Effects of stand attributes in evaluating even-aged loblolly pine volume with LiDAR

By;

Sarah F. Hagan

advised by:

Dr. Nicolette Cagle
&
Dr. Jennifer Swenson

April 28, 2017

Masters project submitted in partial fulfillment of the

requirements for the Master of Environmental Management degree in

the Nicholas School of the Environment of

Duke University

Effects of stand attributes in evaluating even-aged loblolly pine volume with LiDAR

Abstract

The purpose of this project is to determine the practicality of using LiDAR technology in the field as a primary tool for forest inventory. Specifically, this project uses variables generated from Quality Level 2 (QL2) LiDAR data obtained from the state of North Carolina Floodplain Mapping Program to investigate the overall goodness of fit of Loblolly pine volume based on ground measurements. Seven stands in the Piedmont and coastal regions in North Carolina were used in this study. Volume was calculated using pre-harvest cruise data and was regressed against the LiDAR generated predictors of height and canopy cover. The analysis was conducted on both plot level and at a mid-sized management level, of theoretical harvest units (THUs). These LiDAR derived variables were only moderately successful at estimating loblolly pine volume at the plot level (R^2 =0.45) and at the THU level (R^2 = 0.37). When ground calculated height was regressed against LiDAR estimated height, no bias was detected indicating that while model fit was modest, the overall approach was correct.

Introduction

Though overall trends indicate a decline in US economic contributions to the global forest products industry (Prestemon et al., 2015), forest products have contributed $912 million to the state of North Carolina alone, making it the state's top manufacturing industry. Contrary to most US trends, North Carolina timber prices are high; paper products lead in the state's domestic and export markets, and market demands for North Carolina timber, fluff, and pulp are expected to continue to rise (McConnell et al., 2016). In a high value industry that encompasses everything from construction material to bathroom tissue to biofuel, it is essential to begin discerning what sort of product an individual tree will become and how much it is worth from the very early years of a tree's growth. The dominant timber tree in the American southeast is Loblolly pine (*Pinus taeda*) and about 2.7 million acres (over 14%) of North Carolina is dedicated to growing these trees solely as sustainable forest products in pine plantation. (McConnell et al., 2016).

Determining the worth of one's trees is usually measured in ascertaining tree quality, its potential marketability, and calculating the volume of timber on a given stand. In the American southeast, this is done by cruising timber manually. Individuals visit each stand and take measurements to determine overall stand representation. These manual measurements can be time and labor intensive, and human error is a constant battle in calculating accurate volume assessments.

In the southeastern United States and elsewhere, point sample prism timber cruising is a commonly used field measurement technique due to its simplicity and time effectiveness. Point sampling has no fixed plot radius and the plot size depends on the tree sizes themselves. Large trees are sampled over a larger area and smaller trees over a smaller area because the technique is based upon a tree's basal area, or cross-sectional area at breast height, rather than their abundance (Avery & Burkhart, 2002). In plantation pine forests, one can expect trees to be fairly uniform in height and DBH (diameter at breast height) so it makes sense that a method which samples according to the area of the tree, would be a fairly accurate method with which to collect data.

Prism cruising is an ideal field method technique for the reasons mentioned above, but there are drawbacks to using it in a study comparing data derived from field gathered data to airborne derived data. First, as mentioned above, there is no set radius for plots taken using point sampling. Also, when underbrush restricts line-of-sight and visibility, the accuracy of cruise measurements drop. Related to this is that point sampling collects comparatively fewer data points than does fixed plot sampling and when a cruiser is careless in measurements, mistakes take on greater weight as they are calculated to apply at stand scale (Avery & Burkhart, 2002).

As early as the 1980s and 90s scientists and foresters recognized the potential of LiDAR (light detection and ranging) in streamlining the efficiency of forest measurements. Traditional forest measurement techniques are carried out in the field using manpower. These techniques are both time and labor intensive and end up costing money both in the field and at harvest if measurements were taken incorrectly. LiDAR has the potential to both reduce the time that it takes to estimate volume for a particular stand and even increase the accuracy of those volume measurements.

According to the National Oceanic and Atmospheric Administration, LiDAR is "a remote sensing method that uses light in the form of a pulsed laser to measure ranges (variable distances) to the Earth. These light pulses—combined with other data recorded by the airborne system— generate precise, three-dimensional information about the shape of the Earth and its surface characteristics." (National Ocean Service). Other countries with economies with a significant stake in forest products such as New Zealand, South Africa, and Scandinavian countries have begun to test and use LiDAR as a primary tool in determining timber volume.

While some countries outside of our own have integrated LiDAR as a standard tool for forest measurements, the United States is still very much stuck in the realm of the theoretical in terms of published research. Only a few US studies focused testing LiDAR's capabilities in a practical sense (Deo et al., 2016 Roberts et al., 2005). We have moved on from viewing LiDAR as a simply a tool with "strong application potential in forest resource management" (Evans et al., 2006), however much of the research existing within the United States hardly exceeds the boundaries of the metaphorical lab. In that 2006 review for the Forestry Chronical, Evans et al .(2006) discussed the viability of LiDAR becoming the newest tool for forest measurements in the US when two years prior, the Norwegians had already successfully tested the first large-scale operational project using LiDAR as the primary inventory tool (Naesset 2004).

One of the few examples of practical application studies within the US examined the accuracy of using variable radius prism plot cruise data against traditional fixed radius plot field data (Deo et al, 2016). Although fixed radius plots have an obvious advantage when being compared to spatial data obtained from overflights (such as LiDAR), variable radius plots are more practical as the fast efficient field surveys of choice of timber companies. Deo et al. found that while variable radius plots are the most accurate choice when conducting a timber volume study with LiDAR, BAF 10 prism cruising was the optimal variable radius option (Deo et al., 2016). This study serves at the first link between practical, commonly used forest measurement techniques and LiDAR analysis.

LiDAR is a tool that has been shown to not only accurately model and predict timber volume but has the potential to significantly reduce the time and labor spent in methods traditionally associated with southeast timber field measurements. While many studies have accurately modeled and predicted volume using LiDAR in numerous combinations, the specific goal of this study was to determine whether the North Carolina Quality Level 2 (QL2) dataset can accurately estimate timber volume calculated from common-practice southeastern plantation pine field measurements. Quality Level 2 means that this data source is of a lower, coarser quality (2 pulses/m^2) than that of some LiDAR datasets (more than 10 pulses/m^2): it was collected and distributed by the state of North Carolina to be free and open to the public.

