Prediction of aboveground component biomass for coastal Douglas-fir (*Pseudotsuga menziesii var. menziesii*)

Robert James Swan

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Committee members:

Chair: Eric Turnblom

Gregory Ettl

Daniel Vogt

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University of Washington

Abstract

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Robert James Swan

Chair of Supervisory Committee:

Dr. Eric Turnblom

School of Environmental and Forest Sciences,

College of the Environment, University of Washington

Contemporary forests are being managed for more uses simultaneously than ever before. Alongside historically important forest products such as timber and game, forests are often concurrently managed for a multitude of diverse anthropogenic goals such as wildlife habitat, biodiversity, recreation, ecosystem services, and bioenergy. The effective balancing of these varied goals requires more precise and accurate tools than previously. This study developed one such set of tools for measuring components of above ground biomass for the coastal Douglas-fir, *Pseudotsuga menziesii var. menziesii.* Many current methods for estimating above ground component biomass for coastal Douglas-fir may be insufficient for landscape, stand, and individual tree-level estimations, due to their disuse of important environmental variables. This study generated and utilized an extensive dataset of 32 destructively sampled Douglas-fir trees throughout maritime Oregon and Washington State. The study employed a balanced orthogonal

experimental design considering age, stand density, crown position, elevation, and latitude. These samples came from both planted and naturally regenerated stands on public and private forestlands from a range of landowners. All stands were primarily composed of Douglas-fir, with the majority of stands having a single cohort, and the remainder having two cohorts. This dataset was combined with a similar dataset of 30 trees sampled at a single location in southwestern Washington State. The following were the component biomass equations produced in this study: 1.) Total Aboveground Biomass, 2.) Slash, 3.) Foliage, 4.) Live Branch Bark & Wood, 5.) Dead Branch Bark & Wood, 6.) Stem Bark, and 7.) Stem Wood. An eighth set of component equations for the 5 biomass components was developed using the ratio method, but its usefulness was limited. All response variables were analyzed and reported in terms of dry pounds (lbs).

Contents:

Chapter 1. Introduction:

Coastal Douglas-fir has had its component biomass modeled in the past by researchers such as Gohlz (1979), Ares et al. (2007), Harrison (2009), and Nay & Borman (2014), among others (Fischer 2013). The majority of these models take the allometric form, $\ln(Y) = B_0 + B_1 * \ln(DBH)$, Where Y = Biomass and DBH = Diameter at Breast Height. Their models have shown themselves to be effective predictive models in many situations. Models of this form are straightforward and require only the measurement of Diameter at Breast Height, making them both easy and cost-effective to apply. However, the simplicity of these models leaves them vulnerable to the substantial variability that occurs throughout the range of coastal Douglas-fir. Variation within landscape, stand, and tree level variables can have large impacts on the accuracy of these allometric equations, decreasing their utility in a world where extremely accurate predictions are essential for meeting management goals.

Many other researchers such as Marshall (1995), Hann (1997), and Ares et al. (2007) have also investigated the impact of various landscape and stand level variables upon tree biomass, but rarely have a wide array of these been scrutinized within a single study or applied to the equations produced. Assorted studies have demonstrated that many of these variables have significant effects upon the allocation of biomass throughout the aboveground components of the tree. Landscape level variables such as latitude and elevation have been shown to influence the development of crown in coastal Douglas-fir as well as in other similar species present in the coastal Pacific Northwest (Hann 1997, Cross et al. (In review)). Stand level variables such as stand density are well-documented to affect the development of crowns in Douglas-fir, with high stand density resulting in shorter live crowns with smaller branches (Harry 1964, Marshall 1995). A wide assortment of variables can influence factors such as wood specific gravity,

influencing the sequestration of carbon in many components of the tree (Kantavichai et al 2010, USDA 1965, USDA 1972). The impact(s) of many other variables may be less well elucidated, especially in cases where many factors vary simultaneously. There are high amounts of variability present in the range of coastal Douglas-fir, and taking these other variables into account is essential in order to achieve the high levels of accuracy and precision expected in modern forest management.

Objectives of this study include the following:

1. Develop multi-variable aboveground biomass and aboveground component biomass models which better account for the enormous level of variability present in the range of coastal Douglas-fir compared to DBH-only models.
2. Determine whether generally accepted relationships between aboveground biomass components and the variables that drive them can be verified across a wide range of growing conditions.
3. Determine the difference(s) in variability of relatively young, small trees compared to relatively old, large trees.

Null hypotheses pertaining to the objectives considered in this study are presented below:

1. Multi-variable models will be no better than DBH-only models at explaining the influence of landscape, stand, and tree level variables on the amount and distribution of aboveground biomass in coastal Douglas-fir throughout western Oregon and Washington.
2. No relationships between variables and aboveground biomass will be unexpected.
3. Older, larger trees will have the same amount of variation among both their overall biomass and their component biomass as younger, smaller trees.

In order to meet the stated objectives and investigate the specified hypotheses, this study sought to develop seven multi-variable allometric models for coastal Douglas-fir (*Pseudotsuga menziesii var. menziesii*) in the coastal Pacific Northwest by utilizing empirical data from destructively-sampled whole trees grown in a wide assortment of conditions. These models have the capacity to explain much of the influence of landscape, stand, and tree level variables on the amount and distribution of aboveground biomass in coastal Douglas-fir throughout western Oregon and Washington. The model produced for total aboveground biomass was developed from the sum of the five major aboveground components of Douglas-fir (Foliage, live branch wood, dead branch wood, bark, and stem wood). A second combination model, "slash", composed of the combination of foliage, live branch wood, dead branch wood, and the stem wood above the 4" diameter top of the tree, was also developed. In addition to these two combination models, independent models for each of the five major components of aboveground biomass (Foliage, live branch wood, dead branch wood, bark, and stem wood) were created. Live and dead branch wood in this study referred to both the wood and the small amount of bark present on branches. Bark in this study referred exclusively to bark directly attached to the primary stem of the tree. A method of determining components as ratios of total aboveground biomass was also investigated, but its usefulness was questionable as formulated. Species-specific component biomass equations such as those produced in this study have a wide variety of modern forest management applications. These equations may be utilized to improve the way forest managers achieve goals such as slash estimation for forest operations, biomass estimation for use as biofuel feedstock, and carbon sequestration on a regional, landscape, stand, tree, or tree component level.

Chapter 2. Methods:

Chapter 2.1 Study Area:

This study took place in maritime Oregon and Washington State. Latitude ranged from 43.92330 degrees north to 48.50128 degrees north, with longitude ranging between 121.6281 degrees west to 123.6086 degrees west. Elevation ranged from 371 feet above sea level to 2,200 feet above sea level**.** Sampling location information, including the number of trees felled, the age of the sample trees, the relative density, latitude, and elevation of the stand, are summarized in *Table 2.1.1*. Trees were collected from a range of private and public land. Of the 62 trees, 56 came from single-cohort, planted stands being managed primarily for timber production. The 6 trees which came from naturally regenerated, dual-cohort stands were all at least 77 years old, and one of the stands was not being managed. Of the trees utilized in the study, 32 were sampled by researchers at the University of Washington specifically for this study. All stands from this University of Washington dataset were predominantly Douglas-fir, both by trees per acre (TPA) and by basal area (BA). The remainder of trees utilized in this study were from a separate study conducted at a single location known as Fall River in Washington State. This Fall River dataset was predominantly Douglas-fir by basal area, although substantial Western hemlock ingrowth dominated by trees per acre. *Figure 2.1.1* illustrates the spatial arrangement of study sites within the states of Oregon and Washington.

Table 2.1.1 - Sampling site location information.

Symbol	Location (Closest town)	Number of Trees	Age (Years)	Relative Density*	Latitude (Decimal Degrees)	Elevation (Feet)	Site Index*	Stand Origin
	Walton	4	40	40, 55	43.92	600	138	Planted
	Lake McMurray	4	40	36, 68	48.32	572	120	Planted
	Concrete	4	39	32, 62	48.50	793	120	Planted
	Silverton	4	40	47, 62	44.87	2200	120	Planted
	Bryant	4	117-120	109, 137	48.25	430, 371	122, 124	Natural
	Darrington	4	80-82	52, 69	48.18	2162, 1329	120, 130	Planted
	Forest Grove	4	80-83	40, 56	45.76	1525, 897	128,138	Planted
	Philomath	2	79-82	44	44.74	1590	114	Planted
	Lyons	2	77-87	93	44.80	861	108	Natural
	Fall River	30	57	Variable	46.72	1095	110	Planted

**Curtis (1982); RD = Basal Area / Quadratic Mean Diameter$^{0.5}$*

**King (1966); Expressed here as feet at 50 year breast height age*

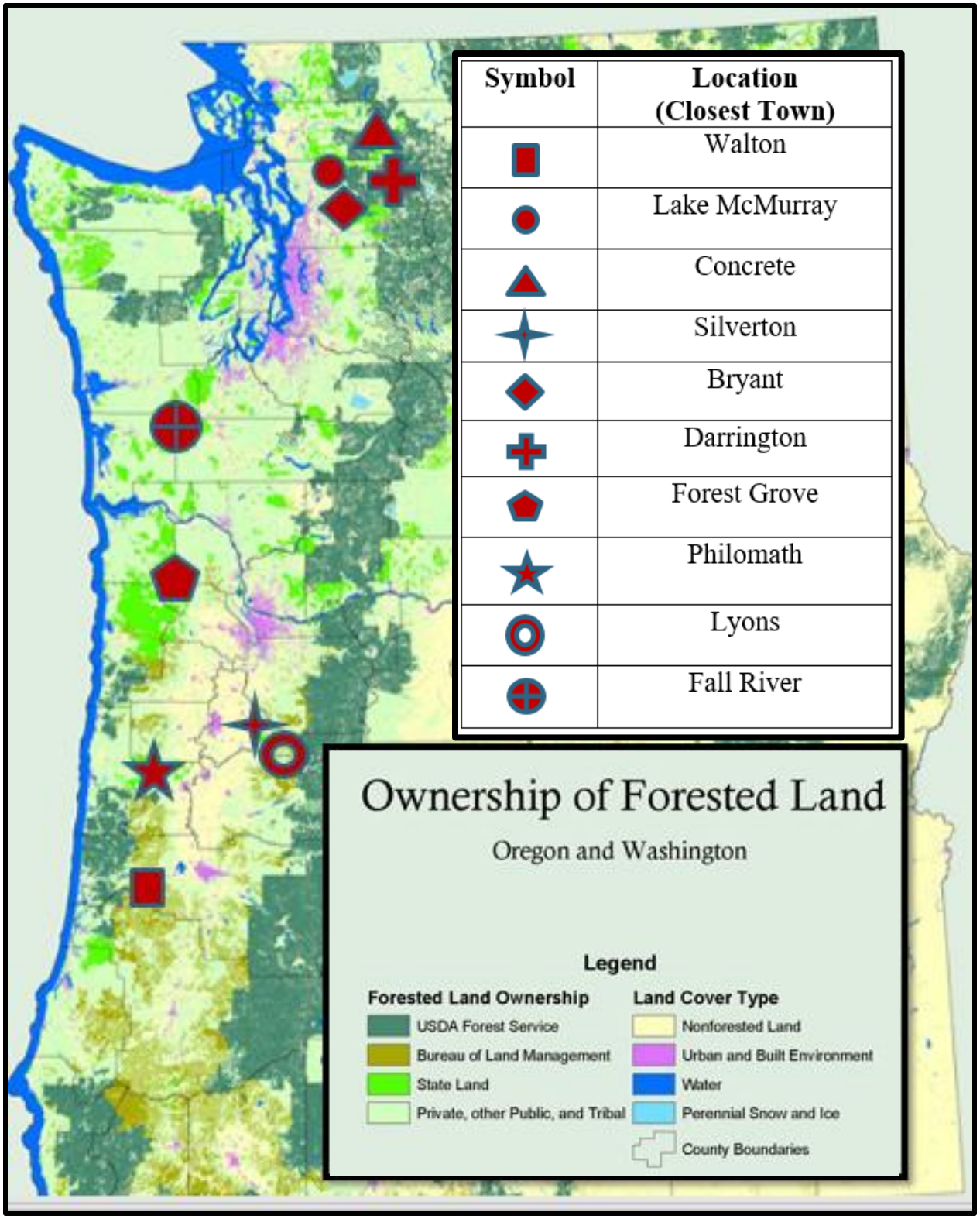

Figure 2.1.1 - Spatial arrangement of study sites within the states of Oregon and Washington, overlaid onto forestland ownership and land cover type. See Table 2.1.1 for site specifics.

