuel. There are issues with this as sequestered carbon, in the form of woody material, will eventually die, rot, and be emitted back into the atmosphere in a short time frame compared to how long it takes fossil fuels to form. An argument can also be made that any carbon sequestered by a forest grown today is replacing carbon that existed in that area as vegetation before humans entered the environment, such as the East Coast of the United States. So while carbon credits are not a long-term solution for storing carbon, as short-term storage, they may help slow climate change (Baral and Guha, 2004; Marland and Schlamadinger, 1997). A positive side effect of managing for carbon credits is that any area set aside for carbon storage and sequestration is in a sense protected, while still providing the landowner with a revenue stream. Regardless of the validity of carbon offsets, the carbon market is continuing to grow and much of the industry is looking for ways to capitalize on it.

With this project, carbon is estimated in the pocosin of the Hofmann Forest in eastern North Carolina, United States. Pocosins are fairly common in eastern North Carolina and many large landholding forestry companies have them as a part of their land base. These areas are extremely wet and restrictions on draining the land, both social and legal, have prevented more of these areas from being converted into plantations. As there are restrictions on these ecosystems, carbon credits may allow landowners to leave these areas untouched while still generating revenue from them. Figure 1.1 shows a map of eastern North Carolina from a survey done in 1999 delineating the pocosin areas. Newer data is available but has added complexities and shows generally the same area. Figure 1.2 shows the Hofmann Forest itself with the pocosin areas used for carbon analysis delineated.

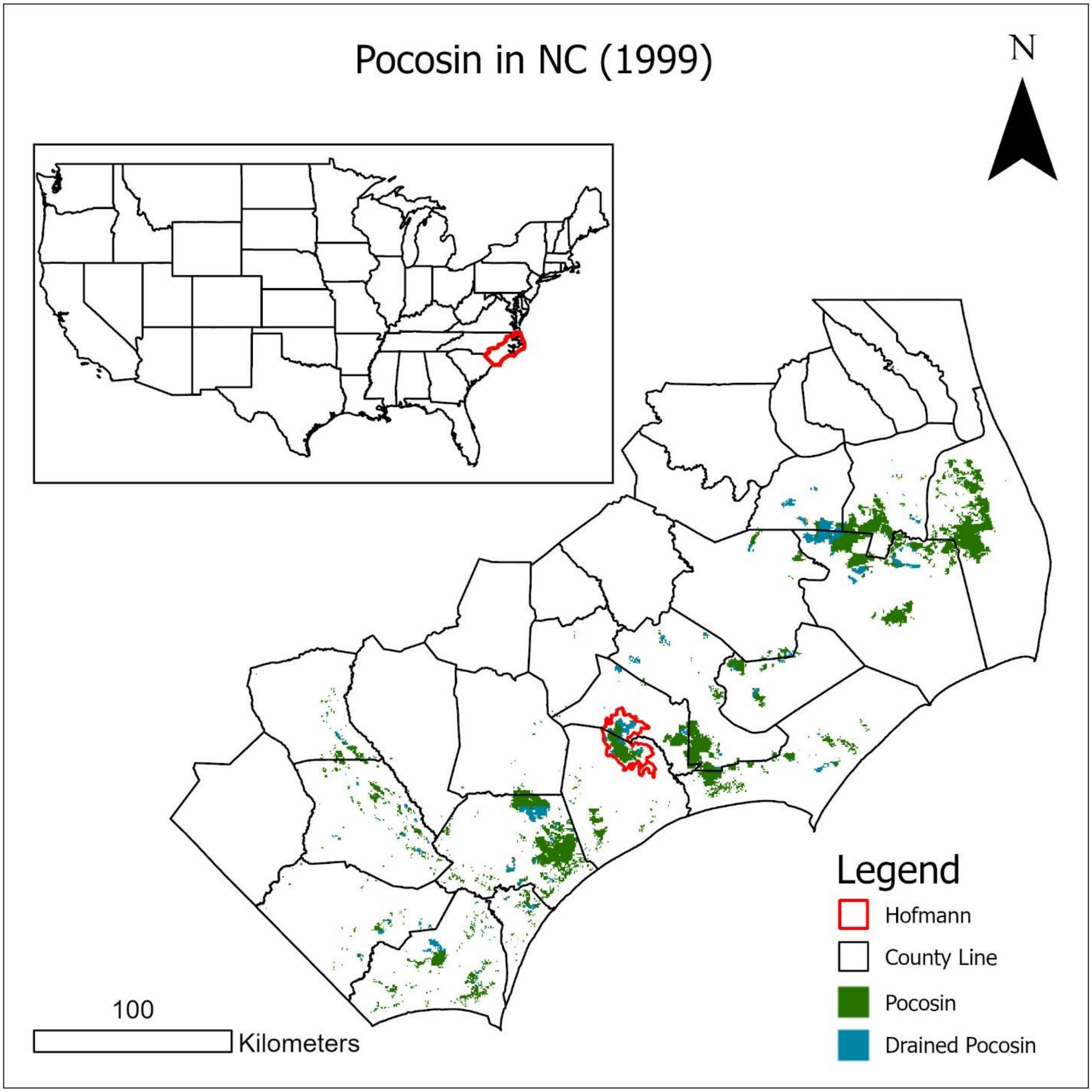

Figure 1.1: Map of the pocosins in Eastern North Carolina (1999) with county lines and the Hofmann Forest boundary.

Source: North Carolina Division of Coastal Management (1999) as cited in Warnell & Olander (2021)

Figure 1.2: Images of the pocosin on the Hofmann Forest.

A: An example of short, relatively dense, overstory. The average estimated understory LAI is 1.8 in this area. (34° 57' 47.97" N, 77° 27' 1.85" W)

B: An example of tall overstory. The understory LAI classification on the left side of the image is low transitioning abruptly to high on the right. (34° 54' 9.13" N, 77° 24' 30.14" W)

The problem that arises is how to measure carbon in these areas with high enough accuracy to sell the measured credits. Practical forestry seems to be in a constant state of balancing statistical accuracy with labor costs for field measurements. Carbon estimation is no different with the profit margins being slimmer as carbon credits are not as valuable as traditional forest products. Remote sensing provides an option for collecting data with little labor involved. In our case, we will be using LiDAR to measure overstory carbon with a minimal number of field plots for validation.

Pocosins have an incredibly thick understory component. While this fact made harvesting biomass plots difficult, both when physically collecting the plots and when navigating the forest, it also was a major reason why carbon was measured in the understory. The sheer amount of biomass in the understory made it feasible to estimate with relatively good consistency and should provide enough carbon to offset the cost of estimating. The images in Figure 1.2 should illustrate the density of the understory. The level of understory seen in the two images in Figure 1.2 is consistent throughout the entire pocosin area.

CHAPTER TWO: OVER AND UNDERSTORY CARBON ESTIMATIONS USING LIDAR FOR THE HOFMANN FOREST POCOSIN IN EASTERN NORTH CAROLINA

2.1. Introduction

The use of airborne light detection and ranging (LiDAR) remote sensing technologies in forestry has quickly become one of the top areas of interest for much of the industry. Use of this active remote sensing to quickly and accurately gather data over a large area is desirable by anyone managing forests, production or otherwise. The ability to use airborne LiDAR opens up more possibilities for estimating three-dimensional forest metrics as opposed to metrics derived from two-dimensional photographic imagery. This is somewhat dependent on the quality of the data. The objective of this research is to develop a method for processing LiDAR into forest metrics for estimating aboveground carbon. For the purposes of this project, the terms carbon, weight, and biomass are essentially synonymous. The end goal is to measure carbon but to do this weight must be measured through estimating standing biomass.

Through this research, carbon will be estimated on the pocosin in the Hofmann Forest in eastern North Carolina (NC). The Hofmann is located just north of Jacksonville, NC, and is split between Onslow and Jones counties. The forest is 31,780 GIS hectares with 7,094 hectares being classified as pocosin by the university. The forest is owned by NC State Natural Resources Foundation, Inc. but the management is split between North Carolina State University (NCSU) and Resources Management Services (RMS). RMS manages the quality production pine stands and the university manages the remaining hectares. The pocosin falls into this latter group. There are several pocosin types which can vary widely in structure. Although this is debatable, the low-density areas are considered here to be true pocosins, while the high-density areas are considered pond pine woodlands, a dryer type of pocosin with a denser and taller forest.

To calculate carbon content, standing biomass, or dry weight in this case, must be measured. Traditionally, many field plots would need to be established and measured to calculate forest metrics to accurately predict standing biomass. With the use of LiDAR, fieldwork can be cut down significantly while still delivering accurate results. For overstory, a tree count was performed using LiDAR which also calculates tree height. This was inputted into dry weight equations (Gonzalez-Benecke, 2014) and carbon was calculated from that using a standard 0.5 conversion factor (Angel et al., 2019; Houghton, 1996; Kinerson et al., 1977; Zhao et al., 2014). Understory carbon estimation proved more difficult as less research was found on this topic. Understory leaf area index (LAI) was calculated from the normalized LiDAR data (Sumnall et al., 2021) and correlated with ground biomass plots that were harvested and weighed. Carbon was directly measured from a subset of these samples.

2.2 Methods

The data analysis for estimating biomass has been broken down into two categories, overstory and understory. The overstory processes measures the dominant, codominant, and a portion of the intermediate trees. For the understory biomass estimations, LAI is measured with LiDAR and a relationship for brush and leaf litter calculated. LiDAR data from the United States Geological Survey (USGS) was used to quantify metrics for both areas to ultimately predict carbon. The forest measures 31,780 GIS hectares with the pocosin counting for 7,094 hectares. Using a mix of aerial imagery, LiDAR, and field inspections, 566 hectares of the pocosin were removed from this project due to either recently harvested areas or an area consisting of different overstory. The goal of removing these areas was to have the remaining areas as uniform as feasible. All area measurements were calculated using NAD 1983 (2011) UTM Zone 18N projection coordinate system.

2.2.1 Airborne LiDAR Data Collection and Software

The LiDAR data was acquired from USGS (U.S. Geological Survey, 2021) using their TNM download web page (v2.0). This data was acquired by Quantum Spatial using a fixed-wing aircraft with a Riegl VQ1560i LiDAR sensor (Table 2.1). Flights were conducted between December 8, 2019, and January 26, 2020, across much of eastern North Carolina in response to the flooding caused by Hurricane Florence. The collected LiDAR data was sectioned into 750 square meter blocks, projected into the UTM zone 18N coordinate system (datum NAD83(2011)), and compressed into LAZ file format. This project utilizes 206 of these files and had an average point density of 21.6 points m^{-2} across this subset. This point density was significantly higher than the advertised average point density of 8 pts m^{-2} across the entire flight.

Table 2.1: LiDAR data collection specifications from Quantum Spatial.

Average Point Density	Flight Altitude (Above ground level)	Field of View	Minimum Side Overlap	RMSE
8 pts m^{-2}	1400 m	58.5°	20%	≤10 cm

By the time field data was collected to use for comparison, the LiDAR data was almost 3 years old. While in most cases this would present problems and likely render the data unusable, with such a slow-growing ecosystem this is likely only a small source of error. Soils in a pocosin are fairly wet ecosystems with standing water common, especially during the winter months when they receive the most rain. The soils have poor nutrient availability and are fairly acidic. All of this leads to slow growth which has allowed this older data to still be viable. A close-up example of the LiDAR data across 100 square meters can be seen in Figure 2.1.