Canopy height and canopy cover density are probably the two most important determinants of volume when using LiDAR (Naesset, 1997; Nelson et al, 1988). Nelson et al. (1988) calculated stand timber volume within 3% of field-measured volume using lidar derived height and canopy cover variables, with canopy cover only having a marginal effect on the outcome. However, they concluded that DBH was still needed to determine volume at plot level and that the height-diameter relationships related to volume are region specific. Nine years later, Naesset (1997) concluded that LiDAR footprint, or distance between scanning lines (which also determines point spacing - tighter distance, tighter spacing) (Gatziolis & Anderson, 2008) may play a significant role in canopy cover's significance in predicting canopy cover. While height explained most of the variation in volume amongst stands, canopy cover seemed to make a significant impact for Naesset. Nelson had used a larger footprint dataset and found less of an effect of canopy cover on estimating volume.

In a more recent study, researchers compared LiDAR estimated volume to final harvest weights and found that LiDAR slightly overestimated volume by 0.6% compared to traditional method's underestimation of 19.8%. This study used a combination of LiDAR derived height and canopy cover variables to determine volume. The dominant species in this study was Lodgepole pine (*Pinus contorta,* White et al, 2010). In another study looking at volume estimation of *Eucalyptus grandis* in South Africa, researchers used LiDAR-derived height variables to determine tree DBH and BA based on existing relationships between all variables and stand stocking. Researchers were able to accurately estimate volume using these variables, though they also noted underestimations of volume. This underestimation was attributed to the inability of LiDAR to pick up the smaller (though merchantable) trees that exist beneath the canopy (Tesfamichael et al., 2010).

The aim of this research is to act as a pilot study to determine the degree to which LiDAR is capable of estimating plantation Loblolly pine volume. Specifically, the goal is determine whether the QL2 dataset is capable of producing variables, height and canopy cover, that will estimate volume calculated from variable radius plot cruise data.

Materials and Methods

Study Area

This study examines the pre-harvest timber volume of seven plantation loblolly pine stands planted between 1980 and 1990 ranging from 50 to 200 acres. The seven stands were cruised in the summer and fall of 2014. Three of the stands are located in the southern Piedmont of North Carolina and the four remaining stands are in North Carolina's coastal plain (Figure 1). A total of 159 plots were cruised, representing 915.9 acres of plantation loblolly pine (Table 1).

Table 1: Summary of stands

Stand	Species	Year Planted	Date Cruised	County	Area(acres)	Number of plots
1	Loblolly	1988	9/15/2014	Richmond	148.34	30
2	Loblolly	1988	11/21/2014	Richmond	201.41	33
3	Loblolly	1988	9/16/2014	Richmond	193.16	31
4	Loblolly	1980	7/25/2014	Sampson	53.95	23
5	Loblolly	1990	10/20/2014	Brunswick	129.83	14
6	Loblolly	1990	8/29/2014	Brunswick	108.99	15
7	Loblolly	1983	11/28/2014	Brunswick	80.28	13
				Total	**915.97**	**159**

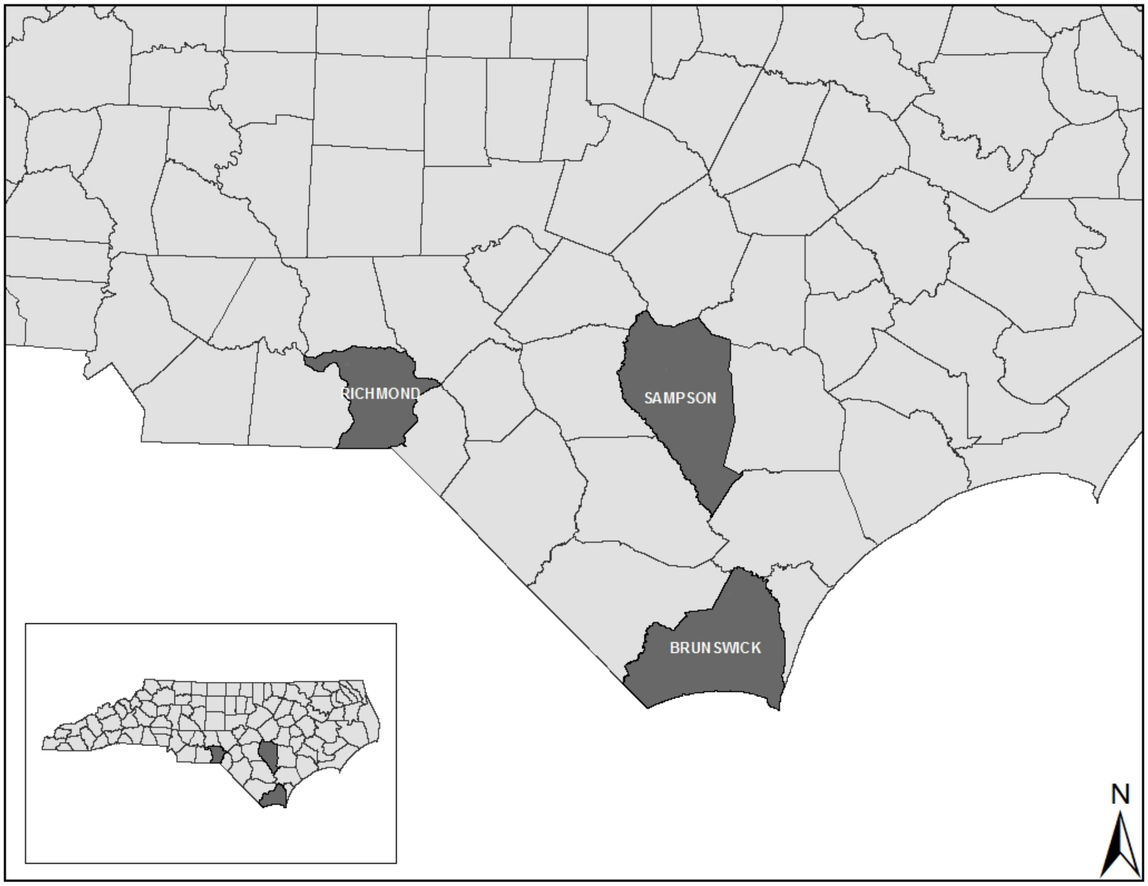

Figure 1: Study Area

Cruise Design

I obtained the pre-harvest cruise data from a private timber management firm in coastal North Carolina. The company from which this data was obtained uses internal cruise designing and timber modeling software. When designing cruises, the company determines acceptable confidence intervals and error by looking at stand density. In stands of greater than 80 tons/acre, the preferred confidence is 90% with an accepted error of +/-10% of the total pine volume. In stands of less than 80 tons/acre, confidence is again 90% but an absolute error of +/-8 tons/acre. The reason for this being that the 10% rule was too costly to reach in lower density stands. In stands with lower density, the confidence interval tightens, requiring an increase in the number of plots to satisfy it. The company's statisticians found that increasing the number of cruise plots solely on stand size did not necessarily produce results that are more accurate and that putting too many plots in small stands was a costly practice. They came up with the following guidelines to help foresters in designing cruises:

Acres <= 3	**3 points total**
Acres 3-10	**1 point/acre**
Acres > 10	**Minimum of 10 points, Maximum of 1 point/acre**

Final harvest cruises are laid out on either a square or rectangular grid and are conducted using the point sampling technique. In North Carolina, in particular, final harvest cruises are carried out at the discretion of the regional forester.

Field Measurements

Cruisers used a 10 basal area factor (BAF) prism and followed the basic point sampling technique as outlined by Avery and Burkhart (2002). When cruising, all "in" trees with a DBH >1 inch were recorded. Trees < 5 inches were considered 'precommercial', 5-8 inches was considered 'pulpwood', 9-11 inches was considered 'chip and saw', and anything over 12 inches was considered sawtimber, depending on tree quality. Total height for all hardwood and pine over 6 inches in diameter were recorded. If a pine had a broken top, forked top, or other defect affecting merchantable height, height was recorded at the defect. Cruisers took a GPS point at each plot center.

Volume Calculations

Only loblolly pine trees with a diameter of 6 inches and above with recorded heights were included in this analysis. Two plots were excluded from analysis because none of the trees in the plot met the above requirements. I used Clark and Saucier's (1990) volume equations for southern pines in the southeast to calculate merchantable volume to a 4-inch top outside of bark (Clark & Saucier, 1990). (Table 2)

Table 2: Plot Averages of field measurement variables including individual tree merchantable volume

Stand	1	2	3	4	5	6	7
DBH (in)	10.31	10.55	12.04	14.68	11.66	10.60	14.73
Height (ft)	64.42	65.33	70.18	71.99	60.98	63.76	77.10
Volume (cuft)	14.77	15.56	22.02	35.90	18.33	15.78	36.23

Extracting LiDAR Variables

The LiDAR data used in this analysis is free and open to the public. The data was compiled by the North Carolina Risk Management Office with the North Carolina Department of Transportation along with the US Geological Survey (USGS). The LiDAR data was collected in the spring of 2014 in leaf-off conditions with traditional linear aerial sensors at an average of two points per meter with an accuracy of

9.25 cm (3.36 in) RMSEz for non-vegetated areas. All data were projected in the North Carolina State Plane Coordinate System, with a horizontal datum of NAD83(2011) and vertical datum of NAVD88 (Geoid 12A), US survey feet.

Before beginning my LiDAR analysis, it was necessary to determine a consistent plot area to use to determine height and canopy cover. Cruising with 10 BAF prisms is a time effective way to collect a representative sample of trees to reflect the stocking of the stand by size class. However, there is no fixed plot size. Plot size can be approximated by multiplying the average DBH by the prisms' plot radius factor, which in this case is 2.75 (Avery & Burkhart, 2002). When choosing a prism angle, one generally aims to have between 5 and 12 "in" trees per plot (Avery & Burkhart, 2002), but this not a hard and fast rule. In this data set plots range from two to eighteen merchantable trees per plot. I used the overall average DBH of 10.3 inches to determine an overall plot size of $1/17^{th}$ acre to use for LiDAR analysis.

All analysis of LiDAR data was carried out using ESRI ArcMap 10.5 (ESRI, 2016). Data was obtained from the North Carolina Spatial Data Download database. Bare earth and above ground class Quality Level 2 .LAS files were downloaded for each stand.

HEIGHT

To determine height from LiDAR analysis, I created a 6 x 6m raster Canopy Height Model (CHM) representing maximum height. To do this, I used the bare earth .LAS files to create a 6m digital terrain model (DTM) to represent the ground surface. I created a digital surface model (DSM), using only first lidar returns classified as vegetation to represent the surface of the canopy. To create each CHM, DTM was subtracted from the DSM to determine difference in elevation, or in this case, tree height. (Figure 2)

Once I determined an overall maximum CHM for each stand, I extracted zonal height statistics by buffering each GPS plot center to a radius of 28.26 ft. This allowed me to obtain an average maximum height for each $1/17^{th}$ acre plot.