Chapter 2.2 Experimental Material and Study Design:

A total of 62 destructively sampled Douglas-fir comprise the dataset utilized for this study. Of these trees, 32 were sampled by researchers at the University of Washington (UW) from 2017-2019. These trees will be referred to as the "UW" data throughout the study.

Collection of the UW study material employed a balanced orthogonal experimental design considering age, stand density, crown position, elevation, and latitude as factors. The first 16 trees of the UW dataset comprised the young strata, and ranged in age from 39 to 40 years old. Initial analysis was conducted by Fletcher Harvey (2018) for his MS thesis at the University of Washington. These data were re-analyzed as part of this more comprehensive study.

The remaining 16 trees of the UW dataset comprised the old strata, and ranged in age from 77 to 120 years old. This provided an overall age range of 39 to 120 years. Only healthy, undamaged trees were selected as potential samples. No trees exhibiting damage or deformities such as bear damage, broken tops, multiple tops, ramicorns, pistol butts, or severe lean were utilized. Stand density was measured by Curtis' relative density "RD" (1982), and density values ranged from 32 to 137. During the sample material collection phase, latitude was generally separated into two groups, with Washington State representing north and Oregon State representing south.

During data collection, sample crown position was classified as either dominant or intermediate. A single tree of each crown class was randomly selected from each stand. As crown position is somewhat subjective, the tree's DBH percentile was utilized. Dominant trees came from the 80^{th} or greater percentile for DBH, while intermediate trees came from the 60^{th} percentile and below. It should be noted that, especially in the stands comprising the old strata, an intermediate crown position became difficult to define by DBH percentile alone, so thorough

observation was used as the primary method for determining an intermediate crown position. Due to this, the diameter percentile of the intermediate trees varied greatly in the older stands. The lowest percentile selected for the intermediates was the 5th, and the highest was the 57th. This wide range was partially due to a variety of factors such as thinning from below that had occurred in some stands in the past. Of stands that had been thinned, only those in which tree crowns had filled growing space were sampled. The shortest amount of time elapsed between thinning and our sampling was 8 years.

The UW dataset was used in conjunction with the dataset from a similar study performed at Fall River by Harrison et al. (2009). This dataset is known as the "Fall River" dataset, and will be referred to as the "FR" data throughout this study. The FR dataset contained 30 trees sampled from a single location with a stand age of 57 years. These trees were sampled as part of an extensive project assessing site productivity on industrial forestland both prior to, and following, harvesting. Sample trees were selected according to height and diameter distributions in order to acquire a representative sample of the entire study site. One important distinction to be made between the FR dataset and the UW dataset is that the stand utilized in the FR dataset experienced substantial establishment of Western hemlock volunteers. By stem count, the site was 52.7% Western hemlock. However, the Douglas-fir trees comprised 53.6% of the stand's basal area, due to their larger average DBH of 14.9 inches compared to the Western hemlock average DBH of 13.1 inches.

Chapter 2.3 Field Methods:

Chapter 2.3.1 Branch Sampling & Measurement:

Upon selection of appropriate sample trees, crown width to the furthest branch tip was measured along the North-South axis and the East-West axis. Prior to the trees being felled, if branches were present within about 7 feet of the ground, they were counted, removed, and stored nearby. This was done in order to create a safe, clear portion of the tree for the faller without the loss of data. After the tree was felled, these branches were later added to the branch weight of the 0-10 foot log.

After the sample trees were felled, the tree was measured and marked into 10 foot logs, up to the point at which the diameter of the tree was 4 inches. This 4-inch diameter location was also marked, and everything above this point was considered "top." Total height was also measured, and relative position of the live and dead crowns were established using the lowest dead branch, the highest dead branch, and the height of live crown base. Live crown base in this study was defined as the point where live branches were present around 75% of the tree. If branches broke off during the felling, branches were returned to their original locations on the stem as accurately as possible by matching branches with their broken stubs, and by diameters alone when this was not possible.

Next, three representative branches were randomly selected from each third of the dead crown, using a random number generation technique. Of the branches in the randomly selected area, the one selected was reasonably similar to the "typical" branch in the vicinity. For instance, an exceptionally large or exceptionally small branch was not considered. The same process was used for the live crown, with the difference that the branch was also required not to have had much of its foliage stripped off as the tree fell. These branches had their diameter at the branch

collar attachment measured and recorded, as well as their current green weight. They were then individually labeled and stored in waterproof bags to be returned to the lab.

Next, the largest live, smallest live, and largest dead branch diameters were measured in each 10 foot log section of the tree. For consistency, diameters were measured perpendicular to the central axis of the tree stem. Following the diameter collection a count of live branches was taken in each log, as was a count of dead branches. Epicormic branches were excluded from these counts. After this, all dead branches were removed and weighed according to their log (ten-foot section). The same was then performed with the live branches, excluding epicormic branches. One notable difference with the live branches was that the foliage was often at least partially stripped from the branches while the tree fell, so after the live branches were measured in each log, loose foliage from that log's vicinity was also collected and weighed to be added to that log's total.

Most methods of branch sampling from the FR dataset were similar to those used to create the UW dataset. Measurements included total sample tree height and height of live-crown-base. Additionally, live and dead branches were weighed and a representative sample of live and dead branches were weighed in the field and dried for wet:dry weight ratios.

Chapter 2.3.2 Stem Sampling & Measurement:

Prior to the trees being felled, the tree was marked with spray-painted bands at 1 foot, 2.75 feet, and 4.5 feet off the ground. The tree was also marked on its North-South axis, with a straight line representing north and a wavy line representing south. *Figure 2.3.1* provides an example of the south side of a typically marked tree immediately prior to falling. This allowed us to keep track of the directionality of the tree regardless of how it rolled after falling.

Figure 2.3.1 - Typically marked tree immediately prior to falling. Horizontal lines are at 1 foot (top of stump), 2.75 feet, and 4.5 feet. This particular tree was on a significant slope, and the horizontal line positions were determined from the upslope side of the tree, as is the convention for DBH measurements. The vertical wavy line represents the southern side of the north-south axis of the tree.

Once felled, the tree was marked with a band at 10 feet, and a perpendicular line was marked on the band with north or south, depending on which was accessible based upon how the log settled. The tree was then marked similarly every ten feet thereafter up until the tree's diameter was 4 inches, where the final cookie was cut and labeled as "top." *Figure 2.3.2* illustrates the location of cookie samples taken from a felled tree. "Cookies" were 2 to 4-inch thick slices of the stem and bark which were perpendicular to the trunk of the tree. Extreme care was taken via markings to label which part of each cookie would have originally faced upwards and northwards when the tree was standing. Cookie sample locations were occasionally destroyed by the impact of the tree striking the ground, causing some skips where a cookie could not be obtained. Where possible, the cookie location was shifted by as much as 5 feet in order to obtain a cookie for that section. Cookies were then stacked in a vehicle, taking care to not knock the bark off, for return to the lab for further analysis. If the weather was dry and warm, or more than 24 hours would elapse before returning to the lab, the cookies were covered with garbage bags and kept wet to avoid moisture loss causing the cookies to change shape/volume.

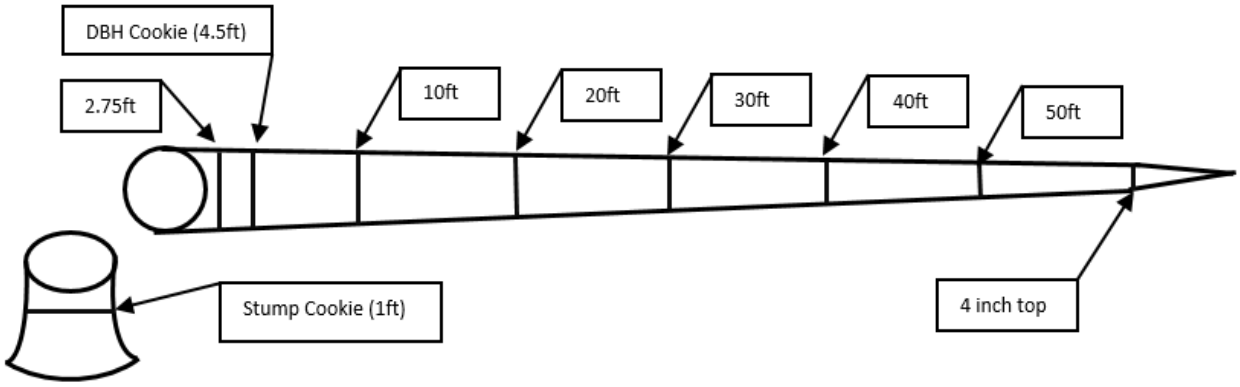

Figure 2.3.2 - Distribution of cookie stem samples on a sample tree after falling.

Chapter 2.4 Lab Methods:

Chapter 2.4.1 Branch Sample Processing:

Upon returning to the lab, the three live and three dead sample branches were processed into small pieces using saws and loppers, and each branch's pieces were placed into individual paper bags. They were then dried at 75 degrees Celsius until there was no significant change in weight.

Immediately following drying, dead branches were weighed. Live branches first had their needles removed by hand, and the foliage and branch wood were each weighed separately. *Figure 2.4.1* shows a live sample branch immediately upon removal from the oven. It was essential to take dry weights immediately upon removal from the oven due to the sample branches re-absorbing ambient moisture very quickly. These weights were then utilized in the conversion of field wet-weights to dry component estimations.

Figure 2.4.1 - Live branch sample immediately after removal from drying oven. Needles were very easy to remove at this point. All needle removal was done in clean containers to prevent loss of biomass. After needles were separated from the branches manually, any remaining wood was picked out and placed into a separate container to obtain wood:foliage ratios.

FR sample branches were processed similarly to the UW samples. Both sets of branches were dried in an oven until no significant weight change was detected. Live branches were also

separated from their needles. These weights were then used to determine the wet to dry ratios as well as the ratio of needles to wood for the branches. These ratios were then used to convert wet field measurements into their dry component estimations.

Chapter 2.4.2 Stem Sample Processing:

Immediately upon returning to the lab, cookie dimensions were measured in 8 cardinal and sub-cardinal directions (N, NE, E, SE, S, SW, W, NW). Diameter measurements were both inside and outside of the bark, and on both the top and bottom faces of each cookie. In addition to this, the cookie thickness was measured at the same 8 cardinal and sub-cardinal directions to determine green volume of both stem wood and bark.

Following dimensional measurements, the bark was removed from the cookies, processed into pieces small enough to be placed into paper bags, and then dried at 75 degrees Celsius until there was no significant change in weight. *Figure 2.4.2* shows a typical load of bark samples in the drying oven.

Figure 2.5.2 - A typical load of bark placed into the drying oven. Note that bags were left open and given ample room in order to facilitate fast and even drying of the samples.

The now bark-less cookies were also dried in the same way, without being placed into paper bags. For some of the largest trees, the lower cookies were too large to fit into the drying oven, so they were split into two or more pieces. Each of the pieces was labeled in order to prevent loss or separation of individual pieces. Cookies that split apart after drying had each of their pieces labeled as well. *Figure 2.4.3* shows cookies after bark removal and drying.