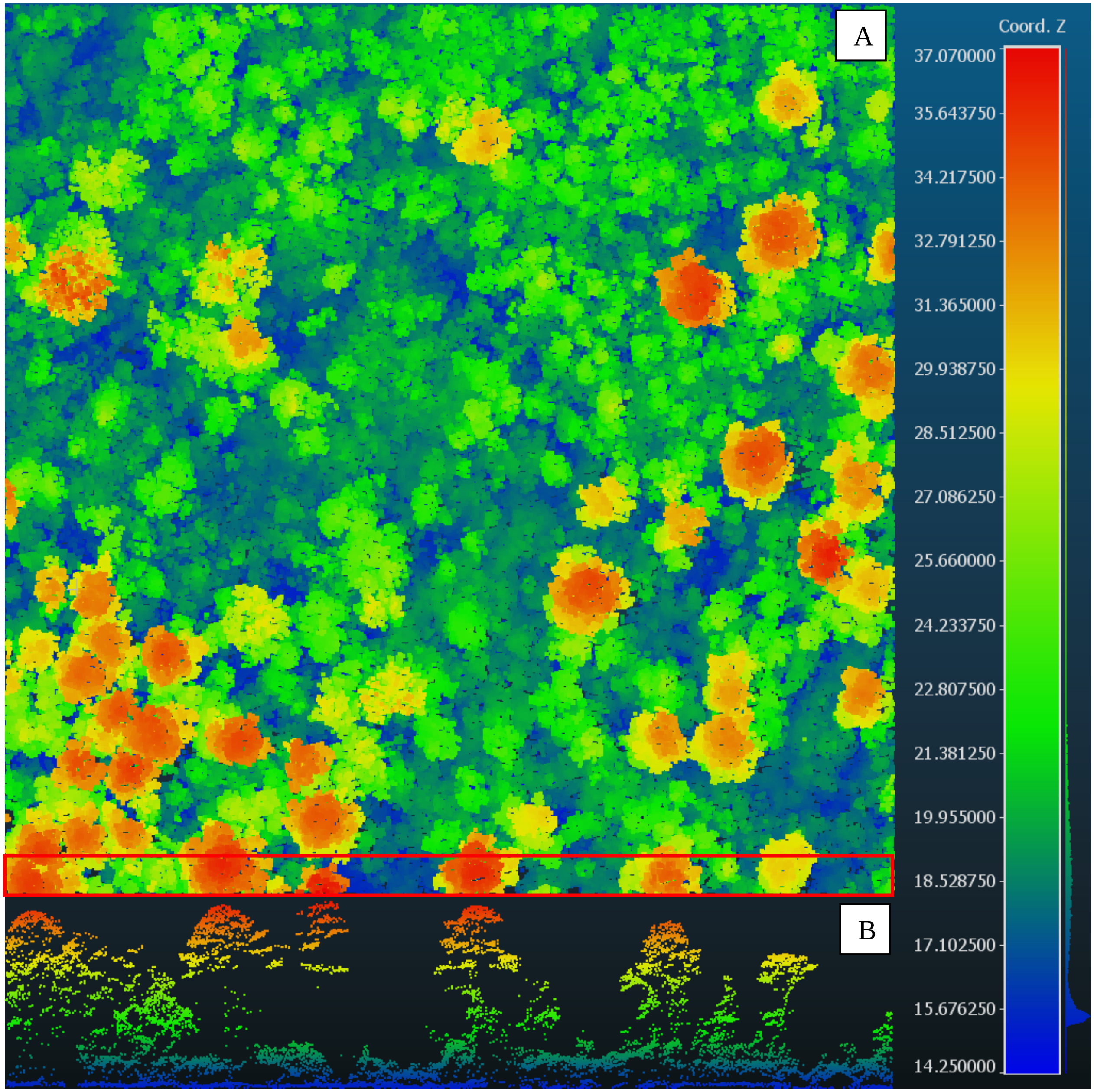

Figure 2.1: Example of non-normalized LiDAR data with a five-meter cross-section.

Figure A shows an aerial view a 100 x 100-meter section of unedited, non-normalized, LiDAR data. The bar on the right side of the Figure is the legend for point height. Since the data has not been normalized in this Figure the earth's surface is not 0.

Figure B Shows a 5-meter-wide vertical view of the lower portion of Figure A. Figure B corresponds to the red box at the bottom of Figure A.

The LiDAR analysis and processing was primarily performed in R software version 4.2.2 (R Core Team 2022). The lidR package was used to read and process the LAZ format files from USGS (version 4.0.2) (Roussel et al., 2020). The terra package (Hijmans et al., 2023) was utilized for the creation of both a digital surface model (DSM) and a digital terrain model (DTM), as well as the subsequent processing of the resulting raster files. From the DSM and DTM, a canopy height model (CHM) was generated to accurately measure individual tree height. R was additionally used for graphing all of the figures in this document.

Outside of R, ArcGIS Pro (version 3.1.2) was used for all mapping and to filter and correct erroneous raster pixels. This was necessary as the LiDAR data from the USGS was not cleaned and inaccurate LiDAR points created errors in the raster file. This step could have been omitted in leu of cleaning the LiDAR data in R. The raster calculator tool within ArcGIS Pro was used to manipulate the raster data. A mix of the statistical software JMP (version 17.0.0) and Microsoft Excel (version 2403) was used for exploratory analysis of the collected field data (Microsoft Corporation, 2021; SAS Institute Inc., 2024). These same software were used to generate linear correlations used for the predictive models.

2.2.2 Overstory Carbon Estimation

To begin estimating overstory carbon, the study site areas were stratified into two stand types based on tree spacing and height. A CHM was made using the LiDAR data, in R, using the ‘terra’ package (Hijmans et al., 2023). A one-meter resolution was used to balance accuracy processing power while giving plenty of resolution to see individual tree canopies. After the CHM was loaded into ArcGIS Pro a correlation was noted between tree height and tree spacing, where areas with taller trees generally had more trees per hectare. This made the stratification of overstory simpler as spacing could be ignored while height was the sole factor used to delineate stand type prior to the selection of field plots locations and further processing.

The creation of a CHM showed a fairly discrete line in the overstory resulting in the decision to have two stand types. To stratify these stands, a 0.04-hectare hexagonal tessellation was overlayed with the CHM in ArcGIS Pro. Any cell of the tessellation intersecting with a CHM resolution ≥15 meters was grouped as tall overstory with the remainder being low overstory. To smooth these areas and mitigate anomalies caused from small canopy gaps, any area comprised of only one tessellation cell without any like cells touching it was grouped into the other class. For example, if one cell was classified as short overstory and all the surrounding cells were tall, the short cell would be converted into a tall cell. The "tall" area (2,613 ha) was predominantly pond pine woodland and the "short" area (3,915 ha) was pocosin.

As a result of outliers within the LiDAR dataset, some raster pixels were well outside of any reasonable statistical margin of error, due to erroneous LiDAR points. Plotting a histogram within ArcGIS Pro of the CHM raster pixels shows that over 99% of the values fall below 30 meters. Using the raster calculator tool, cells below 0 and above 30 were removed (Equation 2.1). To fill the empty raster cells this process left, the raster calculator tool was used again in conjunction with the focal statistic tool to find the average value around these empty cells and fill them based on that information (Equation 1.2). This process created a raster without outlier cells or holes within the data.

Equation 2.1: Equation used in ArcGIS Pro to remove any raster pixels below 0 or above 30.

```
Con(("Raster">0) & ("Raster"<30), "Raster")
```

Equation 2.2: Equation used in ArcGIS Pro to fill in empty raster pixels.

```
Con(IsNull("Raster"), FocalStatistics("Raster", NbrRectangle(2,2, "CELL"), "MEAN"), "Raster")
```

Replace "Raster" with the correct reference for the imported CHM.

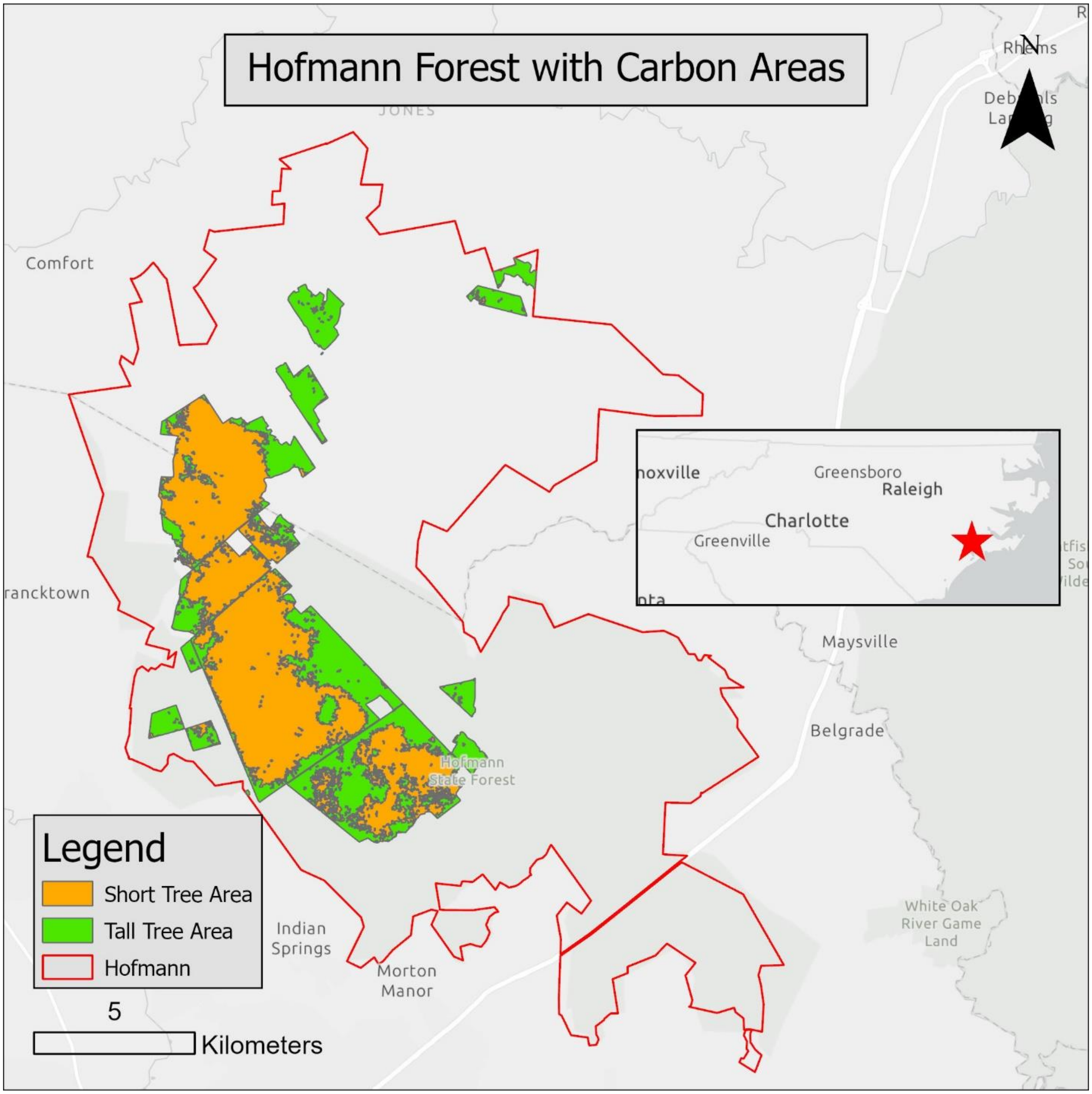

Figure 2.2: Map of the pocosin areas on the Hofmann Forest with tall and short overstory delineated.

Once the stands were stratified and the raster cleaned, the CHM was imported back into ArcGIS Pro. A comparison was then done with different parameters using the locate_trees function with a local maxima filter in the lidR package in R to determine the best function for this application (Roussel and Aury 2022). An area of 150 square meters was selected based with a bias towards an area with varying tree stem density across the 150 square meters. Factors used for this comparison were window size and input data, CHM versus raw LiDAR data. Repetitions were run for validation using a mix of fixed, linear, and exponential window sizes. Determining the most accurate formula was performed within ArcGIS Pro by visually comparing the LiDAR derived tree positions against manually plotted tree locations from the CHM and LAS files. False positives will naturally occur as well as missed trees, especially since the pocosin is a natural forest and the trees are randomly spaced. To eliminate a bulk of these false positives, a 5-meter minimum height was added to the function.