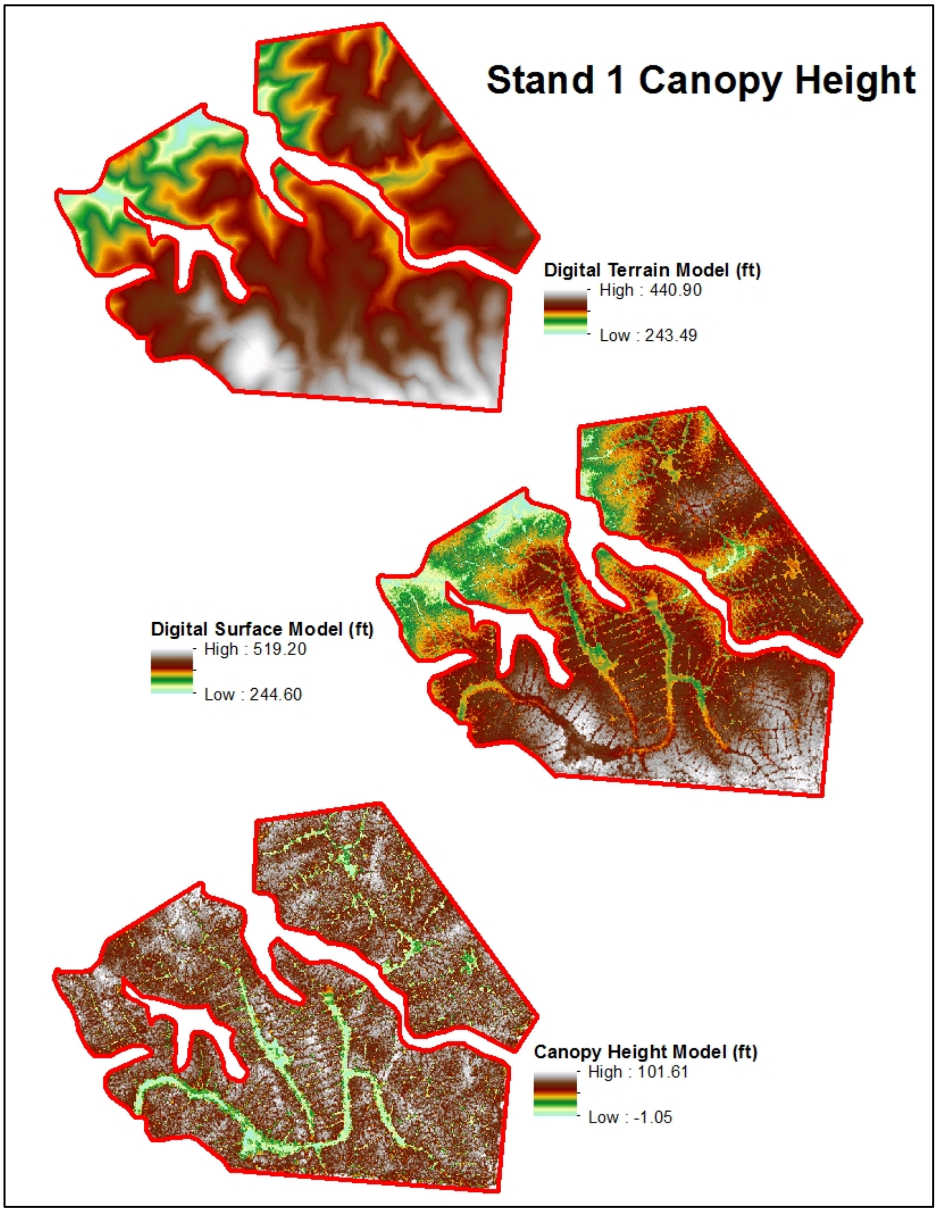

Figure 2: DTM, DSM, and CHM for Stand 1

CANOPY COVER

To determine canopy cover, I created 6 x 6m rasters from the bare earth and aboveground data using LAS point statistics as Raster. This tool averages the points within the 6 x 6m cells for returns and classes indicated. I created a ground point count raster using the bare earth dataset and ground classes only. To create a canopy point count, I used only vegetation classes and first returns. I got a total point count by adding ground and canopy together. To determine canopy cover itself, I simply divided the canopy point count by the total point count. Canopy cover is essentially the percentage of ground area covered by a tree's canopy, and so this process produced values between 0 and 1, representing the percentage of area covered. (Figure 3) Once overall canopy cover was determined for each stand, I extracted zonal canopy coverage statistics by buffering each plot center with a radius of 28.26 ft.

Plot averages for the individual stand are summarized in Table 3.

Table 3: Plot averages of LiDAR variables

Stand	1	2	3	4	5	6	7
Max Height (ft)	71.79	68.88	75.79	73.76	64.39	62.12	81.95
Canopy Cover (%)	0.67	0.64	0.70	0.87	0.70	0.79	0.87