Figure 2.4.3 - De-barked and dried cookies from throughout the study. Note that the brighter colored cookies had their bark removed while still wet, and the darker colored cookies had their bark removed after drying. Wet bark removal proved to be far more effective and efficient.

After drying, cookies and bark weights were measured immediately upon removal from oven to determine dry mass. These values were used in order to estimate bark, stem, and total aboveground biomass of the trees.

The cookie volume measurements were slightly different for the FR dataset. The FR cookie volumes were determined through four perpendicular bark thickness measurements, two wood diameter measurements, and three cookie thickness measurements. Following measurement, they were processed in the same way as the UW cookies.

Chapter 2.5 Modeling Dataset Description:

The UW and FR datasets were combined to create a full dataset of 62 trees. *Figure 2.5.1* shows the age distribution of the sample trees, which provides a range of harvest-age trees into trees which would be classified as mature or maturing. This complete dataset was utilized for three out of the seven models created; the slash model, the foliage model, and the live branch wood model. The dead branch wood model utilized a subset of 60 trees due to two of the UW dataset trees missing their dead branch data. A subset of 58 trees was utilized for the remaining three models; the bark model, the stem wood model, and the total aboveground biomass model. This subset was due to the lack of stem information from the four trees in the UW Silverton location.

Twelve predictor variables were utilized in the analyses, consisting of three levels - individual tree-level, stand-level, and landscape-level. Individual tree-level predictors analyzed were DBH (Inches), tree total height (Feet), live crown ratio (Proportion of total height covered in living, non-epicormic branches), live crown length (Feet), height to live crown base (Feet), age (Years), DBH percentile, and DBH to quadratic mean diameter ratio. Stand-level predictors were trees per acre (TPA), and relative density (RD). Landscape-level variables were latitude (Decimal degrees), and elevation (Feet above sea level). *Table 2.5.1* summarizes the twelve predictor variables used in these analyses.

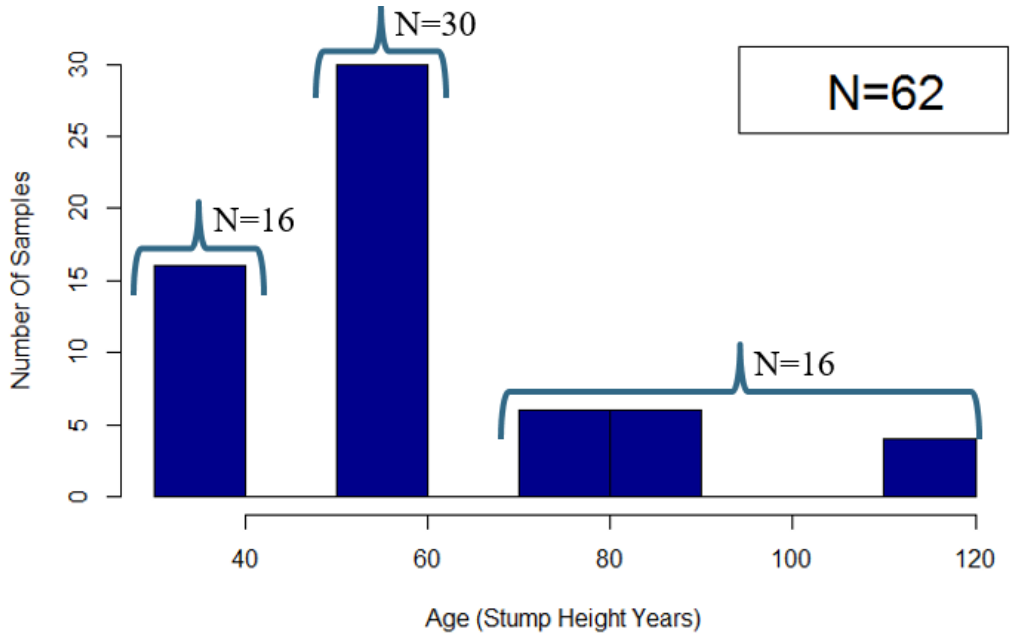

Figure 2.5.1 - Distribution of sample tree ages.

Table 2.5.1 - Summary table of predictor variables

Variable	Description	Units	Minimum	Average	Maximum
DBH	Diameter at breast height	Inches at 4.5 Feet	5.9	18.46	33.7
Total Height	Height of Tree	Feet	75	119.91	189.5
Live Crown Ratio	Proportion of the sample covered in live branches	Proportion	0.12	0.38	0.56
Live Crown Length	Length of the tree with live branches	Feet	15	45.71	73
Height of Live Crown Base	Height of the lowest area with live branches around 75% of the stem	Feet	38	74.19	128.5
Age	Age of the tree since being over 1 foot tall	Years	39	63	120
DBH Percentile	Percentile of sample DBH compared to other trees in the stand	Percentile	1.16	66.86	100
DBH:QMD Ratio	Ratio of DBH to the stand's Quadratic mean Diameter	Ratio	0.42	1.16	2.01
Trees Per Acre	Number of trees per acre in the vicinity of the sample trees	Trees / Acre	61	216.3	402
Relative Density	Quantifies the competition the trees are experiencing (Curtis 1983)	Basal Area/ $QMD^{0.5}$	32.23	55.66	137.25
Latitude	North latitude of the stand	Decimal Degrees	43.92	46.76	48.50
Elevation	Elevation of the stand above sea level	Feet	371	1018	2162

Chapter 2.6 Modeling Techniques:

Each component biomass model produced in this analysis was individually developed using strict manual forwards selection and backwards elimination, with an alpha (α) of 0.05. For all component models except for the dead branch model, the Box-Cox method indicated that a natural log transformation was appropriate for the response variable of dry weight in pounds, as in *Figure 2.6.1.* For the dead branch model, the Box-Cox method indicated that a square root transformation of the response variable was needed. For many, but not all, of the predictor variables, analysis of R-squared values and residual plots indicated that natural log transformations of the predictor variables were appropriate. The use of a natural log transformation varied for the individual predictors depending upon the equation being modeled. *Figure 2.6.2* and *Figure 2.6.3* demonstrate the effectivity of a log-log transformation at improving the linearity of the predictor-response relationship and reducing heteroscedasticity.

In addition to the individually regressed component models utilized in this study, a method involving the use of seemingly unrelated regressions "SUR", was used for modeling each of the biomass components as a proportion of the total aboveground biomass model. This "ratio" approach was investigated utilizing some of the methods of Jenkins (2003). In order to ensure that the sum of the ratios was 1.0, all but one of the components would be modeled this way, and the final component would be estimated as the remainder after the other component proportions were calculated. In this study, all five components were tested as the component to be calculated via subtraction, and the component which generated the worst performing ratio model was selected for estimation via subtraction. In this case, the stem wood ratio model was found to be the worst, as it consistently under-predicted the ratio of stem wood compared to

observations. For this reason, stem wood was selected as the component to be calculated via subtraction.

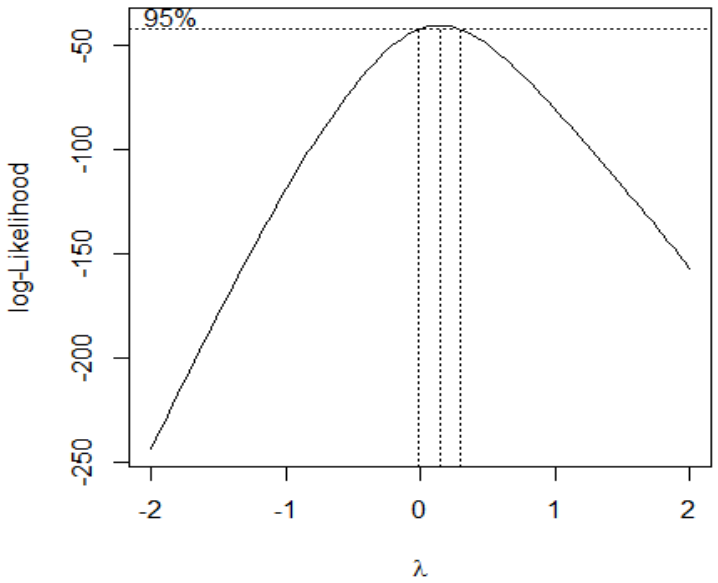

Figure 2.6.1 - Box-Cox plot for slash response. A lambda (λ) 95% confidence interval about a value of 0 indicates that a natural log transformation is appropriate for the response variable.

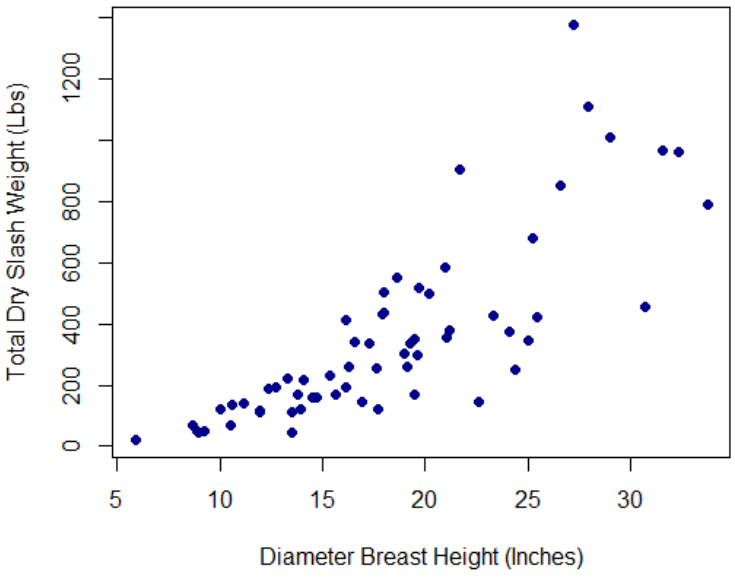

Figure 2.6.2 – Slash weight over DBH. Note the non-linear relationship between the predictor and the response, as well as the variance heteroscedasticity.

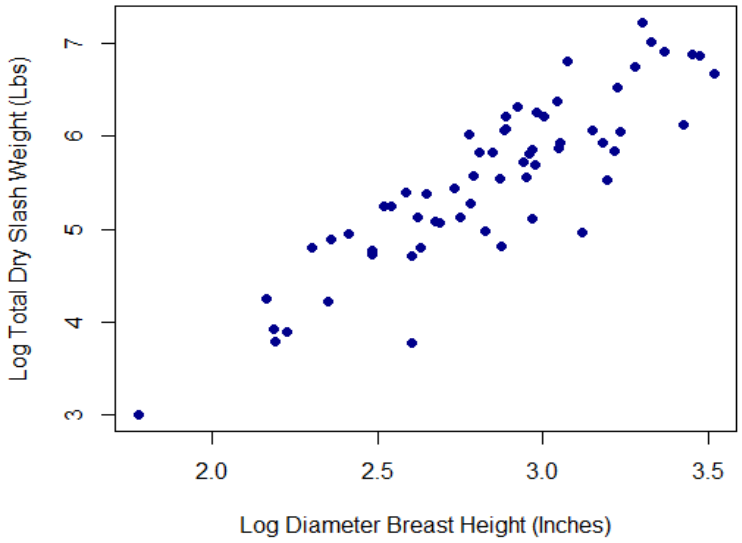

Figure 2.6.3 – Natural log of slash weight over natural log of DBH. Note the increased linearity of relationship between the predictor and the response, as well as the reduced heteroscedasticity, compared to that in Figure 2.6.2.

Residuals (*Figure 2.6.4)* were inspected during the modeling to assess model lack-of-fit. If forwards and backwards models differed, Akaike's Information Criterion (AIC) was used to choose the most parsimonious model. Following selection of the most parsimonious model, interaction effects were tested for all models, and it was found that interactions did not significantly improve the fit for any of the models developed in this study.