To calculate dry weight and ultimately carbon, a relationship between total height and diameter was first evaluated. A random sample of 82 trees throughout the Hofmann was taken in October of 2023 to create the height-to-diameter relationship. No trees within 30 meters of a ditch were selected to avoid edge bias. Once the diameter was estimated for the overstocked trees, a 95% confidence interval was calculated to provide an upper and lower estimate of carbon. Diameter was measured using a steel loggers tape and height was measured using a TruPulse 200 Rangefinder/Hypsometer.

For calculation weight and carbon, a lack of data for pond pine made it necessary to use data for loblolly. Pond pine has a specific gravity of 0.492-0.493 (Bramlett 1990; Taras and Saucier 1970) while loblolly is slightly lower at 0.47-0.486 (Jordan et al. 2008; Jenkins et al. 2003). Since pond pine has a slightly higher specific gravity, the weight calculated from these formulas should be slightly lower than the actual weight of pond pine. Pond pine also has higher branch retention compared to loblolly adding another factor that should increase the weight of pond pine versus loblolly. While underestimation is not desirable, the difference should be fairly low and will act as a level of conservation in the final estimation. Dry weight was calculated using the whole tree formula for loblolly pine from Gonzalez-Benecke (2014) (Equation 2.3). For simplicity and the type of data measured, the formula using only diameter and height was selected given the previously calculated metrics. This formula calculates weight for the main bole, branches, and needles.

Equation 2.3: Whole tree dry weight prediction for loblolly pine in the southeast.

$$Dry\ weight = 0.026256 * (DBH^{2.015144}) * (Ht^{0.864052})$$

Weight; kilograms. DBH; centimeters. Height; meters

This formula was selected based on a comparison of similar equations (Baldwin 1987) and vetted against green-weight measurements (Clark III and Saucier 1990) and green-dry weight ratios calculated from unpublished data sets (Albaugh 2024). For this project, a carbon conversion factor of 0.5 was used for overstory trees (Angel et al., 2019; Houghton, 1996; Kinerson et al., 1977; Zhao et al., 2014). This value is based on data for loblolly pine from these sources, but is generally considered to be the standard for converting any biomass to carbon.

An important final note on overstory is not all of the mature trees were pond pine. The next most prevalent species was loblolly bay (*Gordonia lasianthus*). There is not a proven method for species differentiation yet using LiDAR so all trees were treated as pond pine. The only documentation available for loblolly bay density reported an average specific gravity of 0.388 (Gresham 2006), significantly lower than that of pond pine. After visual assessments, an estimated 15% of the overstory is comprised of loblolly bay but there were no physical measurements taken to validate this. Aside from occasional loblolly pine, any other species of overstory trees were negligible and practically nonexistent.

2.2.3 Understory Carbon Estimation

Understory carbon estimations started by estimating understory LAI using LiDAR. A 5-square-meter grid metric was generated after imputing the processed LiDAR data into R based on methods developed for loblolly pine plantations (Sumnall et al., 2021). Overstory and total LAI was measured as an average across the 5-meter grid cell and understory LAI was calculated as the difference in these values. This grid was then imported into ArcGIS Pro to stratify the calculated values based on their distribution. Any value less than 0 was rounded to 0.

The first level of stratification for understory used the existing level of overstory stratification of tall and short explained in section 2.2.2. An additional layer of stratification was added based on the calculated understory LAI and was separated into high, medium, and low LAI based on Jenks Natural Breaks algorithm (De Smith et al., 2018) in the data calculated by ArcGIS Pro. This created six separate areas (Tall or Short overstory, by low, medium, and high LAI understory) to be sampled from. Area in hectares was then calculated for each of these areas as seen in Table 2.2.

Table 2.2: Area of understory LAI classes and the number of field plots taken in each area.

Classification (Layer-LAI class)	Area (ha)	Percent of Total Area	Number of Plots Collected
Tall-High	96.4	1.48%	2
Tall-Medium	1202.3	18.41%	15
Tall-Low	1315.6	20.14%	6
Short-High	225.3	3.45%	3
Short-Medium	1298.9	19.88%	6
Short-Low	2393.8	36.65%	16

To generate a correlation between biomass and carbon, 48 field plots were established to collect understory biomass in mid-November of 2023. Of these 48 plots, 25 were in the short classification and 23 in the tall classified areas with the number of plots collected in each area being approximately proportional to the area covered by the respective classification (Table 2.2). The number of plots does not perfectly align with the classification area proportions due to accessibility constraints in the field and auspiciously having more time to collect plots than initially planned. Due to the size of the Hofmann and the limited accessibility, plot locations were necessarily biased towards accessible areas near trail systems. These trails were randomly made by hunters through the largest sections of the pocosin and no pattern was seen to indicate changes in the understory in relation to these trails. Based on the predicted number of plots able to be measured, grid cells were selected to be measured proportionally to the area represented by this classification.

After the trail polygons were established, any grid cell within one meter of the trail edge was selected and exported as a potential plot. From these, any cell that either intersected the trail, was within 50 meters of a road (major ditch), or was within 10 meters of the overstory delineation lines was removed. Any cell with an understory LAI value of 0 was also removed as this was considered to be an error in the original calculation. From this selection, the 48 plots were selected using a random number generator.

In the field, the selected grid cells were located using a phone GPS and a 1 square meter plot was cut to measure biomass. All vegetation under 10 cm in diameter was harvested and weighed on-site to the nearest 0.1 kg. Brush, leaf litter, and down woody material were weighed separately. After weighing biomass on the entire plot, a sub-sample was collected in 30-gallon paper bags and reweighted for later analysis. These sub-samples were then chipped and another subsampled collected in a small paper lunch bag. These samples were then dried in a mechanical convection drying oven and weighed periodically until their weight stabilized. At this point, water content in the samples had been removed and the samples were reweighed for their final dry weight. In addition to the drying process, three randomly selected samples were sent for carbon analysis so a conversion factor could be calculated specifically for understory carbon.

After the samples were dried, analysis was done correlating green and dry weight to the estimated LAI. This was done using JMP statistical software (SAS Institute Inc., 2024). We assumed that if p-values were less than 0.05, we reject the null hypothesis. Hence there is a significant relationship between the variables in the linear regression model. Additionally, the R-squared value was computed for each relationship to assess the strength of the correlation.

2.3 Results

2.3.1 Overstory

After analyzing different parameters for performing a tree count using R, a window size in Equation 2.4 was determined to be the most accurate. This function used the CHM compared to the normalized LiDAR data on a 150 square meter selection of the pocosin. A wide range of window sizes was used along with comparing CHM and LiDAR with and without a five-meter minimum height (Table 2.3). After the locate_trees function was completed, a total of 1,567,193 observations were made with a mean height of 10.92 meters, a median height of 10.50, and a standard deviation of 3.88 meters. A histogram of the plotted trees across the pocosin can be seen in Figure 2.3. Subsets of the output from the locate_trees function was overlaid with a CHM for 6 of these areas as an example of how this process was conducted (Figure 2.4).

Equation 2.4: Tree locating variable window size using a CHM used in R.

$$\text{radius} = HT \times 0.1 + 3$$

Table 2.3: Variable radius window size permutations evaluated when automatically delineating individual tree crown locations from LiDAR or a LiDAR-derived canopy height model (CHM). Where x is equal to raster-cell height.

Window size (m)	Tree count w/o min CHM	Tree count w/ 5 m min CHM	Tree count w/o min LAS	Tree count w/ 5 m min LAS
3	870	601	1228	698
6	320	308	384	348
Linear: HT*0.1+3	833	573	950	543

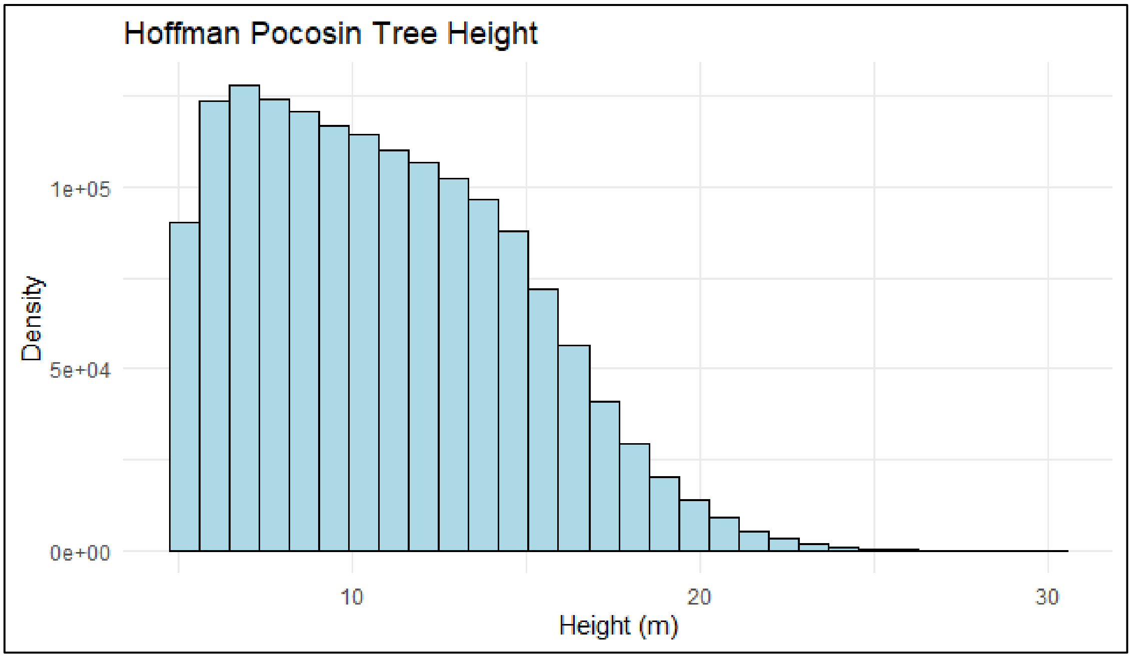

Figure 2.3: Histogram of the trees in the pocosin area counted using R.