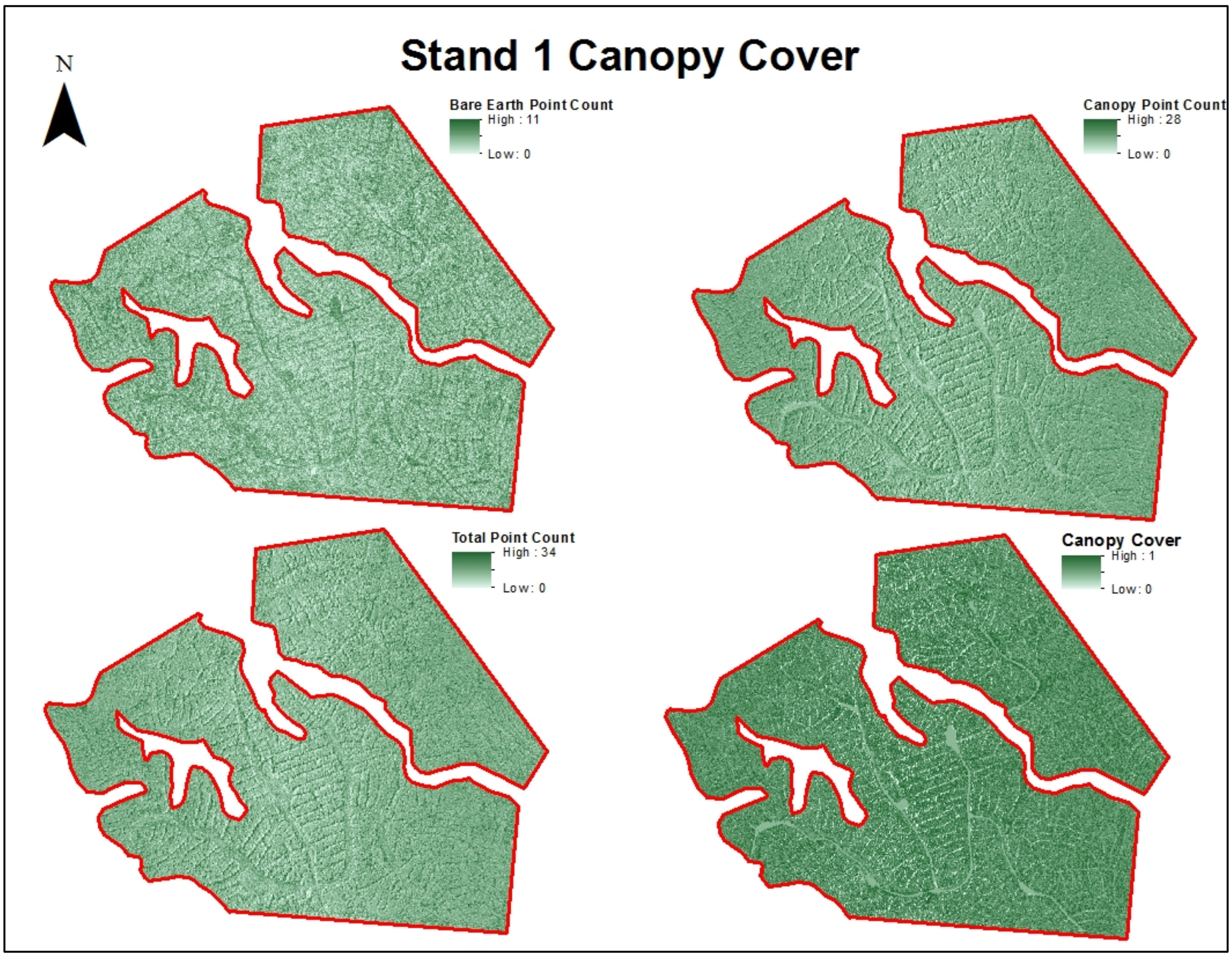

Figure 3: Point count rasters used to determine Canopy Cover

Data Analysis

PLOT LEVEL

I examined the goodness of fit of LiDAR derived height and canopy cover at plot level in predicting timber volume totals derived from field measurements using a multiple regression analysis. Height and canopy covered were evaluated as individual variables and as interacting variables in each scenario. I tested twelve models exploring the effects of stand age and region on the fit of the model. RStudio (RStudio Team, 2015) was used in this analysis.

$$y = \propto + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$$

$$y = \propto + \beta_1 x_1 + \beta_2 x_2 + (\beta_3 x_1 x_2) + \varepsilon$$

The first models examined the goodness of fit of height and canopy cover to predict volume over all seven stands (157 plots). The five remaining models broke the data into subsets looking at goodness of fit of the models in the Piedmont (93 plots), Coastal Plain (64 plots), 25 year age class (29 plots), 30 year age class (93 plots), and 35 year age class (35 plots). (Table 4) The stands were grouped according to age class in a five year increments. Age class was determined to be the age at which the trees would have been in 2014 when the field data was collected and the LiDAR flown.

Table 4: Number of plots per stand attribute subset

	25 Year AC	30 Year AC	35 Year AC
Piedmont	0	93	0
Coastal Plain	29	0	35

THEORETICAL HARVEST UNITS

Besides examining fit at the plot level I also evaluated height and canopy cover against volume at a mid-range management unit that I am calling Theoretical Harvest Units (THUs). These THUs represent a portion of a stand that could be cut in times of market saturation, undesirable weather conditions, or economic uncertainty. I divided each stand into an appropriate number of THUs based on factors such as accessibility, existing logging decks, streams and ditching systems, and boundary lines. (Table 5) There were a total of 17 THUs in the final analysis.

Table 5: THU Analysis Variables

THU	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Height	55.30	55.34	54.53	57.56	51.78	49.54	51.48	60.40	60.30	50.87	54.00	47.99	52.10	50.83	47.28	65.06	61.00
CC	0.69	0.68	0.69	0.68	0.63	0.63	0.63	0.72	0.69	0.90	0.85	0.75	0.67	0.81	0.79	0.89	0.87
VOL(cf)	111,553	171,945	134,124	71,603	168,090	126,335	171,365	248,570	462,228	52,129	72,046	120,437	46,726	184,293	100,600	127,292	82,040

Results

Field Measurements

Using individual tree height and DBH, I calculated merchantable volume to a 4 inch top for each tree in the seven stands and used the plot average in this analysis. Stands 4 & 7 (the two oldest stands) had the most volume and largest trees. The two youngest stands (5 & 6) were roughly comparable to the in between-aged stands 1-3. (Table 2) To determine overall THU volume, I used traditional point sampling calculations as outlined by Avery & Burkhart and George Oderwald (Avery & Burkhart, 2002; Oderwald, 1990) (Table 5).

LiDAR Variables

LiDAR estimated a higher canopy than did field measurements (Table 3). The two oldest stands again had the highest canopy cover while stand 1 & 2 had the lowest.

Data Analysis

PLOT LEVEL

When I combined height and canopy cover as the main effects in a multiple regression to assess volume, overall goodness of fit rose, which indicates that canopy cover has at least some effect on predicting volume. I assessed the two variables as separate predictors and as an interaction. When the analysis accounted for the interaction between height and canopy cover, the fit of the model rose in all data groupings. I obtained an R^2 value of 0.45 explaining the interaction of height and canopy cover in predicting volume over all 157 plots, with p-values less than 0.0001. When broken down into stand attribute data subsets, R^2 values ranged from 0.00 (35-year age class, no interaction) to 0.57 (25-year age class with and without an interaction term) (Table 6). Besides the interaction model for all seven stands, the model performed the best in terms of fit *and* significance was the multiple regression for coastal stands (no interaction). This model returned an R^2 of 0.50 with intercept and maximum height coefficient p-values less than 0.001 and a canopy cover coefficient p-value less than 0.05.

The overall model returned results of high significance from both models and it follows that when the data is broken down into smaller subsets, significance is affected. The 25-year age-class stands have a lower significance, in part because they are the smallest sub-sample size, while the piedmont is the largest sub-sample.

Table 6: Multiple regressions examining LiDAR derived height and canopy cover as predictors of volume
(x) indicates an interaction term

	All Stands	All Stands(x)	Piedmont	Piedmont(x)	Coast	Coast(x)	25	25(x)	30	30(x)	35	35(x)
(Intercept)	-42.44 ***	148.75 ***	3.52	199.22 **	-55.44 ***	-130.27	3.79	-2.90	3.52	199.22 **	35.13	-167.52
	(6.77)	(44.22)	(6.01)	(60.91)	(11.73)	(115.09)	(13.65)	(61.93)	(6.01)	(60.91)	(28.39)	(291.97)
MAXHt	0.45 ***	-2.23 ***	0.29 ***	-2.49 **	0.84 ***	1.91	0.42 ***	0.52	0.29 ***	-2.49 **	0.09	2.85
	(0.08)	(0.62)	(0.08)	(0.86)	(0.13)	(1.63)	(0.11)	(0.94)	(0.08)	(0.86)	(0.30)	(3.96)
CanCov	43.76 ***	-208.38 ***	-10.23	-298.57 **	29.34 *	119.93	-18.74	-10.17	-10.23	-298.57 **	-5.89	230.38
	(6.49)	(58.02)	(8.23)	(89.68)	(13.49)	(139.27)	(11.45)	(78.25)	(8.23)	(89.68)	(25.35)	(339.74)
MAXHt:CanCov		3.53 ***		4.08 **		-1.28		-0.13		4.08 **		-3.21
		(0.81)		(1.26)		(1.96)		(1.20)		(1.26)		(4.60)
R^2	0.38	0.45	0.14	0.23	0.50	0.51	0.57	0.57	0.14	0.23	0.00	0.02
Adj. R^2	0.38	0.44	0.12	0.21	0.49	0.48	0.54	0.52	0.12	0.21	-0.06	-0.08
Num. obs.	157	157	93	93	64	64	29	29	93	93	35	35
RMSE	8.25	7.80	4.70	4.47	9.39	9.44	3.79	3.87	4.70	4.47	9.94	10.02

*** p < 0.001, ** p < 0.01, * p < 0.05

THEORETICAL HARVEST UNITS

I calculated average height and canopy cover, and total merchantable volume for each individual unit and analyzed both the multiple regression and multiple regression with interaction term. When I scaled up in area to THUs, I saw some differences in fit. When examining this larger unit area, fit of the model went down (Table 7).