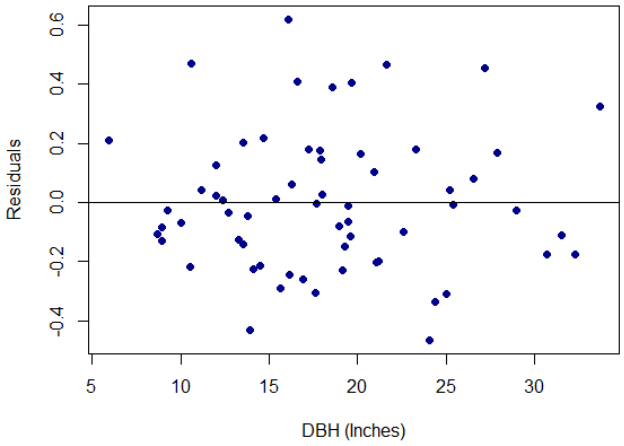

Figure 2.6.4 – Slash residuals over DBH. Note the random distribution of the residuals, indicating a satisfactory model with homogeneous variance.

Following their development, some of these models displayed indications that multicollinearity may have been affecting the predictor coefficients. For instance, an indicator of multicollinearity found in the initial foliage model was the presence of a negative coefficient for the model's DBH predictor. DBH was shown to be clearly positively related to foliage with a separate plot of the foliage observation over DBH. Knowing this, the presence of an opposite coefficient from the expectation was an indication that DBH was likely highly correlated to one or more of the other predictor variables in the model.

To investigate this, the variance inflation factor (VIF) was examined to determine if predictor correlation existed. Predictors in all models were tested. Correlations among all predictors with high VIF were calculated. A Principle Components Analysis (PCA) was performed to assess the contribution of each component to the model. *Figure 2.6.5* displays a PCA performed on the foliage model prior to the highly correlated predictors being removed. Note that the sixth and seventh components explain little additional variance compared to the first five components. In this model, the decision was made to include five components, in order to utilize the components which had relatively large gains in variance explanation. In this way, it allowed us to obtain the most added explanatory power from each component added. This decision is subjective, however, and the decision could be made to have more or fewer components depending upon the degree of explanation desired and the preference for more or less terms utilized in the model. If a more precise model is desired, more components could be added at the expense of model simplicity. Oppositely, if a simpler model is desired, fewer components could be used at the expense of precision.

In the foliage model, after determining that five components would be utilized, each of the two pairs of highly correlated predictors had one of their predictors eliminated from the

model. Preference for retention was given to predictors that are both easier to measure and more likely to be desired by individuals using the model, such as DBH. This resultant model was then chosen as the final model.

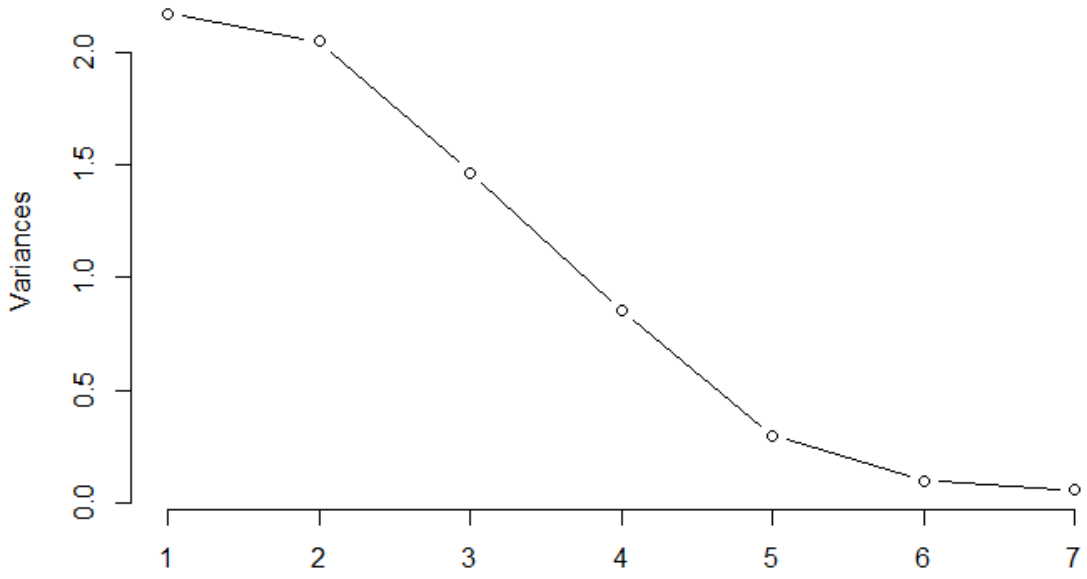

Figure 2.6.5 – Principle Component Analysis performed on a model prior to the highly correlated predictors being removed. Note that the sixth and seventh components explain little additional variance compared to the first five components.

Chapter 3. Results:

Chapter 3.1 Total Aboveground Biomass Model

The final model for estimating total aboveground biomass ("AGB"), composed of the combination of the tree's foliage, live branch wood, dead branch wood, bark, and stem wood, is as follows:

$$\ln(\boldsymbol{AGB}) = -2.05 + 1.67 * \ln(\boldsymbol{DBH}) + 0.18 * ln(\boldsymbol{Crown\ Ratio}) + 1.13 * ln(\boldsymbol{Total\ Height}) - 0.001 * \boldsymbol{TPA}$$

Where **AGB** = Aboveground biomass in dry pounds,
DBH = Diameter at Breast Height (in.),
Crown Ratio = Live crown length divided by total tree height,
Total Height = The total height of the tree from base to tip (ft),
TPA = Trees per acre.

Standard errors and p-values for each of the coefficients of the original model are displayed below in *Table 3.1.1*.

Table 3.1.1 – Total aboveground biomass model intercept, predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	-2.05	0.67	0.00338
ln(DBH)	1.67	0.10	$2e^{-16}$
ln(Crown Ratio)	0.18	0.08	0.00171
ln(Total Height)	1.13	0.19	0.03067
TPA	– 0.001	0.0002	$3.88e^{-7}$

Model Pseudo R-Squared is 0.953, meaning this model explains 95.3% of the variability observed in total aboveground biomass. Root Mean Squared Error (RMSE) is 586 pounds, and Mean Absolute Error (MAE) is 331 pounds. MAE equates to 10.5% of the overall average of the dataset's dry total aboveground biomass weight of 3163 pounds. The model has a small underestimation bias, under-predicting by an average of 45 pounds, or 1.4% of the overall average of the dataset's dry total aboveground biomass weight. *Figure 3.1.1* displays the total aboveground biomass model predictions and observations in relation to DBH. *Figure 3.1.2* displays the relationship between predictions and observations, indicating model effectiveness.

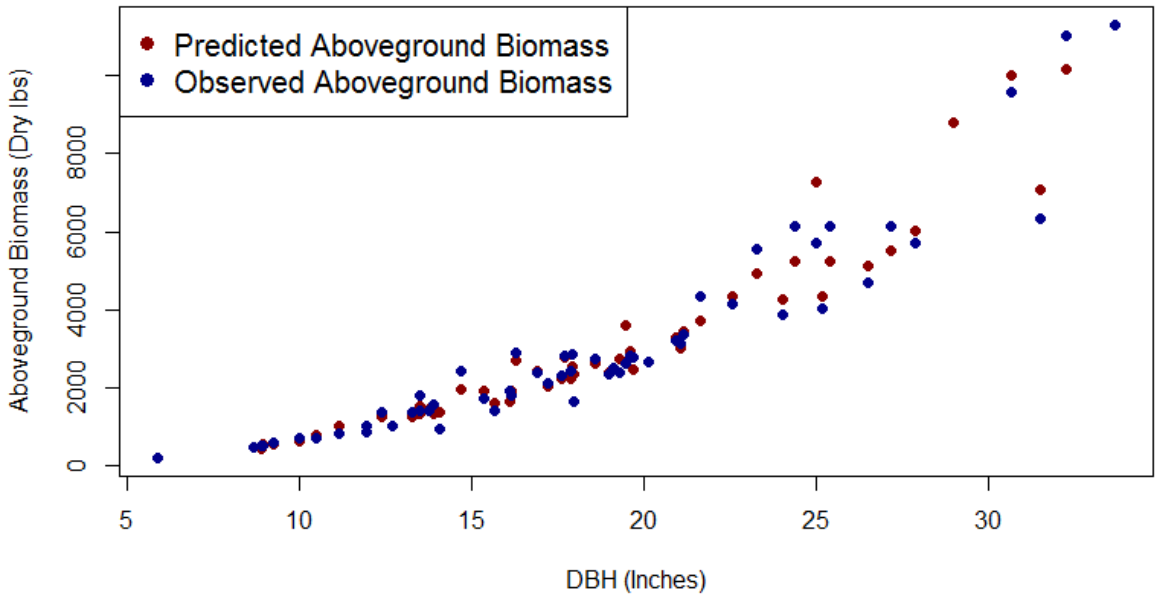

Figure 3.1.1 – Total AGB model predictions and observations in relation to DBH.

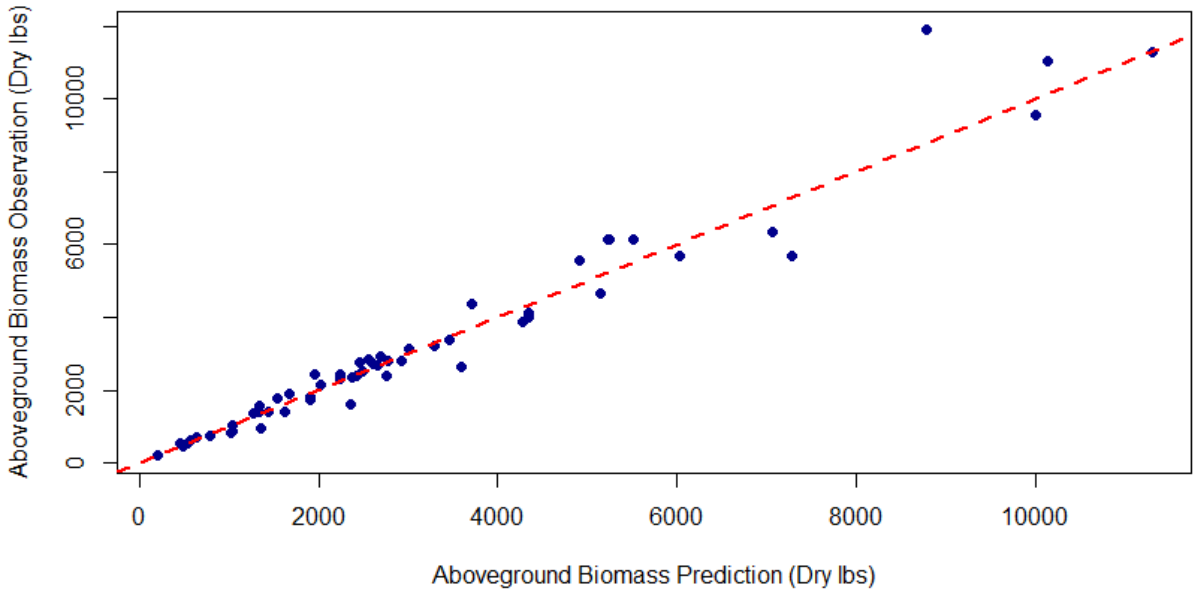

Figure 3.1.2 – Total aboveground biomass model predictions compared to observations, with a dashed red line of slope 1 overlaid. Points to the right of (below) the dashed red line indicate over-predictions, points to the left of (above) the dashed red line indicate under-predictions.

Table 3.1.2 - Benefit of each additional predictor term to the total aboveground biomass model. Note that increased R^2 values indicate the model explains more of the variation present in the data, and lower AIC values indicate a more parsimonious model.