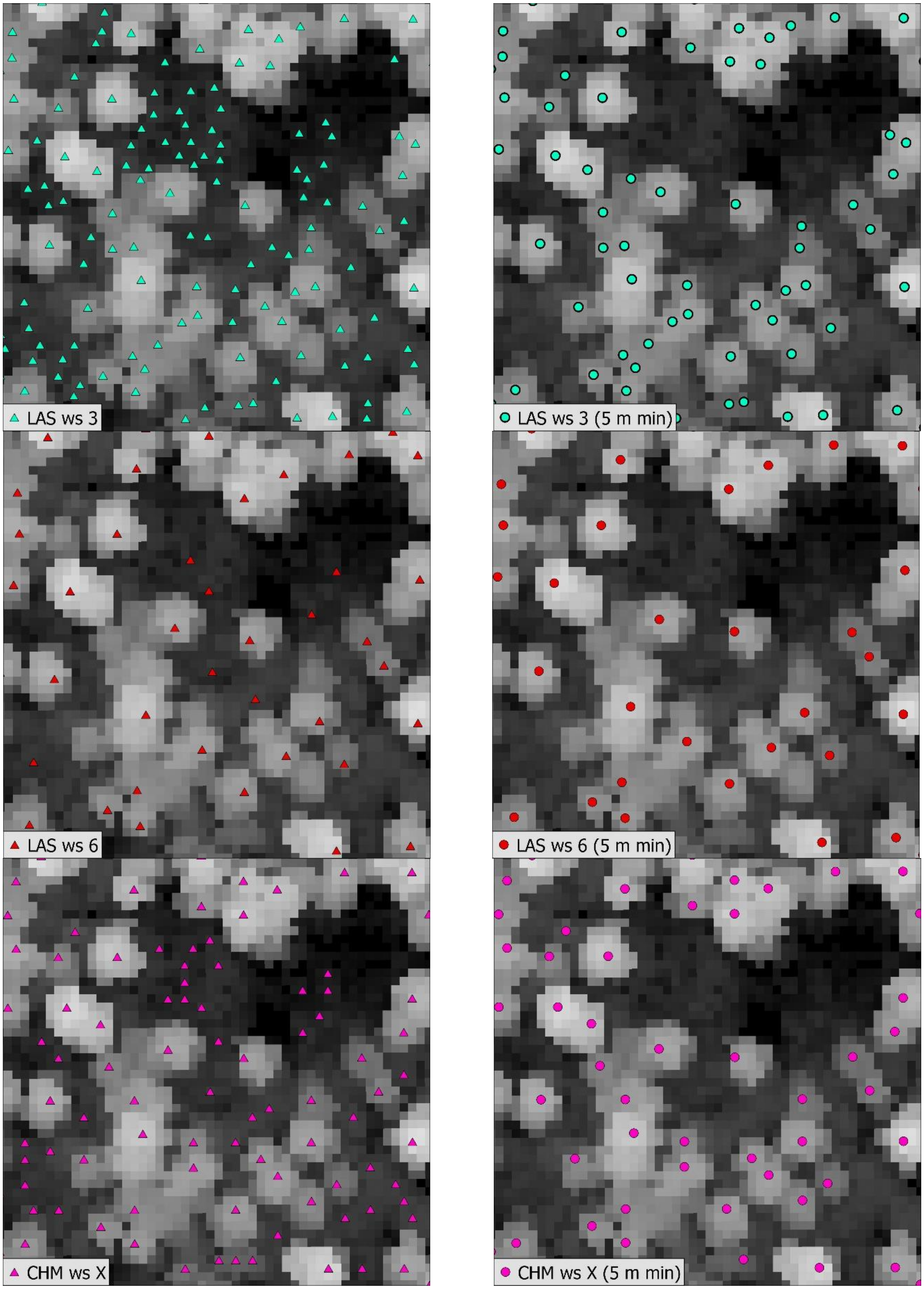

Figure 2.4: Tree crown locations overlaid on a CHM for 3 window sizes from LiDAR or a LiDAR-derived canopy height model (CHM).

A relationship between height and diameter was calculated using a linear regression from pond pine measured on the Hofmann Forest (Figure 2.5). An R^2 value of 0.557 was estimated with a *p*-value of <0.0001 using an F-test. These results are consistent with similar studies in the literature (Hulshof et al., 2015). Stand stratification decreased the statistical power as well as the use of alternative models. A Root Mean Square Error (RMSE) for predicting diameter from the derived linear model was calculated as 6.413 with a bias of -0.006. Tree height had a maximum and minimum recorded height of 22.3 and 7.9 meters respectively. Tree diameter had a maximum and minimum of 65.0 and 17.5 centimeters.

Table 2.4: Statistics for measured overstory pond pine in the Hofmann Forest.

Measurement	**N (Tree Count)**	**Mean**	**Median**	**SD**
Total Height (m)	82	14.29	13.72	3.50
DBH (cm)	82	34.52	33.53	9.07

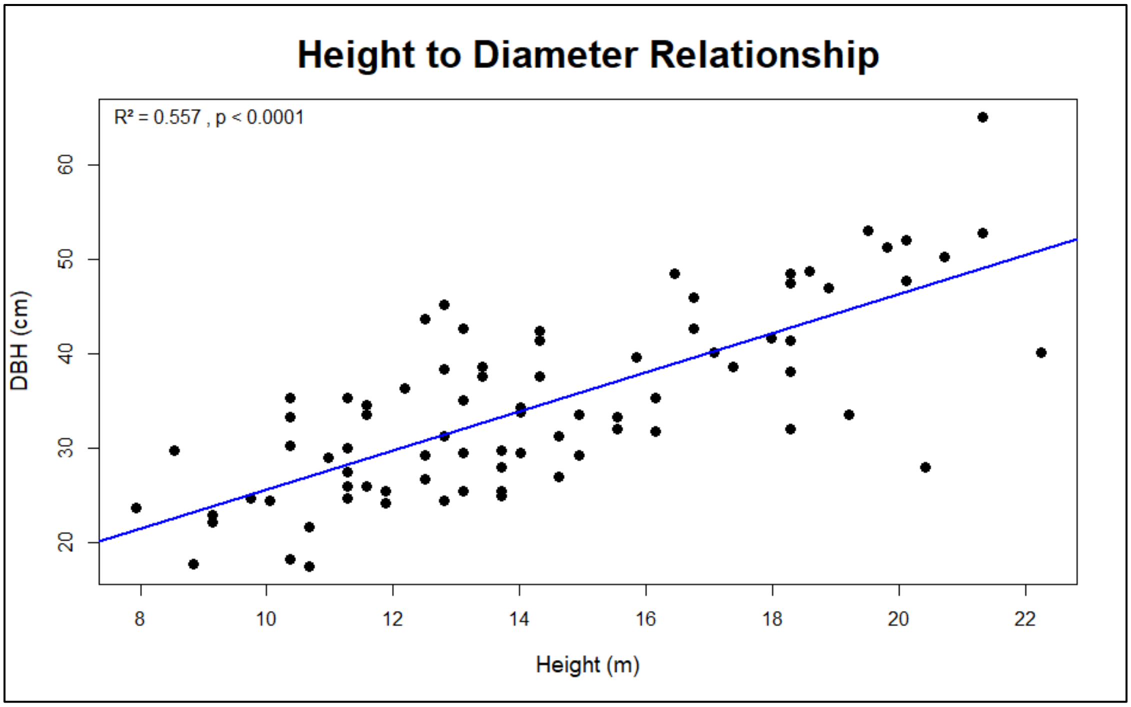

Figure 2.5: The relationship between height (meters) and DBH (centimeters) for pond pine on the Hofmann Forest with R^2 and *p*-value displayed.

Equation 2.5: Prediction of DBH (cm) from total tree height (ht) in meters.

$$(2.072*ht) + 4.915 = DBH$$

Dry weight was estimated on an individual tree basis using measured height and estimated diameter (Gonzalez-Benecke 2014). The formula used was selected based on a comparison of similar equations (Baldwin 1987) and vetted against green-weight measurements (Clark III and Saucier) and green-dry weight ratios calculated from unpublished data sets (Albaugh 2024). For this project, a carbon conversion factor of 0.5 was used for overstory trees (Angel et al., 2019; Houghton, 1996; Kinerson et al., 1977; Zhao et al., 2014). This value is based on data for loblolly pine from these sources, but is generally considered to be the standard for converting any biomass to carbon.

Total carbon measured on an individual tree basis gave an estimated 166,631 metric tonnes. Using a 95% confidence interval, an upper and lower diameter for each tree was measured and carbon was recalculated for an upper and lower limit of 188,181 and 145,623 tonnes respectively. Unlike understory, the change in tall versus short overstory did not yield any noticeable difference in accuracy.

2.3.2 Understory

Once LAI was estimated on a 5 square meter grid from the LiDAR data, the distribution of understory LAI across the pocosin was plotted on a histogram with all negative values rounded to 0 (Figure 2.6). A high number of returns show a value of 0, 15% of all plots. This is not the case on the ground based on observation and most of these values are considered to be erroneous. Statistics for understory LAI can be seen in Table 2.5 with additional statistics for all values not equal to 0. The largest of these areas is the Short-Low classification covering 37% of the pocosin area. Of the total 15% of plots with an understory LAI return of 0, 13% fall into the Short-Low category. An example of the 5 square meter understory LAI grid can be seen on Figure 2.7 and the defined ranges of the Low, Medium, and, High understory LAI Classifications can be seen in Table 2.6.

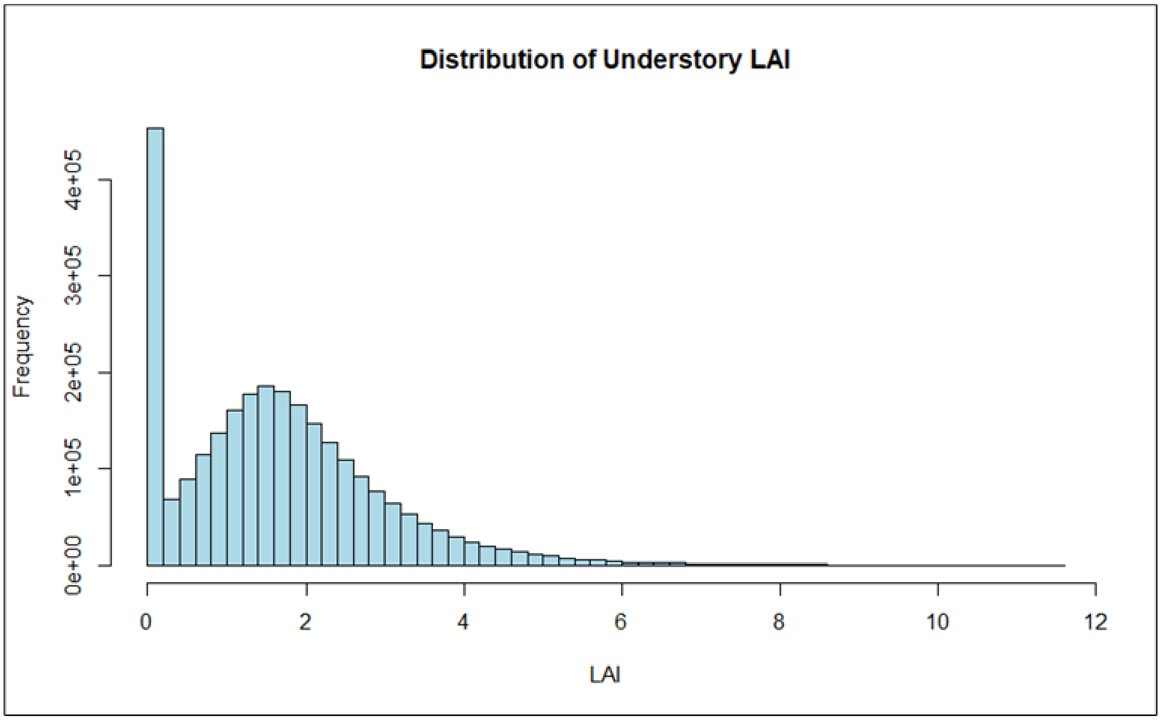

Figure 2.6: Distribution of understory LAI across the pocosin on the Hofmann Forest.

Table 2.5: Statistics for understory LAI on a 5-meter grid. Summary statistics for understory leaf area index (LAI) was calculated for all cells (ALL) and all cells for LAI values above 0 (≠ 0).

LAI estimate	N	Mean	Median	SD
Understory (ALL)	2,633,779	1.64	1.53	1.28
Understory (≠ 0)*	2,230,379	1.94	1.75	1.17

* When the five square meter LAI metric was generated, any number less than zero was rounded to zero. These plots were considered to be erroneous and were removed for more accurate statistics.