Table 7: Plot vs THU analysis results

	Plot Level		THU Level	
Variable	**Ht+CC**	**Ht*CC**	**Ht+CC**	**Ht*CC**
Intercept	21.85***	21.21**	144199***	152010***
Height	0.45***	0.34***	8076	11918*
CanCov	43.76***	43.89***	-405896	-392959
Ht*CC		3.53***		-74981
R^2	0.38	0.45	0.25	0.37

Discussion

It is surprising that the goodness of fit between plot level and THU went down rather than increased (R^2=0.47 to R^2=0.37 with interaction). One very prominent reason for this could be fact that if there are mistakes made while cruising using the point sampling technique, they will only magnify themselves as they are scaled up (Avery & Burkhart, 2002). It could be that the volume calculations while accurate at plot level, simply fell short once scale up. It would be interesting to see how this method would apply with sufficient stands to test.

Similar studies have seen low fit like I found. Early tests of LiDAR that used similar approaches (using height and canopy cover to estimate volume) produced R^2s=0.47 (Nelson, 1988), and 0.472 (Naesset, 1997) with majority conifer stands. These studies were conducted in the early days of LiDAR technology and also were tested on the basis of fixed radius plot field data. Newer, comparable studies far exceed my findings. However, I am using a coarser resolution data and I use field data based on variable radius plots rather than fixed radius plots.

As I have addressed goodness of fit results and in the above paragraph, I have referred to the results of the model including the interaction term. The difference in the two models is simple; the multiple regression with only height and canopy cover as main effects looks at the individual terms on their own and determines how each alone estimates volume. When the interaction term is added, the model immediately determines how height affects canopy cover and vice versa and how *that* relationship between the two improves or impairs the model.

In the case of this dataset (for the most part) the relationship between height and canopy cover improve the model's estimation of volume indicating that both variables have some sort of affect individually, and more importantly, their combined relationship adds fit. I say for the most part, because in the analysis of 25-year-old stands, the interaction term actually had no affect on the fit of the model (Table 6). I believe that this particular idiosyncrasy has to do with those particular stands' location and regional effects. For example, studies have suggested that variables such as stand density, stand age, topography, and site quality (Naesset 1997, 2001; White et al, 2014) have the ability to influence LiDAR's effectiveness in determining volume. While I was limited by my quantity of data, I believe some of differences in model fit might be attributed to some of these regional and stand effects.

Fit for coastal stands rose to R^2=0.51 with the interaction term compared to overall fit of Piedmont stands R^2=0.23. And while the age distributions among my stands made an age analysis moot, it happened that both 25-year and 35-year stands were located in different areas within the coastal region, so a subregional analysis also took place by happy accident. The 25-year stands, 5 & 6, are located adjacent to each other while 35-year stands, 4 & 7, are located 60 miles from each other in separate counties, though both technically coastal. While fit for the 25-year stands went up from overall coastal fit (R^2=0.51 to 0.57), fit for 35-year stands went down, markedly (R^2=0.51 to 0.02). It is impossible to say what specific variable is responsible for the differences in fit, though there are significant differences between piedmont and coastal plain and even within the coastal plain region itself. These differences include things such as topography, site index, vegetation ecology in the understory, soils, and even tree genetics. Further study is needed to determine how these variables affect volume estimation in southeastern loblolly pine.

No model seemed to fit the 35-year age class well. Besides regional effects, another explanation for the poor fit is because the 35-year age class actually consisted of two different planting years. While the 25 and 30-year age classes were planted in 1990 and 1988, respectively, the stands making up the 35-year age class were planted in 1980 and 1983, respectively. Difference in age and especially that difference in location could account for the model's poor performance. A larger sample size would have been ideal in this circumstance in order to narrow down the possibilities of what was causing the models' poor fit.

I would also hypothesize that extreme weather events could influence LiDAR's effectiveness in determining volume. Stands 5 and 6 are located just about 12 miles north of North Carolina's south facing coastline in Brunswick County. Between the years 1991-2014, 18 hurricanes either struck or passed within 50 nautical miles of these two stands. These stands took nearly direct hits in 1996 with Hurricane Fran and in 2006 with Hurricane Ernesto, (NOAA, 2017). Extreme weather events such as hurricanes and ice storms can do a great deal of damage to any tree. When hurricane force winds sweep through or heavy ice settles in treetops, branches and even leader stems snap and entire trees and come down. Industrial plantation loblolly are genetically bred for quick rotation and high quality logs specifically for the region in which they are planted. A southeastern loblolly is not necessarily bred to withstand the rare winter weather events it may face, and that is something a landowner must weigh against productivity.

More recent studies have begun to focus on individual tree measurements that contribute to volume, sawlog volume, and effects of plot radius on determining overall volume. One such study determined that volume estimations were not significantly affected when plots dropped below 0.074 acres. But as noted above, my study was comprised of 1/17th acre plots, which is the equivalent to 0.059 acres (Watt & Watt, 2016). Fine resolution LiDAR is also in the early stages of being able to detect individual tree DBH (Rabadán et al., 2016).

As mentioned above, researchers have finally turned to study the obvious affects of variable radius plots (VRP). While VRP accuracy isn't as high as fixed radius plots (FRP), they have the ability to be assessed against LiDAR data (Deo et al, 2016). Deo et al. (2016) examined the effectiveness of several different VRP BAF angle sizes, ultimately determining that, in their region, BAF 10 is not only the least biased of the prism factors they tested, but it also produced volume estimates statistically consistent with FRP results. They concluded that the reason for this was that in older stands with larger DBHs, BAF 10 was able to tally at least 4 trees per plot, while other BAFs were not. (Which is nearly consistent with Avery & Burkhart's recommendation of 5-12 trees per plot for BAF 10.) Deo et al. (2016) also suggest that VRP are probably only effective in these older, larger DBH stands.