Predictor Added	Change in R^2	Model Pseudo R^2	Change in AIC	Model AIC
DBH	0.889	0.889	-	-25.8
TPA	0.029	0.918	-6.5	-32.3
Total Height	0.031	0.949	-22	-54.3
Crown Ratio	0.004	0.953	-3.2	-57.5

Chapter 3.2 Slash Model

The final model for estimating slash, composed of the combination of the tree's foliage, live branch wood, dead branch wood, and stem wood above a 4" top (topwood), is as follows:

$$\ln(\boldsymbol{Slash}) = 7.62 + 1.41 * \ln(\boldsymbol{DBH}) + 0.69 * (\boldsymbol{Crown\ Length}) + 0.62 * ln(\boldsymbol{DBH}:\boldsymbol{QMD\ Ratio}) - 0.18 * ln(\boldsymbol{Elevation}) - 0.10 * (\boldsymbol{Latitude}) - 0.73 * ln(\boldsymbol{RD})$$

Where **Slash** = The sum of foliage, live branch wood, dead branch wood, and "top" wood in dry pounds,

DBH = Diameter at Breast Height (in.),
Crown Length = Length in feet from live crown base to top of tree,
DBH:QMD Ratio = The DBH of the sample tree divided by the quadratic mean diameter of the stand,
Elevation = Elevation of the stand above sea level in feet,
Latitude = North latitude of the stand in decimal degrees,
RD = Curtis' Relative Density of the stand.

Standard errors and p-values for each of the coefficients of the original model are displayed below in *Table 3.2.1*.

Table 3.2.1 – Total slash model intercept, predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	7.62	1.57	$1.05e^{-5}$
ln(DBH)	1.41	0.16	$2.6e^{-12}$
Crown Length	0.69	0.16	0.034067
ln(DBH:QMD Ratio)	0.62	0.17	0.000488
ln(Elevation)	- 0.18	0.08	$2.32e^{-7}$
Latitude	- 0.10	0.03	0.000699
ln(RD)	- 0.73	0.12	$9.11e^{-5}$

Model Pseudo R-Squared is 0.859, meaning this model explains 85.9% of the variability observed in slash. Root Mean Squared Error (RMSE) is 112 pounds, and Mean Absolute Error (MAE) is 69 pounds. MAE equates to 19.5% of the overall average of the dataset's dry Slash weight of 355 pounds. The model has a small underestimation bias, under predicting by an average of 13 pounds, or 3.6% of the overall average of the dataset's dry slash weight. *Figure 3.2.1* displays the slash model predictions and observations in relation to DBH. *Figure 3.2.2* displays the relationship between predictions and observations, indicating model effectiveness.

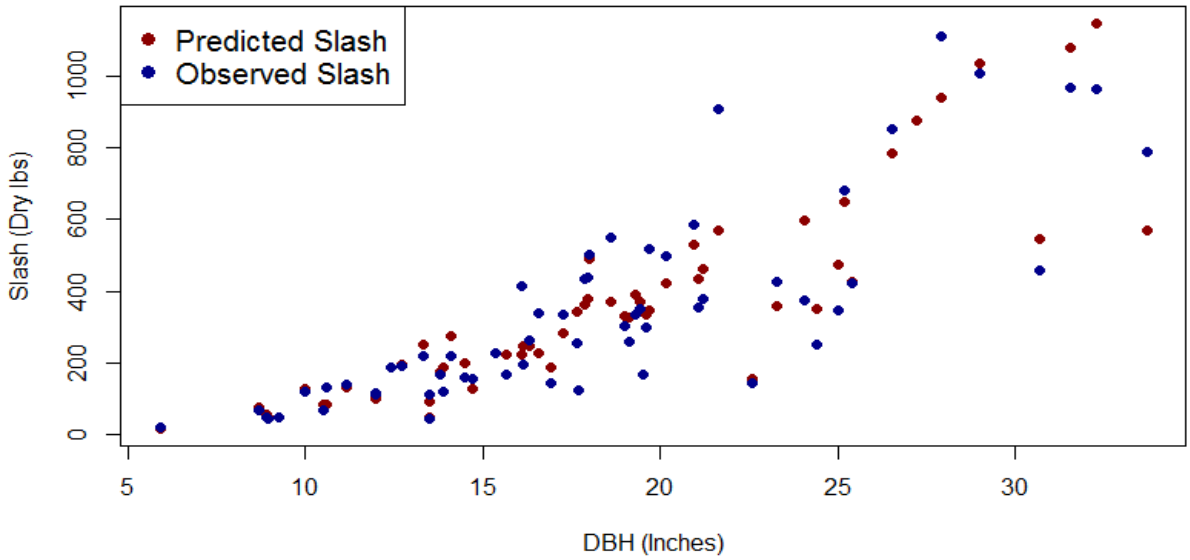

Figure 3.2.1 – Slash model predictions and observations in relation to DBH.

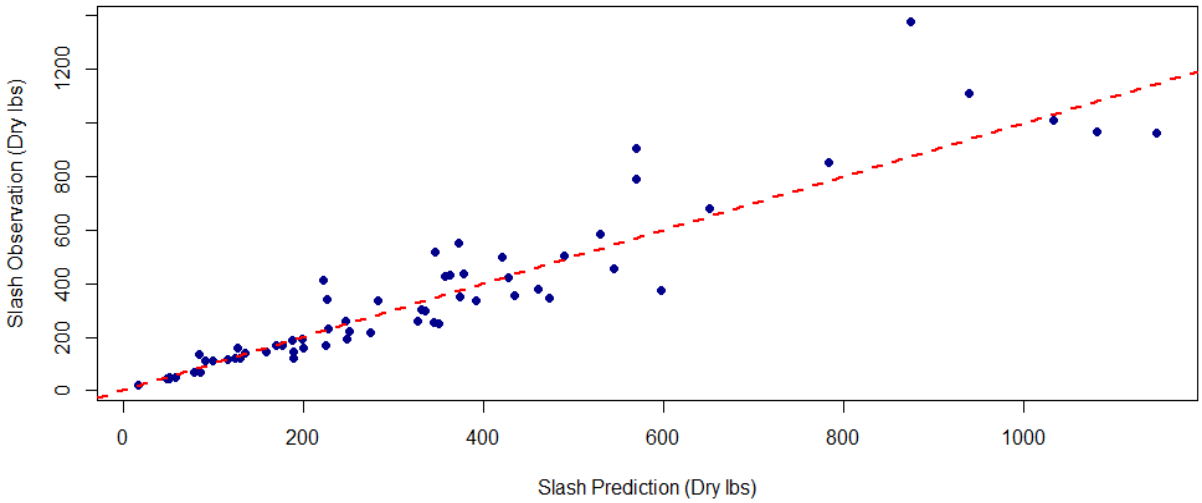

Figure 3.2.2 – Slash model predictions compared to observations with a dashed red line of slope 1 overlaid. Points to the right of (below) the red line indicate over-predictions, points to the left of (above) the red line indicate under-predictions.

Table 3.2.2 - Benefit of each additional predictor term to the slash model. Note that increased R^2 values indicate the model explains more of the variation present in the data, and lower AIC values indicate a more parsimonious model.

Predictor Added	Change in R^2	Model Pseudo R^2	Change in AIC	Model AIC
DBH	0.644	0.644	-	76.2
Relative Density	0.128	0.772	-30.5	45.7
Live Crown Length	0.014	0.786	-12.7	33.0
Latitude	-0.028	0.758	-5.9	27.1
DBH:QMD Ratio	0.087	0.845	-12.5	14.6
Elevation	0.014	0.859	-3.1	11.5

Chapter 3.3 Foliage Model

The final model for estimating total foliage is as follows:

$$\ln(\boldsymbol{Foliage}) = 6.08 + 0.05 * (\boldsymbol{DBH}) + 1.97 * ln(\boldsymbol{Crown.Ratio}) + 1.17 * \ln(\boldsymbol{Height\ Crown\ Base}) - 0.001 * (\boldsymbol{TPA}) - 0.12 * (\boldsymbol{Latitude})$$

Where **Foliage** = The foliage (needles) of the tree in dry pounds,
DBH = Diameter at Breast Height (in.),
Crown Ratio = Live crown length divided by total tree height,
Height Crown Base = The height in feet at which the tree stem was covered ¾ of the way around with living, non-epicormic branches,
TPA = Trees per acre,
Latitude = North latitude of the stand in decimal degrees,

Standard errors and p-values for each of the coefficients of the original model are displayed below in *Table 3.3.1*.

Table 3.3.1 – Foliage model intercept, predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	6.08	2.32	0.01131
DBH	0.05	0.02	0.00446
ln(Crown Ratio)	1.97	0.41	0.00839
ln(Height Crown Base)	1.17	0.49	0.01992
TPA	-0.001	0.0007	$1.42e^{-5}$
Latitude	-0.12	0.05	0.01937

Model Pseudo R-Squared is 0.603, meaning this model explains 60.3% of the variability observed in foliage. Root Mean Squared Error (RMSE) is 28 pounds, and Mean Absolute Error (MAE) is 18 pounds. MAE equates to 30.8% of the overall average of the dataset's dry foliage weight of 59 pounds. The model has a very small underestimation bias, under predicting by an average of 1 pound, or 1.3% of the overall average of the dataset's dry foliage weight. *Figure 3.3.1* displays the foliage model predictions and observations in relation to DBH. *Figure 3.3.2* displays the relationship between predictions and observations, indicating model effectiveness.

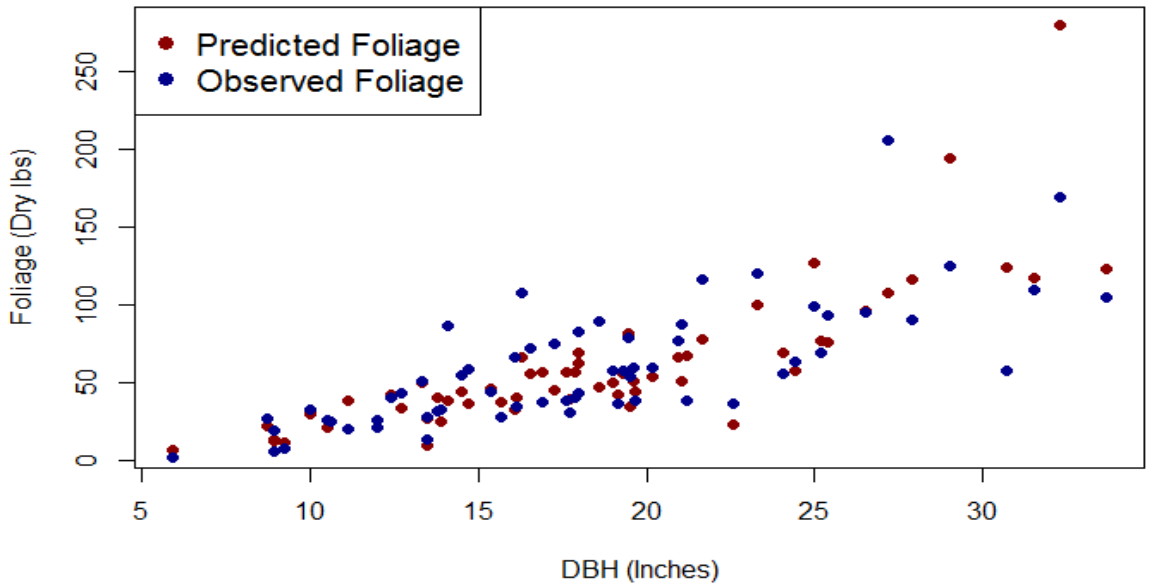

Figure 3.3.1 – Foliage model predictions and observations in relation to DBH.