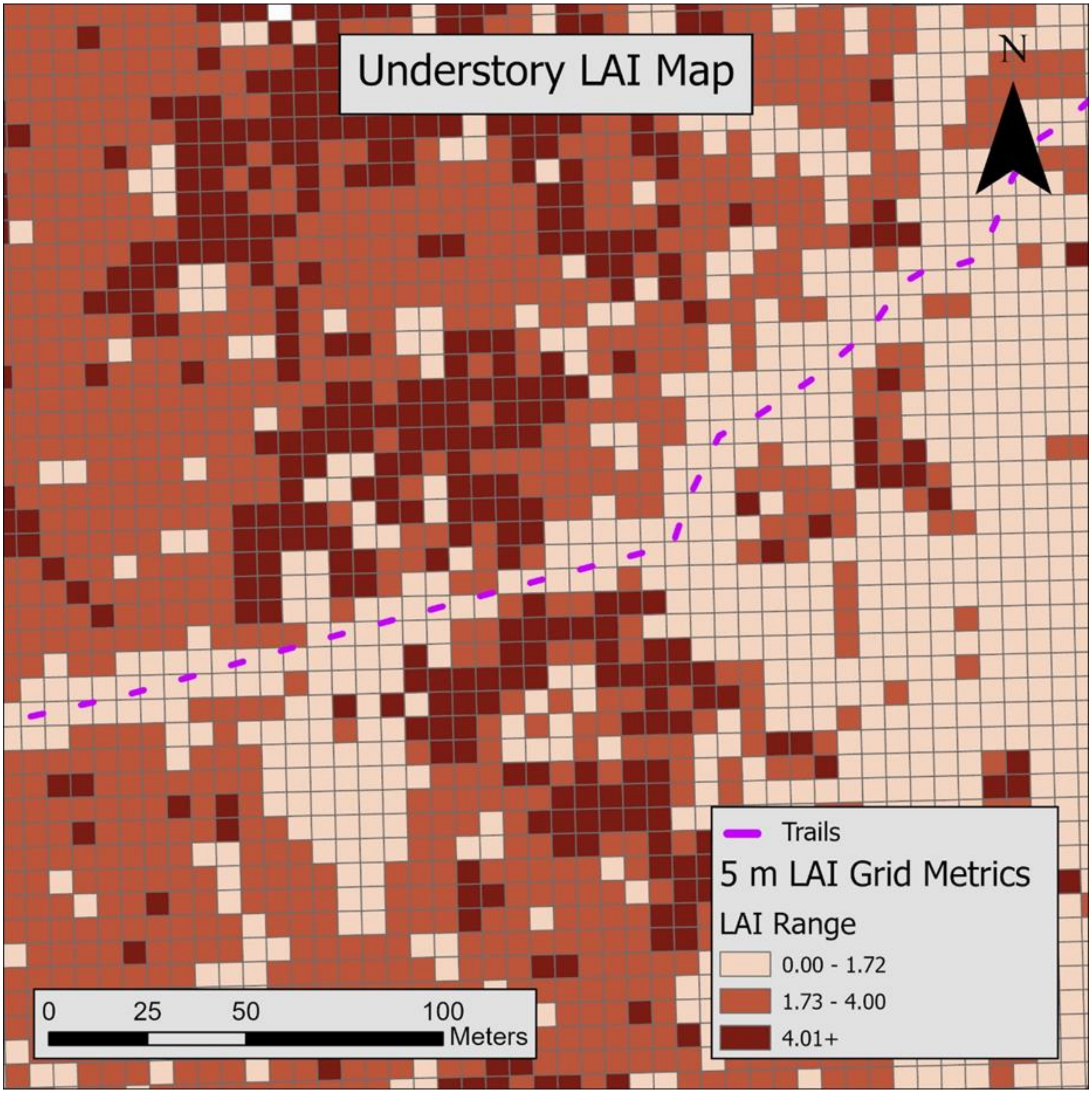

Figure 2.7: Map of a subsection of the 5-meter LAI grid metric for understory.

Table 2.6: Understory LAI Classification Based on LAI Range.

Classification	**Low**	**Medium**	**High**
LAI Range	0 – 1.72	1.73 – 4.00	4.01 +

Using the collected understory green weight data from the 48 plots, relationships were calculated between LAI and green weight. Weight classification was broken down by: (i) brush only, (ii) brush and leaf litter, and (iii) all weights and separated by tall and short overstory. Understory stratification was not used as not enough plots were taken in each section to allow for proper statistical analysis. After analysis, the following Table 2.7 was generated using a linear regression of the stated variations. Table 2.8 shows the P values for these metrics.

Table 2.7: Linear R^2 values for regression between understory leaf area index and green weight.

Material	**Short**	**Tall**	**All**
Brush Only	0.001	0.284	0.054
Brush and Leaf	0.001	0.293	0.072
All Understory	0.001	0.005	0.009

Table 2.8: Significance (*p*) values of the linear regression between understory leaf area index and green weight.

Material	**Short**	**Tall**	**All**
Brush Only	0.889	0.009	0.113
Brush and Leaf	0.886	0.008	0.065
All Understory	0.886	0.760	0.531

Based on the estimated understory LAI (Sumnall et al., 2021) and collected field plots, the correlation between understory LAI and understory biomass showed itself to be significant in areas where there was a continuous overstory with *p*-values less than 0.05 in the tall overstory areas. In the short overstory areas where the trees were fairly sparse, almost savannah-like in appearance, there was no usable correlation for predicting understory biomass. Per the data that was collected, three linear equations were calculated for predicting green weight, dry weight, and carbon from understory LAI.

Table 2.9: Green, dry, and carbon weight regression equations for predicting kg m^{-2} from understory leaf area index in the tall classified pocosin area.

Measurement	**Slope coefficient (β_1)**	**Intercept (β_0)**	**R^2**	***p*-value**
Green Weight	1.146	3.325	0.29	0.0076
Dry Weight	0.7828	2.341	0.40	0.0028
Carbon	0.7168	0.504	0.54	0.0002

The regression model is:

Equation 2.6 the standard linear regression model formula:

$$y = \boldsymbol{\beta}_1 \times x + \boldsymbol{\beta}_0$$

where y is the weight in kg m^{-2}, β_1 is the slope coefficient, β_0 is the intercept, and x is the understory LAI. R^2 and p values for each model are presented in Table 2.9.

A custom carbon conversion was created from drying samples and sending them for carbon analysis. A total of three samples weighing an average of 6.26 grams were sent for elemental analysis. The specific carbon values derived were 44.94%, 44.99%, and 46.69%, with the average carbon content being 45.54%. This average was used as the conversion factor for calculating understory carbon from dry weight. Using these formulas, total green weight, dry weight, and carbon were estimated across the 2,613 hectares of the tall area (Table 2.10).

Table 2.10: Total green, dry, and carbon weights in tonnes across the tall overstory area.

Green Weight (Tonnes)	Dry Weight (Tonnes)	Carbon Weight (Tonnes)
141,194	98,272	44,753

2.4 Discussion

The methodology used for overstory carbon estimation is a straightforward procedure based on the literature surrounding this topic (Mohan et al., 2021). The issue is that the majority of research has gone into looking at managed pine plantations. While it is understandable why, it does pose some issues when applying the methods to a natural area. A pocosin is still the best-case scenario for a natural stand as the predominant species is pond pine, a species very similar to loblolly pine, and the structure is fairly uniform across the stand. Compared to a mixed hardwood stand, working in a pocosin is significantly better due to the diverse overstory typically found in hardwood stands.

The accuracy of predicting diameter based on tree height produced a similar R^2 and *p*-value consistent with similar research (Hulshof et al., 2015). Although the R^2 value is lower than might be desirable, a strong *p*-value and a bias close to 0, lends validity to the model. No model will ever be perfect, especially in a natural environment such as a pocosin. It will ultimately be up to individual companies within the industry to decide what is an acceptable allowable error for their specific uses. Predicting diameter based on the measured height on an individual tree basis should prove incredibly useful. Field labor for timber inventory is time-consuming and expensive. Utilizing remote sensing could potentially eliminate a large part of field inventory we can saving time and money, while potentially delivering more accurate results.

The main problem that was not addressed here is the portion of hardwood in the pocosin. While this is relatively insignificant, it is still a metric that would prove useful to stratify. Future work on this project may include looking at the spatial correlation of the overstory trees. Loblolly bay tends to grow in clumps so wherever there are multiple trees near each other they are likely bay. It is also important to note that while most of these methods can be transferred to other areas with minor adaptations, a custom diameter prediction model will need to be made for each site based on its overstory component. With enough data from a range of areas, diameter prediction models would likely be able to be reused. This research only collected data from one specific location, the Hofmann Forest, so using a model created from this data set in an area may produce erroneous results.

Understory is less represented in the literature and protocol for estimating biomass is scarce at best. Similar research has been done to estimate understory biomass, however, no research was found on areas with as dense understory vegetation as a pocosin (Shrestha et al., 2021; Wing et al., 2012). Looking at the tall overstory area, LAI seems to be an acceptable method for predicting biomass while in the short areas it was not. This difference is likely due to understory LAI not specifically being measured (Sumnall et al., 2021). Instead, total and overstory LAI were measured and the difference was assumed to be the understory. This methodology was developed for loblolly pine plantations and seemed to work well where there was continuous overstory, but in the areas where there were few overstory trees, the model seemed to have difficulty delineating where the understory was. These results show the methods used for plantations can be adapted for natural areas with little alteration so long as there is significant pine overstory.

Although difficult to prove without more field data, these methods should provide a more accurate estimation of biomass than the more traditional way of extrapolating directly from field measurements. For a rough comparison and validation of the methods tested here, extrapolation of sample plots was done for green weight. From this, 159,007 tonnes of brush and leaf litter green weight was estimated in the tall areas. Using this method, 200,996 green tonnes were estimated in the short area.

An additional level of verification could also be done by measuring LAI on the ground. LAI was not measured in the field due to time and equipment constraints but would have been interesting to have for comparison. Without this verification data, LAI should still be visually estimated in the field as was done here. It is important to note that even though a useable correlation was found between understory LAI and biomass, LAI could still be over or underestimated by the LiDAR. Retraining the model or coming up with a simple adjustment formula would be possible with a calculated conversion if deemed necessary.

This leads to another possible issue with this project which was the time difference. Between the time the LiDAR data was collected and field plots measured, almost three years had passed. While this was not enough to affect overstory estimation based on pond pine growth rate, understory change was more difficult to quantify. There is simply not enough data to estimate how much the understory in a pocosin can change in three years. Based on what is known about the ecosystem and the slow growth of the overstory, particularly pond pine, the understory is likely slow-growing as well (Fowells 1965). Regardless of this, the calculated correlations are still significant in predicting biomass. The unanswered question is if the methods used here would have a different correlation between LAI and biomass than if new LiDAR data had been used. This would not affect the end result for this project, just whether the formulas would be accurate on another site with newer data.

Another point to be discussed is Hurricane Florence which struck North Carolina in September of 2018 approximately 30 miles south of the Hofmann Forest. The LiDAR data provided by USGS was originally collected to improve topography maps for predicting floods in eastern North Carolina. This hurricane may have damage the understory and removed leaves causing the leaf area to be artificially low at the time of the LiDAR flight. This should not affect the end result of this project, total carbon in tonnes, but would mean that the models created for predicting biomass would be questionable.

The development of these understory equations was done to aid forest managers in quantifying understory biomass to sell carbon credits, but also aid in management decisions. Having a measurement of understory biomass will allow forest managers to make decisions on management practices such as woody understory control based on actual data. Another potential use might be sight selection for understory biomass harvest for pellets. As of yet, there is no market for this product, but with the continuing demand for wood pellets, it may yet develop. The methods used to measure understory could also be applied to wildlife management, potentially for estimating species quantity based on cover. Invasive plant species could also be measured such as measuring the spread of a dense understory species such as Chinese privet through an otherwise sparse understory.

2.4 Conclusions

Quantifying overstory carbon proved to be a straightforward procedure with good accuracy when comparing the predicted DBH to the measured DBH. While the height-to-diameter correlation is consistent with what is found in the literature, an R^2 value of 0.557 is less than ideal for a predictive (Hulshof et al., 2015). It is believed that any error from this is offset by the ability to count every tree, but this is difficult to prove at this scale. The results of this study have demonstrated that determining carbon quantity from aerial LiDAR-derived LAI also proved to be an acceptable method, and therefore has a great deal of potential for forest managers. Although no correlation was found for areas with sparse overstory, this does not prove that LAI does not correlate with biomass in these areas, and thus warrants future research. Just that the described datasets or methods for finding a relationship between LAI and carbon quantity are limited in this scenario. This research also quantifies the understory in a way that can allow other researchers or industry professionals to determine if understory is worth measuring for other applications, such as targeting understory herbicide application or monitoring of regeneration.

CHAPTER THREE: IN-DEPTH ANALYSIS AND EXPLANATION OF THE PROJECT

This section intends to elaborate on the how and why of this project. Explaining the project in more detail will hopefully allow the reader to understand why certain decisions were made over others and guide any future projects related to this field. This section will also include any unused data, R code, final thoughts on what should have been different, and any suggestions on what may be useful to look at in the future.