When Deo et al. (2016) examined older stands at plot level with max DBHs ranging between 13 and 32 inches at a plot radius of approximately 29ft. Young stands hand max DBHs ranging from approximately 11 to 13 inches Minimum DBH measurements were only noted for FRP collection, which was 10cm, or 3.9 in. My own data was very similar. I examined trees ranging from 6 to 24 inches, which were cruised with a BAF 10 prism. My LiDAR extracted plot radius was slightly smaller than Deo et al. (2016), at 28.26ft. While the analysis and LiDAR variables were slightly different between the two studies, results were similar. Deo et al. (2016) found R^2 for BAF10 old stands to be 0.239 and young stands to be 0.289. On the plot level with similar data, I found R^2 of 0.45. (Deo et al. 2016)

When I determined my plot radius for the LiDAR analysis, I based it on the average DBH for all trees in the study. To make this a truly usable volume estimation technique, individual plot radii must be determined based on average plot DBH. This would determine a far more accurate radius per plot. There are also far more LiDAR variables that can be added to exclude undergrowth under the canopy, account for variations in elevation, etc. These would probably help boost fit and add accuracy to height and canopy estimates.

Conclusions

Overall, the LiDAR derived variables only modestly estimate field measured volume. However when field calculated volume was regressed against lidar estimated volume, little, if any, bias was detected indicating that though the R^2s are suboptimal, this particular analysis is a practical approach for estimating Loblolly pine volume. Based on these circumstances, I am comfortable saying that factors such as the QL2 LiDAR data, imprecision in using variable radius plot field data, and unaccounted regional effects probably play heavily into the models' performances.

As a pilot study, this serves as an excellent indication of where to focus further study. With LiDAR being used currently as a primary inventory tool in places such as Norway (Naesset, 2004) and having early success ((R^2=0.47) estimating volume for pinestands (Naesset, 1997), I am confident that LiDAR can easily be integrated into the southeaster timber industry, given the proper attention. Advances in technology and new studies are cropping up everyday that give us more insight into timber volume estimations.

There are many ways to continue to study the practical application of LiDAR in timber inventory. My thoughts on the matter are to concentrate on regional effects on a single a single species on the stand level. My interest lies in helping to develop a Loblolly specific volume model for timber producers in the American southeast. The technology is at our fingertips. A little bit of time and effort is all that is needed to come up with a suitable volume estimation which is equal to or surpasses to that which is produced in the field.

REFERENCES

Avery TE & Burkhart HE. 2002. Forest Measurements. 5th Edition. McGraw-Hill, New York.

Clark A & Saucier JR. 1990. Tables for estimating total-tree weights, stem weights, and volumes of planted and natural southern pines in the southeast. Research Division, Georgia Forestry Commission. Georgia Forest Research Paper 79.

Deo RK, Froese RE, Falkowski MJ, & Hudak AT. 2016. Optimizing variable radius plot size and LiDAR resolution to model standing volume in conifer forests. Canadian Journal of Remote Sensing. 42(5): 428-442.

Environmental Systems Research Institute (ESRI). (2016). ArcGIS Release 10.5. Redlands, CA.

Evans DL, Roberts SD, & Parker RC. 2006. LiDAR – A new tool for forest measurements? The Forestry Chronicle. 82(2): 211-218.

Gatziolis D & Anderson HE. 2008. A Guide to LiDAR Data Acquisition and Processing for the Forests of the Pacific Northwest. United States Department of Agriculture, Forest Service. Pacific Northwest Research Station.

Lauri K, Peuhkurinen J, Malinen J, Suvanto A, Maltamo M, Packalen P, & Kangas J. 2008. The use of airborne laser scanning to estimated sawlog volumes. Forestry. 81(4): 499-510.

McConnell TE, Jeuck J, Bardon R, & Hazel D. 2016. North Carolina's Forests and Forest Products Industry by the Numbers, 2013. North Carolina Cooperative Extension Service. NC State University Extension Forestry.

Naesset, Erik. 1997. Estimating timber volume of forest stands using airborne laser scanner data. Remote Sensing of Environment. 61(2):246-253.

Naesset, Erik. 2001. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data Remote Sensing of Environment. 80(1):88-99.

Naesset, Erik. 2004. Accuracy of forest inventory using airborne laser scanning: evaluating the first Nordic full-scale operational project. Scandinavian Journal of Forest Research. 19(6):554-557.

National Oceanic and Atmospheric Administration: Historical Hurricane Tracks. United States Department of Commerce: [Accessed 2017 January 01]. https://coast.noaa.gov/hurricanes/.

National Ocean Service: What is LiDAR? US Department of Commerce, National Oceanic and Atmospheric Administration; [Accessed 2017 March 3]. http://oceanservice.noaa.gov/facts/lidar.html.

Nelson R, Krabill W, & Tonelli J. 1988. Estimating forest biomass and volume using airborne laser data. Remote Sensing of Environment. 24(2):247-267.

Nilsson, Mat. 1996. Estimation of tree heights and stand volume using an airborne Lidar system. Remote Sensing of Environment. 56(1): 1-7.

North Carolina Department of Safety: Spatial Data Download. North Carolina Floodplain Mapping Program: [Accessed 2016 December-2017 January]. https://rmp.nc.gov/sdd/.

Oderwald RG. 1990. Point sampling: Instruction Manual. Department of Forestry, Virginia Polytechnic Institute: Blackburg, VA

Peuhkurinen J, Maltamo M, Malinen J, Pitkänen J, & Packalén P. 2007. Preharvest measurement of marked stands using airborne laser scanning. Forest Science. 53(6):653-661.

Prestemon JP, Wear DN, & Foster MO. 2015. The Global Position of the U.S. Forest Products Industry. United States Department of Agriculture, Forest Service, Research and Development. Southern Research Station.

Rabadán MV, Peña JS, & Adán FS. 2016. Estimation of diameter and height of individual trees for *Pinus sylvestris* L. based on the individualizing of crowns using airborne LiDAR and the National Forest Inventory data. Forest Systems. 25(1):1-11.