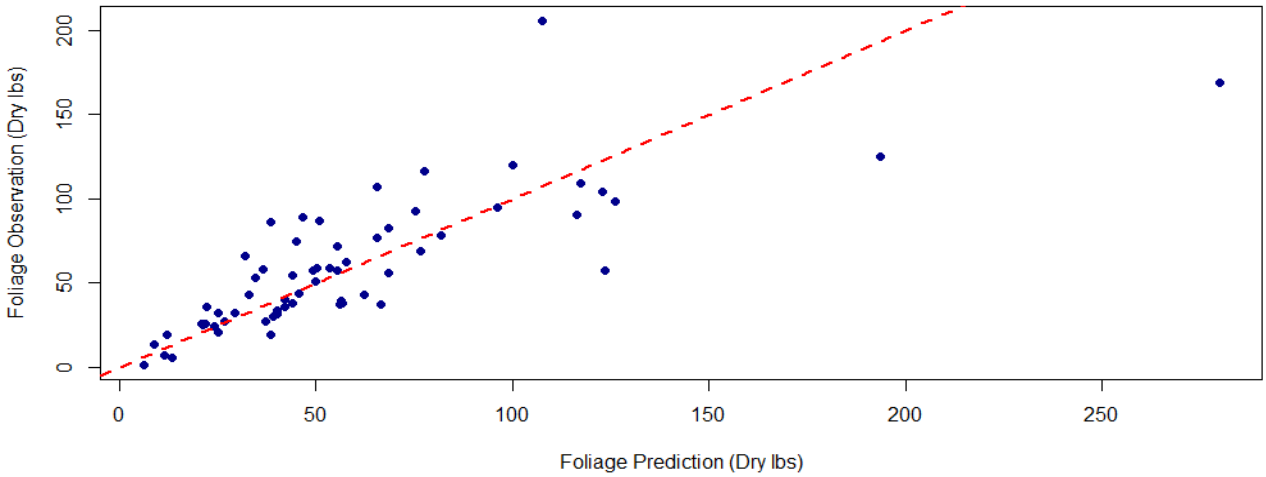

Figure 3.3.2 – Foliage model predictions compared to actual observations with a dashed red line of slope 1 overlaid. Points to the right of (below) the red line indicate over-predictions, points to the left of (above) the red line indicate under-predictions.

Table 3.3.2 - Benefit of each additional predictor term to the foliage model. Note that increased R^2 values indicate the model explains more of the variation present in the data, and lower AIC values indicate a more parsimonious model.

Predictor Added	Change in R^2	Model Pseudo R^2	Change in AIC	Model AIC
DBH	0.481	0.481	-	108.5
TPA	0.052	0.533	-0.8	107.7
Live Crown Ratio	0.077	0.610	-18.6	89.1
Height Crown Base	-0.030	0.580	-1.4	87.7
Latitude	0.023	0.603	-5.8	81.9

Chapter 3.4 Live Branch Wood & Branch Bark Model

The final model for estimating total live branch wood is as follows:

$$\ln(\boldsymbol{Live\ Branch\ Wood}) = 3.54 + 2.37 * \ln(\boldsymbol{DBH}) + 0.59 * \ln(\boldsymbol{Crown\ Length}) - 0.06 * \boldsymbol{Latitude} - 0.31 * \ln(\boldsymbol{RD}) - 0.78 * ln(\boldsymbol{Height\ Crown\ Base})$$

Where **Live Branch Wood** = Live branches and attached bark (without needles) in dry pounds,
DBH = Diameter at Breast Height (in.),
Crown Length = Length from live crown base to top of tree,
Latitude = North latitude of the stand in decimal degrees,
RD = Curtis' Relative Density of the stand,
Height Crown Base = The height in feet at which the tree stem was covered ¾ of the way around with living, non-epicormic branches.

Standard errors and p-values for each of the coefficients of the original model are displayed below in *Table 3.4.1*.

Table 3.4.1 – Live branch wood model intercept, predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	3.54	1.23	0.005780
ln(DBH)	2.37	0.17	$2e^{-16}$
ln(Crown Length)	0.59	0.17	0.012398
Latitude	– 0.06	0.03	0.021858
ln(RD)	– 0.31	0.13	0.000196
ln(Height Crown Base)	– 0.78	0.20	0.001338

Model Pseudo R-Squared is 0.880, meaning this model explains 88.0% of the variability observed in live branches. Root Mean Squared Error (RMSE) is 70 pounds, and Mean Absolute Error (MAE) is 46 pounds. MAE equates to 21.4% of the overall average of the dataset's dry live branch wood weight of 213 pounds. The model has a small underestimation bias, under predicting by an average of 8 pounds, or 3.9% of the overall average of the dataset's dry live branch wood weight. *Figure 3.4.1* displays the live branch wood model predictions and observations in relation to DBH. *Figure 3.4.2* displays the relationship between predictions and observations, indicating model effectiveness.

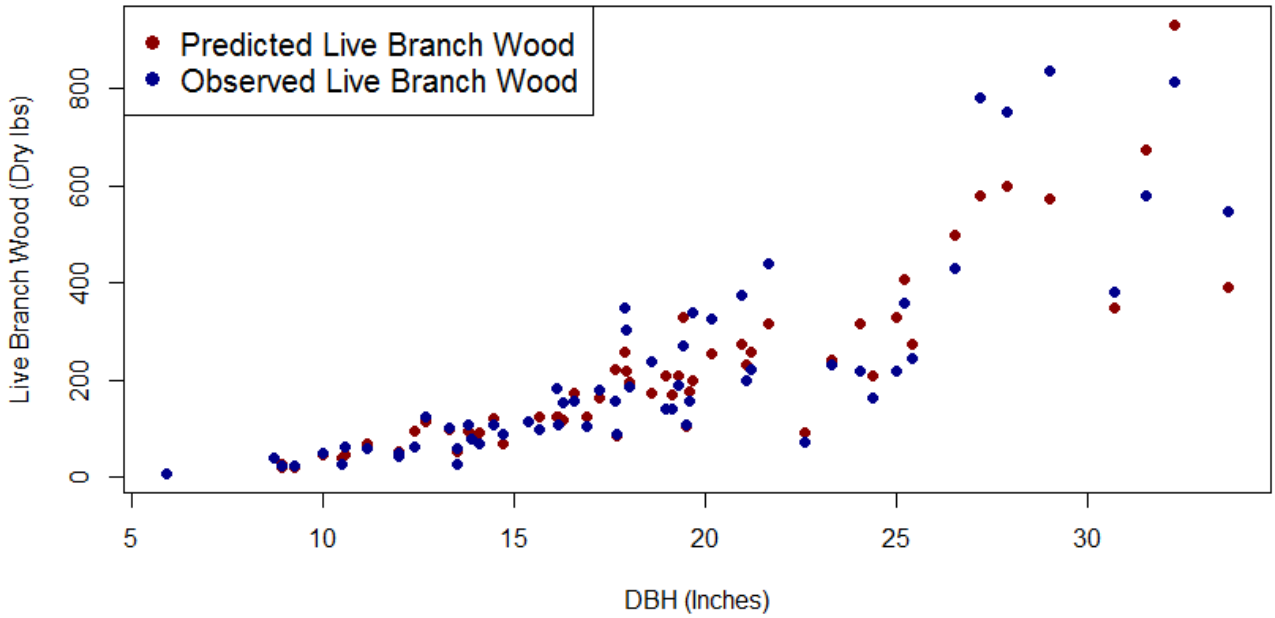

Figure 3.4.1 – Live branch wood model predictions and observations in relation to DBH.

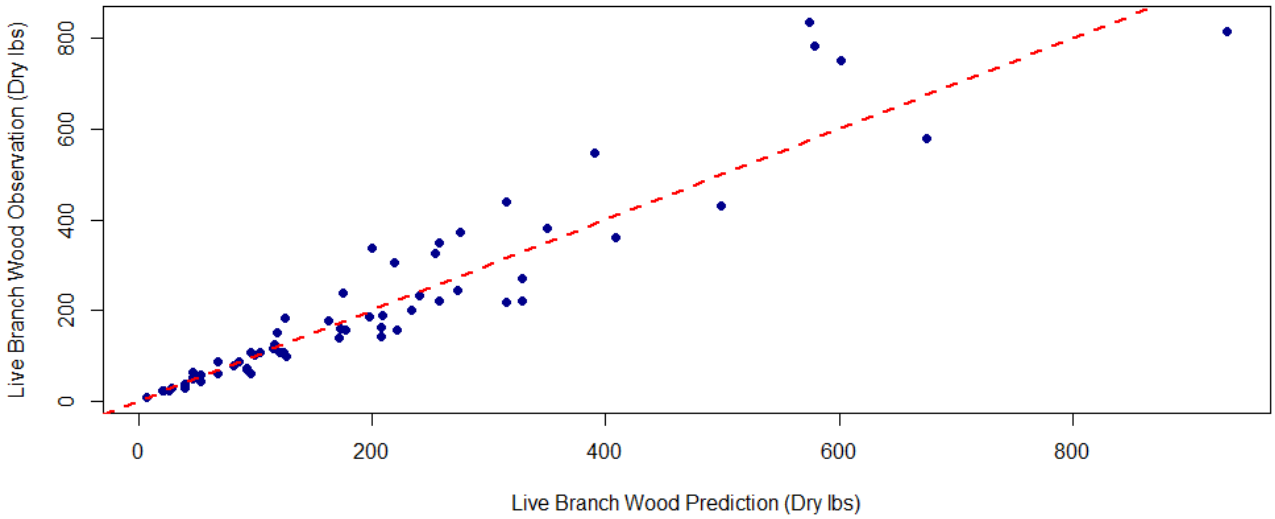

Figure 3.4.2 – Live branch wood model predictions compared to observations. Points to the right of (below) the red line indicate over-predictions, points to the left of (above) the red line indicate under-predictions.

Table 3.4.2 - Benefit of each additional predictor term to the live branch wood model. Note that increased R^2 values indicate the model explains more of the variation present in the data, and lower AIC values indicate a more parsimonious model.

Predictor Added	Change in R^2	Model Pseudo R^2	Change in AIC	Model AIC
DBH	0.711	0.711	-	70.7
Height Crown Base	0.130	0.841	-50.9	19.8
Live Crown Length	0.025	0.866	-2.9	16.9
Latitude	0.007	0.873	-6.7	10.2
Relative Density	0.007	0.880	-3.9	6.3

Chapter 3.5 Dead Branch Wood & Branch Bark Model

The final model for estimating total dead branch wood is as follows:

$$\sqrt{\boldsymbol{Dead\ Branch\ Wood}} = 10.17 + 7.26 * \ln(\boldsymbol{DBH}) + 7.19 * \boldsymbol{DBH{:}QMD\ Ratio} - 27.03 * \sqrt{\boldsymbol{Crown\ Ratio}} - 0.20 * \boldsymbol{Height\ Crown\ Base}$$

Where **Dead Branch Wood** = Dead branches, and their attached bark, of the tree in dry pounds,
DBH = Diameter at Breast Height (in.),
DBH:QMD Ratio = The DBH of the sample tree divided by the quadratic mean diameter of the stand,
Crown Ratio = Live crown length over total tree height,
Height Crown Base = The height in feet at which the tree stem was covered ¾ of the way around with living, non-epicormic branches.

Standard errors and p-values for each of the coefficients of the original model are displayed below in *Table 3.5.1*.

Table 3.5.1 – Dead branch wood model intercept, predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	10.17	5.62	0.075858
ln(DBH)	7.26	2.62	0.007513
DBH:QMD Ratio	7.19	1.98	0.000607
√(Crown Ratio)	-27.03	10.00	0.009090
Height Crown Base	-0.20	0.05	$9.7e^{-5}$

Model Pseudo R-Squared is 0.663, meaning this model explains 66.3% of the variability observed in dead branches. Root Mean Squared Error (RMSE) is 54 pounds, and Mean Absolute Error (MAE) is 35 pounds. MAE equates to 40.8% of the overall average of the dataset's dry dead branch wood weight of 85 pounds. The model has a small underestimation bias, under predicting by an average of 7 pounds, or 8.1% of the overall average of the dataset's dry dead branch wood weight. *Figure 3.5.1* displays the dead branch wood model predictions and observations in relation to DBH. *Figure 3.5.2* displays the relationship between predictions and observations, indicating model effectiveness.