This project began with the desire to measure carbon in the pocosin of the Hofmann Forest to sell carbon credits. While measuring a product for commercial application may not be the typical approach for research, this will hopefully provide useful insight for forestry companies who wish to measure and sell carbon on their own property. This however brings us to our first issue as a standard for selling carbon has not yet been established. Not only is there no standard methodology for measuring carbon, which is what this research focused on, but there is no certainty that carbon can even be sold on these pocosin sites. This problem will ultimately be up to the forest manager to overcome in this instance. Except for understanding that the desired output must be in a format that can easily be interpreted, total tonnes or tonnes meter $^{-2}$ in this case, no other considerations were made to avoid any potential bias.

3.1 Elaboration of Methods

3.1.1 LiDAR

LiDAR was chosen for carbon quantification for two main reasons. One was that the industry has had an interest in using remote sensing as a way to measure its forests, so any research in this field should prove more useful for the industry. Second, free LiDAR data was available from USGS with relatively high pulse density. LiDAR is expensive to collect so this resource was invaluable to the project. Specifics on the quantity and quality of the LiDAR data can be seen in chapter two of this paper.

LiDAR data is fairly simple to understand. An instrument sends laser pulses out and the time it takes to reflect to a sensor on said instrument, along with the GPS coordinate of the device, gives an X, Y, and Z coordinate for that reflected point. This explanation is simplified, but it is all that is needed to understand basic LiDAR. Before any processing, this gives three attributes with each point which should be simple for any calculations. The problem with processing this data arises due to the quantity of these points. For this project, an average of 21.6 points meter^{-2} was measured across 6,528 hectares. Resulting in approximately 1.4 billion points that must be processed. Understanding what a computer's hardware and the desired software can process is an important first step when using LiDAR.

For processing LiDAR, several software programs can prove useful. CloudCompare is great for looking at small data sets (CloudCompare Development Team 2023). It has a simple user interface and a lot of online resources for help. It is also useful for converting .laz files to .las which are the compressed and uncompressed LiDAR file types. CloudCompare cannot hold massive amounts of points though. ArcGIS Pro is another software that can be used for looking at LiDAR. Its main, and possible only, advantage is that most people in the forest industry are very familiar with it. One major problem is that ArcGIS Pro can only read .las files. It also has problems with large data sets such as LiDAR point clouds. ArcGIS Pro is capable of looking at LiDAR in 3D which can again prove useful when visually exploring at the data. Grass GIS and QGIS can also read LiDAR data but both were found to not be as user-friendly, although their ability to process big data makes them worthy of note in this section.

After time was spent on these programs, R was selected as the best option for processing the LiDAR data. R has several packages for reading and manipulating LiDAR data and it can process large data sets without much trouble. When originally designing this project, coding was discriminated against as this process was intended to be as simple as possible so that replication by the industry would be easily accomplished. However, after using the readily available programs listed above, all of which are open source except ArcGIS Pro, it was realized that coding was the only efficient way to process the data.

3.1.2 Overstory

Overstory carbon estimation is the most useful, but also least exciting portion of this thesis. After analysis was done on the tall area of the pocosin, overstory carbon was calculated as 70% of the total carbon on the site. With the high amount of understory vegetation present in a pocosin, it can be assumed that in most other ecosystems, the overstory carbon percentage would be significantly higher. While the ratio of understory to overstory carbon was not the primary goal of this research, it should give a rough idea of the carbon in similar areas so that forest managers can determine if the revenue made from carbon credits would offset the cost of measurement.

3.1.3 LiDAR Alternative

Through the process of determining the best method for performing a tree count, both raw LiDAR data and a processed CHM were used. See Appendix 1 for the tree count code used. After visually validating the tree count in ArcGIS Pro 3D view, the CHM was shown to be the more accurate of the two with the specified window size. Ideally, tree locations could have been accurately located using a GPS, then an assessment could be done comparing what R was able to calculate verses what was physically present. Doing this on multiple areas would have returned the most accurate results, however, the understory density prevented this from happening as the level of vegetation prevented an accurate tree count. An expanded version of Table 2.3 is given below containing all of the measurements when selecting the tree count equation within R (Table 3.1)

Table 3.1: Variable radius window size permutations evaluated when automatically delineating individual tree crown locations from a LiDAR-derived canopy height model (CHM) for all window sizes analyzed. Where x is equal to raster-cell height

Window size (m)	Tree count w/o min CHM	Tree count w/ 5 m min CHM	Tree count w/o min LAS	Tree count w/ 5 m min LAS
3	870	601	1228	698
4	575	479	712	516
5	428	385	496	240
6	320	308	384	348
Linear: HT*0.1+3	833	573	950	543
Linear: HT*0.07+3	866	606	1017	571
Linear: HT*0.05+3	870	610	1065	594
{Exponential} 2.6 * (-(exp(-0.08*(HT-2)) - 1)) + 3	792	532	971	517

Using a CHM versus LiDAR data opened up different possibilities for data manipulation. Specifically, ArcGIS Pro could now be used for more data manipulation as a raster image is much easier to process than LiDAR data. It also raised, in my opinion, the most important question of whether the process for overstory could be replicated with photogrammetry. The answer is likely yes, which would make creating the CHM significantly cheaper and easier than using LiDAR.

LiDAR is expensive to collect and requires special equipment while photogrammetry can be done by anyone with a drone with the ability to fly over the entire area. Any fixed-wing drone would be excellent for this such as an eBee X as having fixed wings makes them more efficient and therefore they can cover a large areas. Multi-rotor drones work just as well but typically have a smaller range on a single battery. Their ability to take off and land and confine spaces can make up for this. The benefits and costs will need to be weighed for each depending on the use. For processing the images, there are numerous software programs that can stitch the photos together. LiDAR does provide a potential for measuring tree form and diameter which photogrammetry could never do in a fully stocked stand. So this is not to say that photogrammetry should take the place of LiDAR. It is just to illustrate that there are other options available that are more cost-effective and potentially just as useful. Individual companies will need to make decisions on what and when to use these tools. There just needs to be an understanding of the cost-benefit analysis depending on the circumstances.

While searching for a way to complete an accurate tree count to calibrate the overstory tree counting model, the managers of the Hoffman Forest, Resources Management Services, lent their time to conduct three drone flights of small areas of the pocosin. These areas were approximately 1 hectare and were intended to represent the three levels of overstory density. These flights were done using an early-generation DJI Phantom multi-rotor drone and the images were imported into Agisoft Metashape for analysis (Agisoft LLC. 2024). At this point, it was realized two of the three areas did not have enough pictures to merge and create a three-dimensional image.

On the one area that was usable, a 3D model was made of the area and in doing so, a point cloud was made that could be exported as a .las file so that the file could be analyzed using the same methods as would be used for LiDAR data. Independent of the main part of this thesis, a comparison of this photo-derived point cloud and actual LiDAR data was performed. After using CloudCompare to clip the two areas into equal sizes, the files were imported into R for analysis. Figures 3.1 and 3.2 show aerial views of the point cloud files as displayed in R. The LiDAR data from USGS (USGS 2021) had already been processed and ground points had been classified, a necessary process in generating a Digital Surface Model (DSM). The photo-derived .las file did not have this and the classify_ground function was used as part of the lidR package in R (Roussel et al., 2020). From here, a CHM was created for each of these data sets using the terra package (Figure 3.3 and 3.4) (Hijmans et al., 2023). Some discrepancies can be seen comparing the LiDAR and photo-derived figures. These are mainly due to two causes. Firstly, the time difference between when the LiDAR data was collected, December 2019-January2020, and the drone flight, October 2023. Second, differences in how the scalar field was calculated on the photo-derived point cloud as no processing was done.

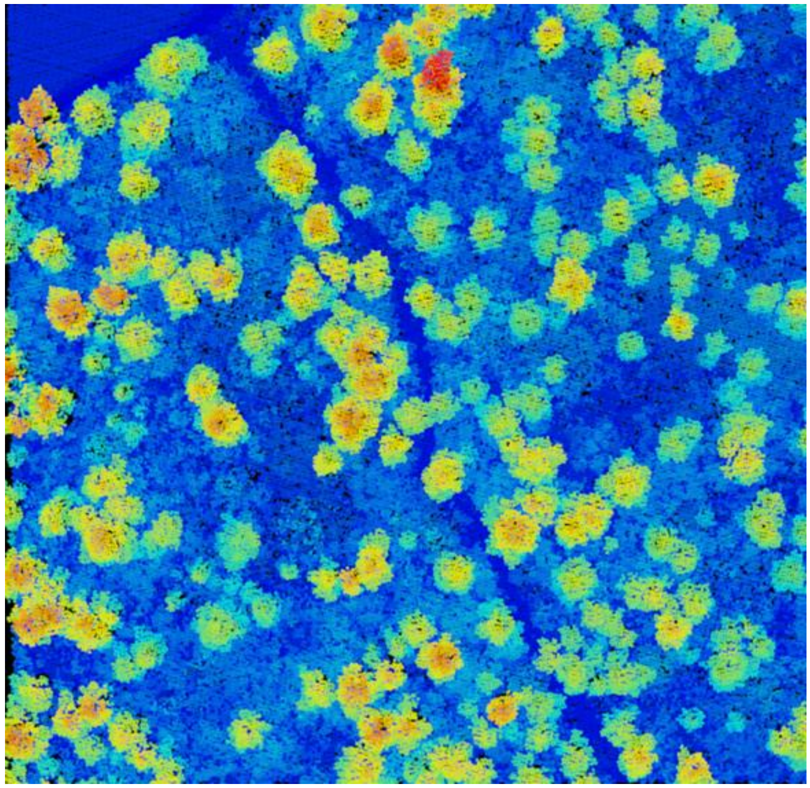

Figure 3.1: Point Cloud using LiDAR data from USGS.

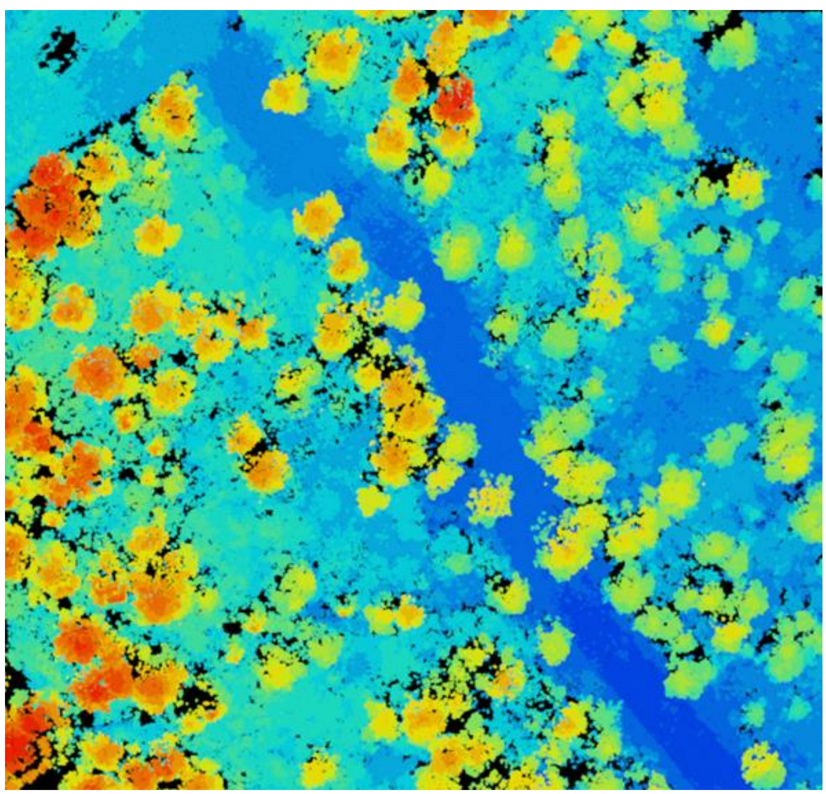

Figure 3.2: Point Cloud using photogrammetry from drone photos.