Roberts SD, Dean TJ, Evans DL, McCombs JW, Harrington RL, & Glass PA. 2005. Estimating individual tree leaf area in loblolly pine plantations using LiDAR-derived measurements of height and crown dimensions. Forest Ecology and Management. 213(1-3):54-70.

RStudio Team (2015). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA

Tesfamichael SG, van Aardt JAN, & Ahmed F. 2010. Estimating plot-level tree height and volume of *Eucalyptus grandis* plantations using small-footprint, discrete return lidar data. Progress is Physical Geography. 34(4):515-540.

Watt MS, Thomas A, Aracil SG, Marshall H, & Watt P. 2013. The influence of LiDAR pulse density and plot size on the accuracy of New Zealand plantation stand volume equations. New Zealand Journal of Forestry Science. 43(15):1-10.

White JC, Wulder MA, & Buckmaster G. 2014. Validating estimates of merchantable volume from airborne laser scanning (ALS) data using weight scale data. The Forestry Chronicle. 90(3):378-385.

APPENDIX:

PLOT LEVEL ANALYSIS R SCRIPT:

```
rm(list = ls())
setwd("C:/Users/sfh6/OneDrive - Duke University/R/Models")
VOLUME<-read.table("VOLUME.txt",header=T)
VOLUME$cenHt <- scale(VOLUME$MAXHt, center = TRUE, scale = FALSE)
VOLUME$cenMEANHt <- scale(VOLUME$MEANHt, center = TRUE, scale = FALSE)
VOLUME$cenCanCov <- scale(VOLUME$CanCov, center = TRUE, scale = FALSE)

library(texreg)
summary(VOLUME)
VOLUME

#all data points
mrHtCanVOL<-lm(GAVOL~MAXHt+CanCov,data=VOLUME)
summary(mrHtCanVOL)

mrHtCanVOLx<-lm(GAVOL~MAXHt*CanCov,data=VOLUME)
summary(mrHtCanVOLx)

#centered
mrHtCanVOL2<-lm(GAVOL~cenHt+cenCanCov,data=VOLUME)
summary(mrHtCanVOL2)

mrHtCanVOLx2<-lm(GAVOL~cenHt*cenCanCov,data=VOLUME)
summary(mrHtCanVOLx2)

#COASTAL PLAIN
coast<-subset(VOLUME,VOLUME$Region==1)
coast
```

```
mrHtCancoast<-lm(GAVOL~MAXHt+CanCov,data=coast)
summary(mrHtCancoast)

mrHtCancoastx<-lm(GAVOL~MAXHt*CanCov,data=coast)
summary(mrHtCancoastx)
```

#centered

```
mrHtCancoast2<-lm(GAVOL~cenHt+cenCanCov,data=coast)
summary(mrHtCancoast2)

mrHtCancoastx2<-lm(GAVOL~cenHt*cenCanCov,data=coast)
summary(mrHtCancoastx2)
```

#PIEDMONT

```
pied<-subset(VOLUME,VOLUME$Region==0)
pied

mrHtCanpied<-lm(GAVOL~MAXHt+CanCov,data=pied)
summary(mrHtCanpied)

mrHtCanpiedx<-lm(GAVOL~MAXHt*CanCov,data=pied)
summary(mrHtCanpiedx)
```

#centered

```
mrHtCanpied2<-lm(GAVOL~cenHt+cenCanCov,data=pied)
summary(mrHtCanpied2)

mrHtCanpiedx2<-lm(GAVOL~cenHt*cenCanCov,data=pied)
summary(mrHtCanpiedx2)
```

#AGE CLASS 25 (1990)

```
AC25<-subset(VOLUME,VOLUME$AgeClass==25)
AC25

mrHtCan25<-lm(GAVOL~MAXHt+CanCov,data=AC25)
summary(mrHtCan25)

mrHtCan25x<-lm(GAVOL~MAXHt*CanCov,data=AC25)
summary(mrHtCan25x)

#centered
mrHtCan252<-lm(GAVOL~cenHt+cenCanCov,data=AC25)
summary(mrHtCan252)

mrHtCan25x2<-lm(GAVOL~cenHt*cenCanCov,data=AC25)
summary(mrHtCan25x2)

#AGE CLASS 30 (1988)
AC30<-subset(VOLUME,VOLUME$AgeClass==30)
AC30

mrHtCan30<-lm(GAVOL~MAXHt+CanCov,data=AC30)
summary(mrHtCan30)

mrHtCan30x<-lm(GAVOL~MAXHt*CanCov,data=AC30)
summary(mrHtCan30x)

#centered
mrHtCan302<-lm(GAVOL~cenHt+cenCanCov,data=AC30)
summary(mrHtCan302)

mrHtCan30x2<-lm(GAVOL~cenHt*cenCanCov,data=AC30)
summary(mrHtCan30x2)
```

#AGE CLASS 35 (1980, 1983)

```
AC35<-subset(VOLUME,VOLUME$AgeClass==35)
AC35

mrHtCan35<-lm(GAVOL~MAXHt+CanCov,data=AC35)
summary(mrHtCan35)

mrHtCan35x<-lm(GAVOL~MAXHt*CanCov,data=AC35)
summary(mrHtCan35x)
```

#centered

```
mrHtCan352<-lm(GAVOL~cenHt+cenCanCov,data=AC35)
summary(mrHtCan352)

mrHtCan35x2<-lm(GAVOL~cenHt*cenCanCov,data=AC35)
summary(mrHtCan35x2)
```

THU ANALYSIS R SCRIPT:

```
rm(list = ls())
setwd("~/MP/OneDrive - Duke University/R/Models")
THULevel<-read.table("THUvol.txt",header=T)

THULevel$cenHt <- scale(THULevel$Ht, center = TRUE, scale = FALSE)
THULevel$cenAcres <- scale(THULevel$Acres, center = TRUE, scale = FALSE)
THULevel$cenCanCov <- scale(THULevel$CanCov, center = TRUE, scale = FALSE)

summary(THULevel)
THULevel

mrTHUlevel<-lm(VOL~cenHt+cenCanCov,data=THULevel)
```

```
summary(mrTHUlevel)

mrTHUlevelx<-lm(VOL~cenHt*cenCanCov,data=THULevel)
summary(mrTHUlevelx)
```

#centered

```
mrTHUlevel2<-lm(VOL~cenHt+cenCanCov,data=THULevel)
summary(mrTHUlevel2)

mrTHUlevelx2<-lm(VOL~cenHt*cenCanCov,data=THULevel)
summary(mrTHUlevelx2)
```