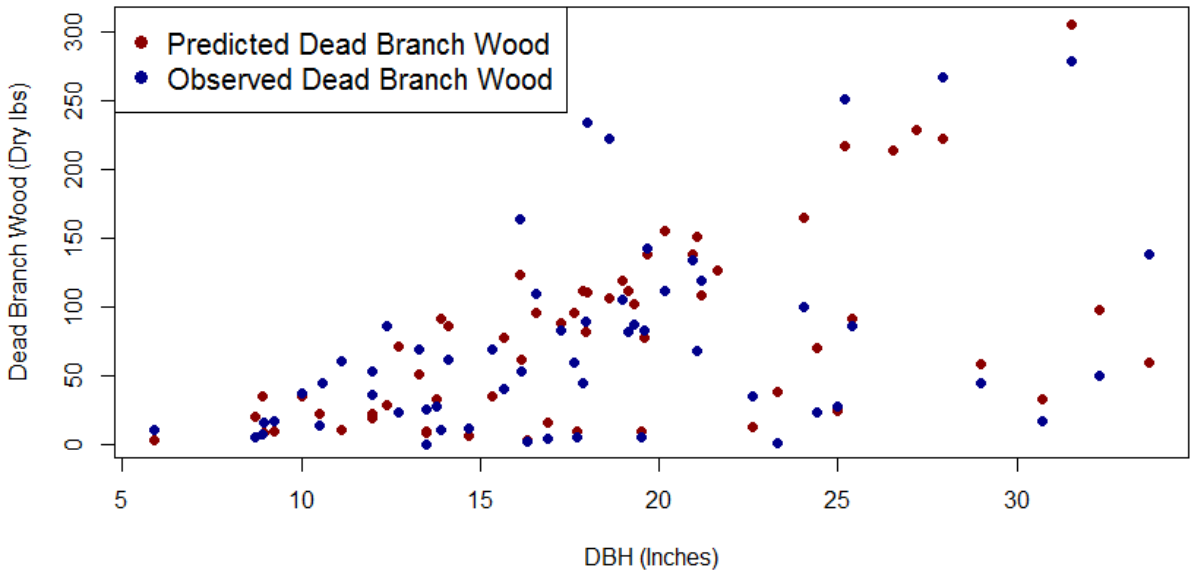

Figure 3.5.1 – Dead branch wood model predictions and observations in relation to DBH.

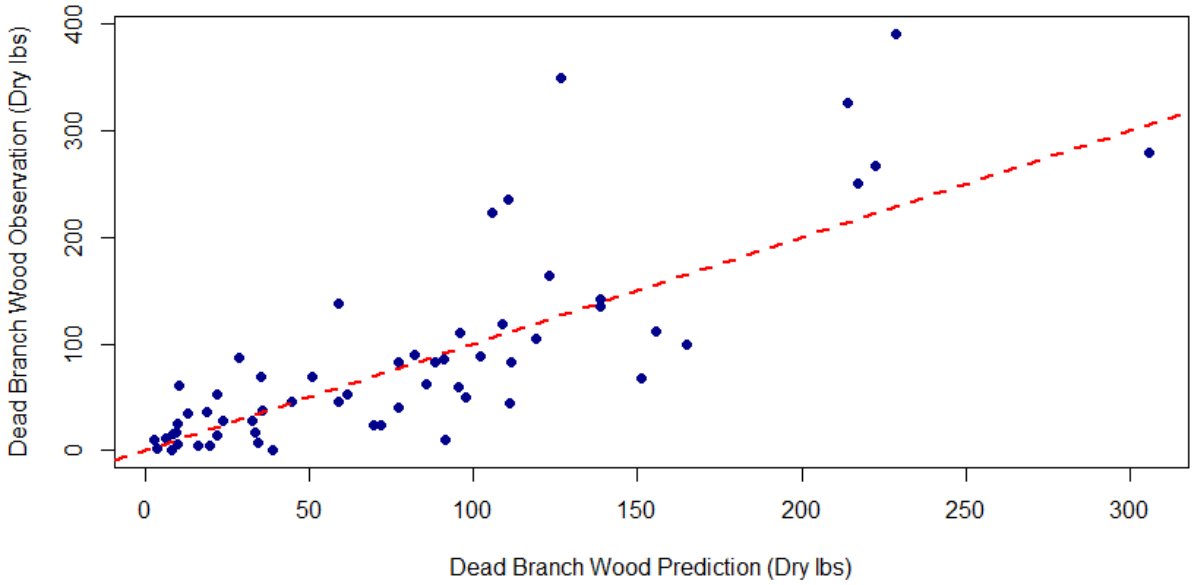

Figure 3.5.2 – Dead branch wood model predictions compared to observations. Points to the right of (below) the red line indicate over-predictions, points to the left of (above) the red line indicate under-predictions.

Table 3.5.2 - Benefit of each additional predictor term to the dead branch wood model. Note that increased R^2 values indicate the model explains more of the variation present in the data, and lower AIC values indicate a more parsimonious model.

Predictor Added	Change in R^2	Model Pseudo R^2	Change in AIC	Model AIC
DBH	0.238	0.238	NA	342.4
Height Crown Base	0.301	0.539	-27.8	314.6
DBH:QMD Ratio	0.102	0.641	-11.1	303.5
Crown Ratio	0.024	0.663	-5.5	298.0

Chapter 3.6 Stem Bark Model

The final model for estimating total bark is as follows:

$$ln(\boldsymbol{Bark}) = -2.52 + 2.80 * ln(\boldsymbol{DBH}) - 0.68 * ln(\boldsymbol{DBH}:\boldsymbol{QMD\ Ratio})$$

Where **Bark**= The bark attached directly to the stem of the tree in dry pounds,
DBH = Diameter at Breast Height (in.),
DBH:QMD Ratio = The DBH of the sample tree divided by the quadratic mean diameter of the stand.

Standard errors and p-values for each of the coefficients of the original model are displayed below in *Table 3.6.1*.

Table 3.6.1 – Bark model intercept, predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	- 2.52	0.37	$8.93e^{-9}$
ln(DBH)	2.80	0.13	$2e^{-16}$
ln(DBH:QMD Ratio)	- 0.68	0.15	$4.25e^{-5}$

Model Pseudo R-Squared is 0.912, meaning this model explains 91.2% of the variability observed in the bark. Root Mean Squared Error (RMSE) is 95 pounds, and Mean Absolute Error (MAE) 61 is pounds. MAE equates to 19.2% of the overall average of the dataset's dry bark weight of 320 pounds. The model has a small underestimation bias, under predicting by an average of 11 pounds, or 3.5% of the overall average of the dataset's dry bark weight. *Figure 3.6.1* displays the bark model predictions and observations in relation to DBH. *Figure 3.6.2* displays the relationship between predictions and observations, indicating model effectiveness.

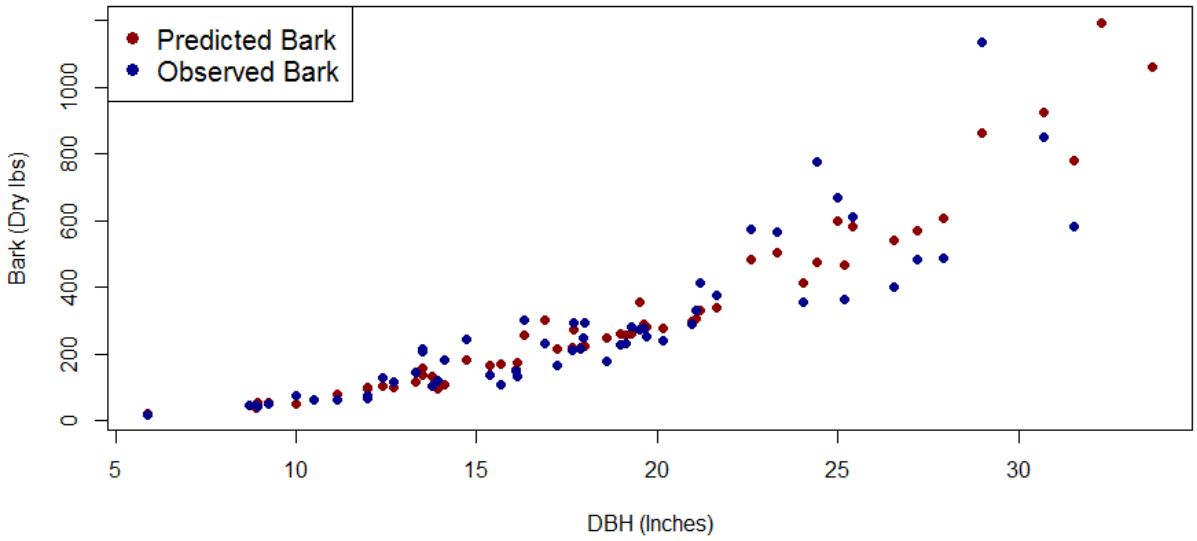

Figure 3.6.1 – Bark model predictions and observations in relation to DBH.

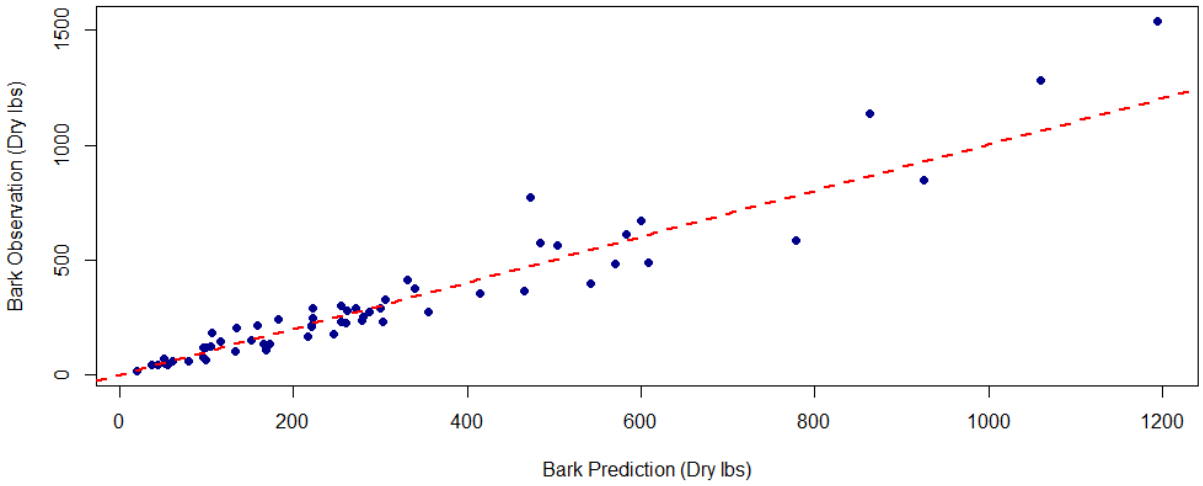

Figure 3.6.2 – Bark model predictions compared to observations. Points to the right of (below) the red line indicate over-predictions, points to the left of (above) the red line indicate under-predictions.

Table 3.6.2- Benefit of each additional predictor term to the bark model. Note that increased R^2 values indicate the model explains more of the variation present in the data, and lower AIC values indicate a more parsimonious model.