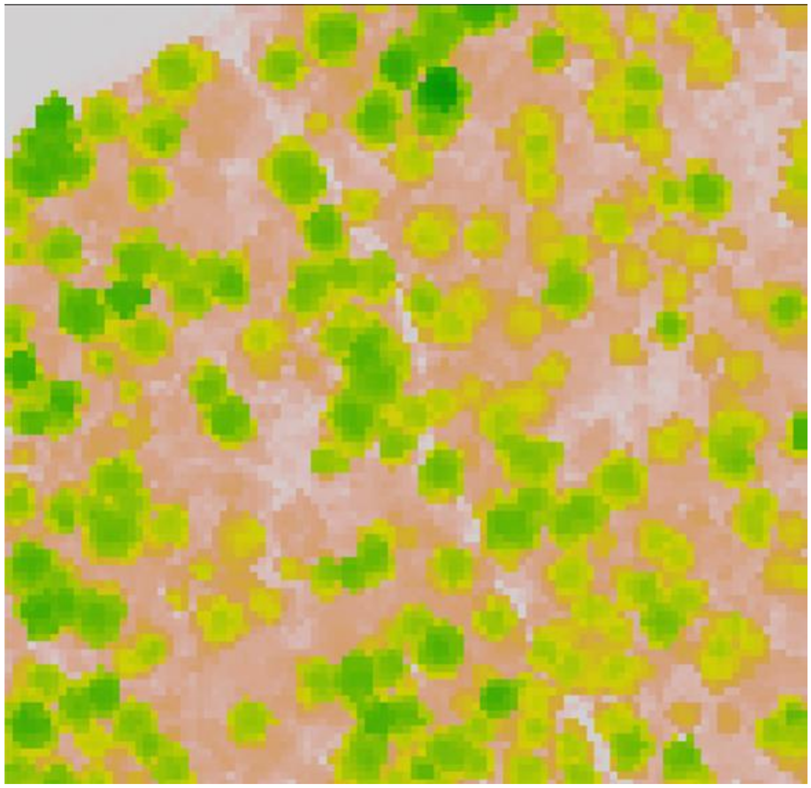

Figure 3.3: CHM using LiDAR data from USGS.

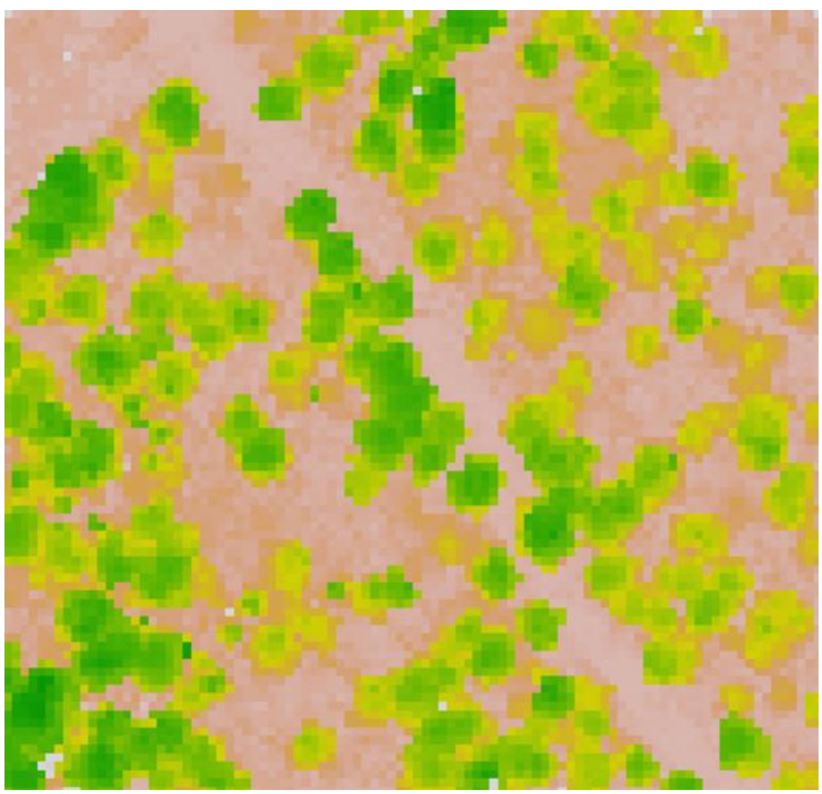

Figure 3.4: CHM using photogrammetry from drone photos.

Visually comparing these two methods shows that photogrammetry can rival LiDAR for overstory analysis. Using the same tree count function as used in the main part of this thesis, a tree count with 237 observations was completed on the LiDAR CHM and a tree count with 248 observations was completed on the photogrammetry CHM. More analysis would have to be performed comparing these methods but this difference is likely due to not properly processing the CHM. This portion of the project did not relate to the main part of this thesis so minimal time was spent on analysis. This section is intended to show there is value in continuing this line of research, particularly when considering cost, as drone flights to take photos are much more cost-effective.

3.1.4 Volume Estimation

Conversions and volume equations for pond pine were unable to be found within the literature. For this reason, data for loblolly pine was substituted. No conversions were done or estimated as the differences were considered to be negligible. Based on comparison data that was readily available, the volume equation that was used required height and diameter as inputs. An argument could be made for developing or finding within the literature a volume equation with only height as in input, however predicting diameter with our own model for the Hofmann was considered to be a more accurate approach.

After deliberation, a dry weight volume equation was used that used height and diameter as the inputs. Many different equations have been developed for loblolly pine estimation but the chosen equation was vetted against other data sets and looked to be the most accurate. This equation predicts the weight of the whole tree; wood, bark, and needles; versus other available equations that only predict the main stem of the tree. Both types of equations were accurate to a sufficient level that neither seemed superior and for the sake of quantifying as much carbon as possible, the whole tree equation was used.

3.1.5 Alternative Strategies

One potential change that may have yielded more accurate results would be using crown width and/or crown volume to predict diameter instead of, or in conjunction with height. The main reason height was used here was the simplicity of measurements both on the ground and with the LiDAR. There are several ways canopy width can be measured with LiDAR, including using a CHM in ArcGIS Pro, but none of these were done in this project due to time constraints. Combining multiple predictors such as height and crown width could have resulted in a higher accuracy for predicting diameter. While combining metrics to attempt to increase accuracy may be worthwhile, an estimation would need to be made based on the individual circumstance on whether the cost of adding this complexity would be outweighed by the benefit of a more accurate diameter prediction.

The component of the overstory that was not pond pine was where the most error was estimated to have occurred in this project. The only other overstory species prevalent was loblolly bay which has different growth habits and density compared to pond or loblolly pine, where the volume equations came from. The simplest way to estimate the bay component would be to establish several plots and measure the ratio of pine to bay. However, with the variation in the overstory and the large area, establishing enough plots to get an accurate estimate would defeat the purpose of using remote sensing to measure the trees. Another possible way would be to look at the growth habits of loblolly bay. From field observations, much of the bay tended to grow in clumps with multiple trees growing within a few feet of each other. So it may be possible to isolate the tree locations derived from the CHM that were within a set distance of each other and presume they are bay trees. This method would not be perfect but may be worth exploring more.

One final observation that was made which has no bearing on this research is the number of witches' brooms seen in the pond pines. In the several days spent on the Hofmann collecting data and making observations for planning the research, I believe I saw at least six witches' brooms. Knowing how rare these are to find in loblolly, it was intriguing how many were spotted on pond pine in such a limited amount of time spent on the forest. This has no meaning for this research but I felt was worth noting.

Figure 3.5: One of several noted witches' brooms growing from a pond pine on the Hofmann Forest.

3.1.6 Understory

For understory biomass/carbon estimation, understory LAI was used to attempt to correlate biomass. Using LAI for the predictor was a difficult choice but was ultimately chosen based on the available resources. R code for estimating LAI was readily available while other factors that may have been useful predictors, such as understory height, were not. Writing code to estimate height and then counting LiDAR pulses below that line would probably be one of the best ways to estimate understory density, especially with higher-density LiDAR data. That level of coding was above this project and LAI was used instead.

This LAI data collected for understory was designed for managed loblolly pine stands and not intended for use in a pocosin. Part of this project was to see if the methods used in loblolly pine plantations would transfer to a natural area such as the pocosin. Understory LAI was not specifically measured but instead total and overstory LAI were the focus of the research (Sumnall et al., 2021). Based on Figure 2.4 and the rounding of any negative LAI values to 0, there is an artificially high number of 0 LAI plots. This brings into question the accuracy of the estimated LAI.

The distribution of the data and the values look like what would be expected which is what led to this data still being used. In addition, the majority of these 0 values fell into the short area which was removed from the study due to an unusable correlation between LAI and biomass. The following Figure 3.6 shows the same graph as Figure 2.4 but with only the data in the tall area. This shows a significant decrease in plots with a value of 0. Future work could be in establishing a similar study to Dr. Sumnall's paper but for a pocosin. More work can still be done on these sparse areas with the existing code. A larger grid size than the 5 square meters used here or using total LAI on grid cells where no trees were plotted may be all that is needed to improve accuracy as this would increase the likelihood of a tree being in the grid cell to aid the model in identifying over versus understory.

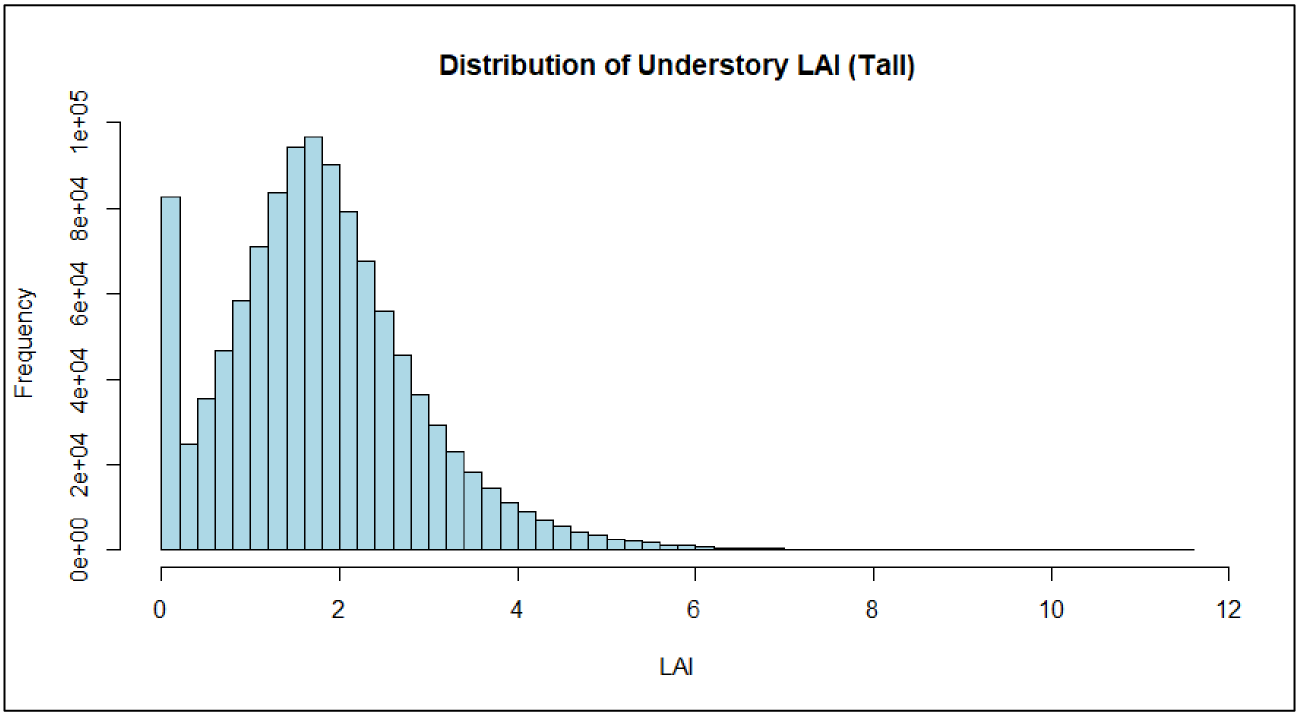

Figure 3.6: Distribution of understory LAI grid values for tall area only.

3.1.7 Plot Selection

Field plots were taken in mid-November when any deciduous vegetation had lost its leaves. Some of the specific species noted were wax myrtle, gallberry, smilax, sweet pepperbush, native bamboo, and different species of bay. The LiDAR data was taken in late December so although the two data collection events were three years apart, the season was the same. In total, 48 understory plots were measured but due to an error in the field, the exact ratios of plots measured versus the percent area covered were not met exactly. Below in Table 3.2 are the number of plots taken in each area.

Table 3.2: Number of plots taken in each understory area class.

Classification	Plots Measured	Percent Measured
Tall-High	2	4%
Tall-Medium	15	31%
Tall-Low	6	13%
Short-High	3	6%
Short-Medium	6	13%
Short-Low	16	33%

Due to the size of the pocosin being evaluated and the difficulty in moving through such a dense understory, a necessary bias was placed on how plots were selected. To penetrate into the pocosin to collect data, an existing trail system was used. An Argo with a scale mounted to a hoist on the back to weigh samples was used so that samples could be processed in the field. These trails were digitized as polygon features using ArcMap Pro. The trail system only existed in the lower portions of the pocosin which left some areas unsampled. The unsampled areas were comprised of equivalent vegetation and an effort to sample them was deemed unnecessary. These trails varied in width between two and five meters wide.

Once the trail polygons were delineated, grid cells located within a one-meter distance from the trail edge were identified and exported as potential plot locations. Subsequently, cells meeting any of the following criteria were excluded: those intersecting with the trail, within a 50-meter proximity to a road (considered a major ditch), or within 10 meters of the overstory delineation lines. Additionally, cells with an understory LAI value of 0 were omitted, as this was deemed an error in the initial calculation process.

Removal of these plots was negligible as they numbered so few. This left grid cells that were within at least one meter of the trail allowing for easy access to sample plots. This means the furthest distance could be a potential of 8.1 meters on the far side of the grid cell. After careful observation, it was determined that there was no noticeable change in the understory caused by being close to these trails. Mostly due to the trails being relatively new.

The selected plots were given identification numbers and a random number generator was used to select a subset plots for sampling. An additional forty plots were selected as spares in the event a plot could not be reached or if plots fell too close to one another. In that case, plots would be moved to promote as even of a distribution of plots across the landscape as possible. These plots were uploaded to ArcGIS online and a field map was created to use for navigating to the plots using an iPhone 11 as a higher quality GPS was not available.

3.1.8 Biomass Collection

Within the one square meter plot, brush, leaf litter, and down woody debris were collected and weighed on a hanging scale accurate to 0.1 kg. This scale was calibrated directly before entering the field. These three categories were weighed separately to allow for the stratification of the samples. Once the plot was located, a square PVC was placed to delineate the plot while collecting the biomass. The understory brush was harvested using a gas-powered hedge trimmer to improve accuracy when collecting the plots. Any woody material above 10 cm DBH was not harvested. This likely left a gap in the carbon estimation of the midstory however this was considered to be a relatively small amount. The leaf litter that was gathered was the loose leaves on top of the duff. Down woody debris was only found on three of the 44 plots and was eventually removed for the analysis as the high weight and low occurrence made the models unusable. The following figures show the process of cutting the brush and the before and after of removing the leaf litter.

Biomass Harvest: Austin Davis Pictured

Before Leaf Litter Collection

After Leaf Litter Collection

Figure 3.7: Images during understory biomass harvest.

Once the plots were harvested and weighed, sub-samples were taken and placed into 30-gallon paper bags. These bags were then weighed and chipped using a small wood chipper. Due to issues with the collection system, three of the 44 samples were lost. Once chipped, the samples were mixed and a sub-sample was collected in a small paper bag. These were placed in a dryer for approximately one week with measurements made at intervals until the samples stopped losing weight and were deemed dry. They were then weighed again to calculate a dry weight conversion. Two different approaches were then used to estimate carbon. The first method was sending ground sub-samples to a lab for carbon analysis. These results can be seen in the methods section of chapter two as they were used for the final analysis and the carbon predicting model in Table 2.9. The second analysis method was placing ground samples into a muffle furnace.

3.1.9 Muffle Furnace

Using the muffle furnace, a total of 30 samples were burned in two batches for loss on ignition testing. 20 samples from the tall overstory and 10 from the short. Only ten samples from the short overstory area were processed due to space in the furnace and because at the time of this testing, it was known no correlation existed between LAI and understory biomass. All 30 samples were averaged together as the understory vegetation was the same so differences in carbon content should be nonexistent. Samples had an average weight of 6.259 g and were burned for 12-16 hours at 500° Celsius (FPC 2023, as cited in Westerman 1990). After the loss on ignition test was complete, carbon was estimated as 58% of the biomass lost (Nelson and Sommers 1996). No correlation was found between LAI and biomass for short overstory. For tall overstory, an R^2 value of 0.40 and a p-value of 0.0028 was found for dry weight. Carbon content had a better correlation with an R^2 value of 0.54 and a p-value of 0.0002. Figure 3.8 below shows the samples before and after burning in the muffle furnace.

Figure 3.8: Ground Understory Biomass Samples Before and After Entering the Muffle Furnace

The issue with this type of test is it is intended for soil samples. The ignition process is intended to show how much organic matter was in a soil sample but with the samples from this study, there was no mineral content. So the results just showed how much ash there was and used a different carbon conversion based on this. Ultimately sending the samples off for carbon analysis was the most accurate way but if that could not have been done, I would recommend using the standard 0.5 conversion for dry weight versus burning the samples and using the 0.58 (Nelson and Sommers 1996) used for loss on ignition. Looking at the biomass samples both ways, the 0.58 conversion from biomass lost compared to the 0.5 conversion for dry weight resulted in an average carbon content of 12% greater using 0.58. Comparing this to the average carbon content from the lab of 45.54%, the loss on the ignition test would have greatly overestimated the carbon content in the pocosin.

CHAPTER FOUR: CONCLUSION AND FUTURE GUIDELINES

This thesis aimed, and to a degree succeeded, to establish a methodology for predicting carbon in a pocosin in eastern North Carolina using LiDAR. This was successively done for overstory with fairly little difficulty. Understory proved more difficult as would be expected and was only applicable in areas of tall overstory. Biomass in areas with short overstory was unable to be predicted based on these methods, but this does not mean there is no correlation between LAI and biomass in these areas.

Based on this research, anyone who wishes to predict carbon in a pocosin should be able to use these methods for an accurate estimation. These methods should also be adaptable for other forest types. One difficulty in adapting this procedure would be using the overstory tree count in areas with a more diverse overstory. As stated, these methods treated all overstory trees as pond pine, ignoring any species differences. In an area such as an upland hardwood, it would be difficult to justify only using volume equations for one species.

Understory may also be challenging to adapt but as long as there is a defined understory and an overstory, the model used here should still be able to estimate LAI for the understory component of a stand (Sumnall et al., 2021). Creating a custom model based on geographical area and vegetation type would be necessary. Using the calculated models calculated in Table 2.9, accurate carbon estimation for pocosin areas should be attainable. Discretion should be used when applying this model two areas depending on their distance from the Hofmann Forest. For any other ecosystem, a new model would need to be made. Without consistency in the carbon market, it is difficult to predict how useful this model will be. A cost-benefit analysis will need to be done to determine whether the estimated understory carbon is enough to offset the cost of estimating.

For understory biomass estimation, LiDAR is the only possible way to directly measure understory variables using remote sensing. It may be possible to predict understory based on overstory measurements but this does not seem likely. It may also be possible to use FIA data to predict models for different types of ecosystems. As FIA plot locations are typically kept confidential, this may be difficult. However, the wealth of data collected from this program is too tempting to ignore.

For overstory measurements, passive remote sensing may be easily substituted for active remote sensing. Photogrammetry, a type of passive remote sensing, is easier and cheaper to obtain than LiDAR and therefore more desirable by the industry. Photos are also easier to work with than raw LiDAR data. Less skill in a decreased need for computing power could potentially allow individual foresters these types of measurements on their own. Future work for measuring overstory, either for carbon or logs for wood products, should focus on this.

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APPENDICES

Appendix 1: R code for overstory tree count

```
###Tree count code for tall pocosin on the Hofmann Forest
###Jacob Bost
###Spring 2024

###clear memory and console
rm(list=ls())
cat("\014")

###load packages
library(lidR)
library(terra)

###Set Working Directory
setwd("C:\\LiDAR")

### read las or laz files into R
las = readLAScatalog("raw_lidar")

###add shapefile to clip LiDAR data
AOI = vect("Shapefiles\\shapefile.shp")

###create rasters and write them
DEM = rasterize_canopy(las, res = 1, p2r(0.15), pkg = "terra")
DTM = rasterize_terrain(las, res = 1, algorithm = lidR::tin())
CHM = DEM-DTM

###save raster to file
writeRaster(CHM,filename = "CHM.tif")

###CHM edits made in ArcGIS Pro

###write a CHM directly in
CHM0_30 = raster::raster("file_location\\chm0-30m.tif")
plot(CHM0_30)

###clip raster
cropped_CHM = crop(CHM0_30, AOI) ###this sets a rectangular box at the maximum extents of the data; makes mask more efficent
clipped_CHM = mask(CHM0_30, AOI) ###this is the "cookie cutter" function for clipping an irregular shape

###save clipped raster
writeraster(clipped_CHM, filename = "Clipped_CHM.tif")

### detect trees with CHM
f2 = function(x) {x*0.05+3}
tree_tops = locate_trees(CHM0_30, lmf(f2, hmin = 5))

###calculate diameter and for CI; 2.099301= calculated confidence interval from measured trees in excel
tree_tops$Predicted_DBH_cm = (2.072*tree_tops$Ht_m) + 4.915
tree_tops$`Upper95%CI_DBH_cm` = ((2.072*tree_tops$Ht_m) + 4.915)+2.099601
tree_tops$`Lower95%CI_DBH_cm` = ((2.072*tree_tops$Ht_m) + 4.915)-2.099601

###Dry weight Gonzalez-Benecke
tree_tops$`DryWeight(tonnes)` = (0.026256*(tree_tops$Predicted_DBH_cm^2.015144)*(tree_tops$Ht_m^0.864052))*0.001
tree_tops$`DryWeightUpper95%CI(tonnes)` = (0.026256*(tree_tops$`Upper95%CI_DBH_cm`^2.015144)*(tree_tops$Ht_m^0.864052))*0.001
tree_tops$`DryWeightLower95%CI(tonnes)` = (0.026256*(tree_tops$`Lower95%CI_DBH_cm`^2.015144)*(tree_tops$Ht_m^0.864052))*0.001

###Carbon Conversion
tree_tops$`Carbon(tonnes)` = tree_tops$`DryWeight(tonnes)` * 0.5
tree_tops$`Upper95%CI_Carbon(tonnes)` = tree_tops$`DryWeightUpper95%CI(tonnes)` * 0.5
tree_tops$`Lower95%CI_Carbon(tonnes)` = tree_tops$`DryWeightLower95%CI(tonnes)` * 0.5
```

```
###Sum Carbon
Carbon_Tonnes = sum(tree_tops$`Carbon(tonnes)`)
`Carbon_Tonnes_Upper95%CI` = sum(tree_tops$`Upper95%CI_Carbon(tonnes)`)
`Carbon_Tonnes_Lower95%CI` = sum(tree_tops$`Lower95%CI_Carbon(tonnes)`)

###save data as R file
saveRDS(tree_tops,file = "tree_tops_with_C.RDS")
```