Predictor Added	Change in R^2	Model Pseudo R^2	Change in AIC	Model AIC
DBH	0.814	0.814	NA	18.1
DBH:QMD Ratio	0.098	0.912	-15.8	2.3

Chapter 3.7 Stem Wood Model

The final model for estimating total stem wood is as follows:

$$\ln(\boldsymbol{Stem\ Wood}) = -10.39 + 2.18 * \ln(\boldsymbol{DBH}) + 1.99 * \ln(\boldsymbol{Latitude}) + 0.85 * ln(\boldsymbol{Total\ Height}) - 0.47 * ln(\boldsymbol{DBH}:\boldsymbol{QMD\ Ratio})$$

Where **Stem Wood** = The wood of the stem of the tree in dry pounds,
DBH = Diameter at Breast Height (in.),
Latitude = North latitude of the stand in decimal degrees,
Total Height = The total height in feet of the tree from base to tip,
DBH:QMD Ratio = The DBH of the sample tree divided by the quadratic mean diameter of the stand.

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Standard errors and p-values for each of the coefficients of the original model are displayed below in *Table 3.7.1.*

Table 3.7.1 – Stem wood model intercept, predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	-10.39	3.41	0.00355
ln(DBH)	2.18	0.19	$1.35e^{-15}$
ln(Latitude)	1.99	0.90	0.03085
ln(Total Height)	0.85	0.26	0.00198
ln(DBH:QMD Ratio)	- 0.47	0.15	0.00193

Model Pseudo R-Squared is 0.926, meaning this model explains 92.6% of the variability observed in stem wood. Root Mean Squared Error (RMSE) is 596 pounds, and Mean Absolute Error (MAE) 319 is pounds. MAE equates to 12.9% of the overall average of the dataset's dry stem wood weight of 2480 pounds. The model has a small underestimation bias, under predicting by an average of 44 pounds, or 1.8% of the overall average of the dataset's dry stem wood weight. *Figure 3.7.1* displays the stem wood model predictions and observations in relation to DBH. *Figure 3.7.2* displays the relationship between predictions and observations, indicating model effectiveness.

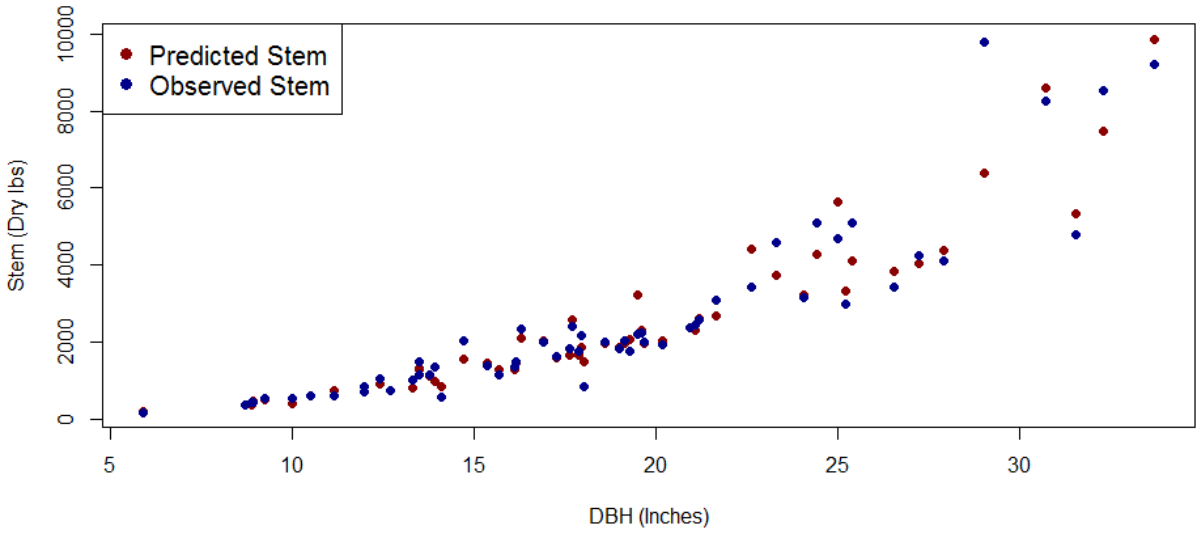

Figure 3.7.1 – Stem wood model predictions and observations in relation to DBH.

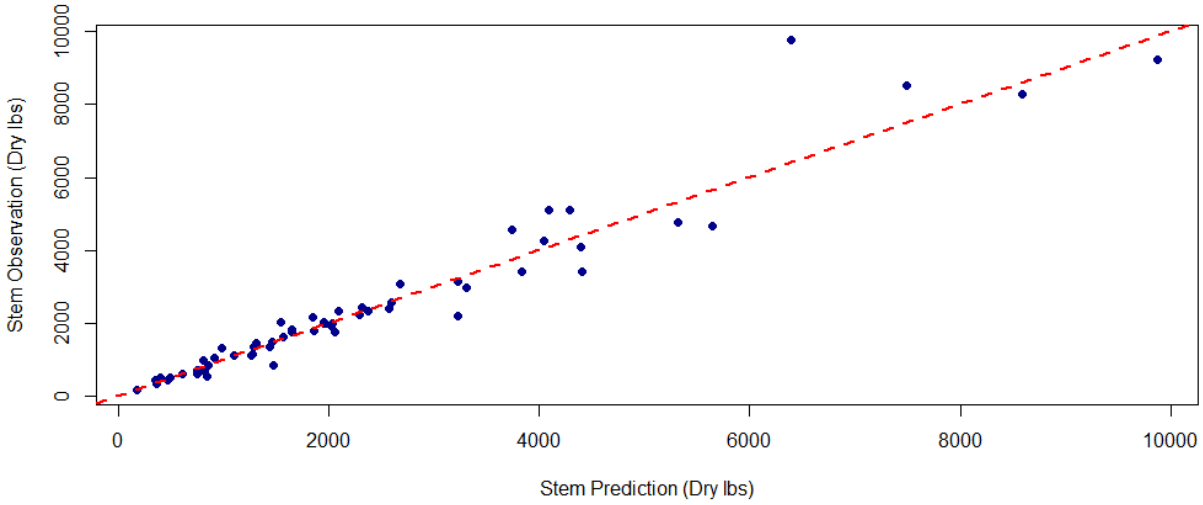

Figure 3.7.2 – Stem wood model prediction compared to observations. Points to the right of (below) the red line indicate over-predictions, points to the left of (above) the red line indicate under-predictions.

Table 3.7.2 - Benefit of each additional predictor term to the stem wood model. Note that increased R^2 values indicate the model explains more of the variation present in the data, and lower AIC values indicate a more parsimonious model.

Predictor Added	Change in R^2	Model Pseudo R^2	Change in AIC	Model AIC
DBH	0.854	0.854	-	7.1
Total Height	0.065	0.919	-27.8	-20.7
DBH:QMD Ratio	0.023	0.942	-5.3	-26.0
Latitude	-0.016	0.926	-3.2	-29.2

3.8 Component Ratio Models

The method utilized by Jenkins (2003) for estimating ratio models for component biomass was to determine the ratio for all but one of the components and then find that component via subtraction of all of the other components from 1.0, in order to ensure that the ratio total comes to 1.0. This method was utilized in this study as well. In this study, all five components were investigated as the component to be calculated via subtraction, and the component that generated the worst performing ratio model was selected as the one to be calculated via subtraction.

In this case, the stem wood ratio model was found to be the worst, as it consistently under-predicted the ratio of stem wood compared to observations. For this reason, stem wood was selected as the component to be calculated via subtraction. Therefore, only models for Foliage, Live branch wood & branch bark, Dead branch wood & branch bark, and Stem bark are presented below.

The final model for estimating the percentage of foliage from the DBH-only total aboveground biomass model is as follows:

$$ln(\boldsymbol{Foliage\ Percentage}) = 0.47 + \frac{3.66}{\mathbf{DBH}}$$

Where **Foliage Percentage** = Percentage of the total aboveground biomass composed of foliage, **DBH** = Diameter at Breast Height (in.).

Standard errors and p-values for the intercept and the coefficient of the original model are displayed below in *Table 3.8.1*.

Table 3.8.1 –Ratio foliage model predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	0.47	0.16	0.0043129
DBH^{-1}	3.66	2.3	0.1225991

Model Pseudo R-Squared is 0.025, meaning this model explains 2.5% of the variability observed. Root Mean Squared Error (RMSE) is 0.46. DBH is not significant at an alpha (α) of 0.05. *Figure 3.8.1* displays the ratio foliage model and observations in relation to DBH.

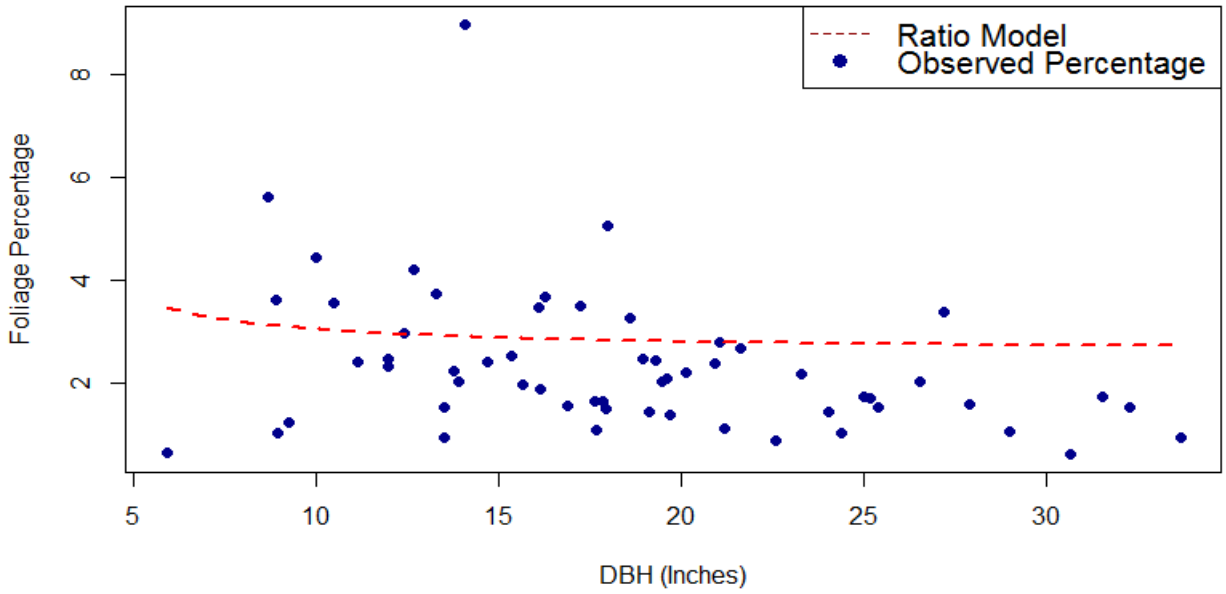

Figure 3.8.1 – Ratio foliage model overlaid onto observed values in relation to DBH.

The final model for estimating the percentage of live branch wood from the total aboveground biomass model is as follows:

$$ln(\boldsymbol{Live\ Branch\ Wood\ Percentage}) = 2.04 + \frac{-3.64}{DBH}$$

Where **Live Branch Wood Percentage** = Percentage of the total aboveground biomass composed of living branches and attached bark (no needles),
DBH = Diameter at Breast Height (in.).

Standard errors and p-values for the intercept and the coefficient of the original model are displayed below in *Table 3.8.2.*

Table 3.8.2 –Ratio live branch wood model predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	2.04	0.15	$2e^{-16}$
DBH^{-1}	-3.64	2.18	0.10095

Model Pseudo R-Squared is 0.030, meaning this model explains 3.0% of the variability observed. Root Mean Squared Error (RMSE) is 0.43. DBH is not significant at an alpha (α) of 0.05. *Figure 3.8.2* displays the ratio live branch wood model and observations in relation to DBH.

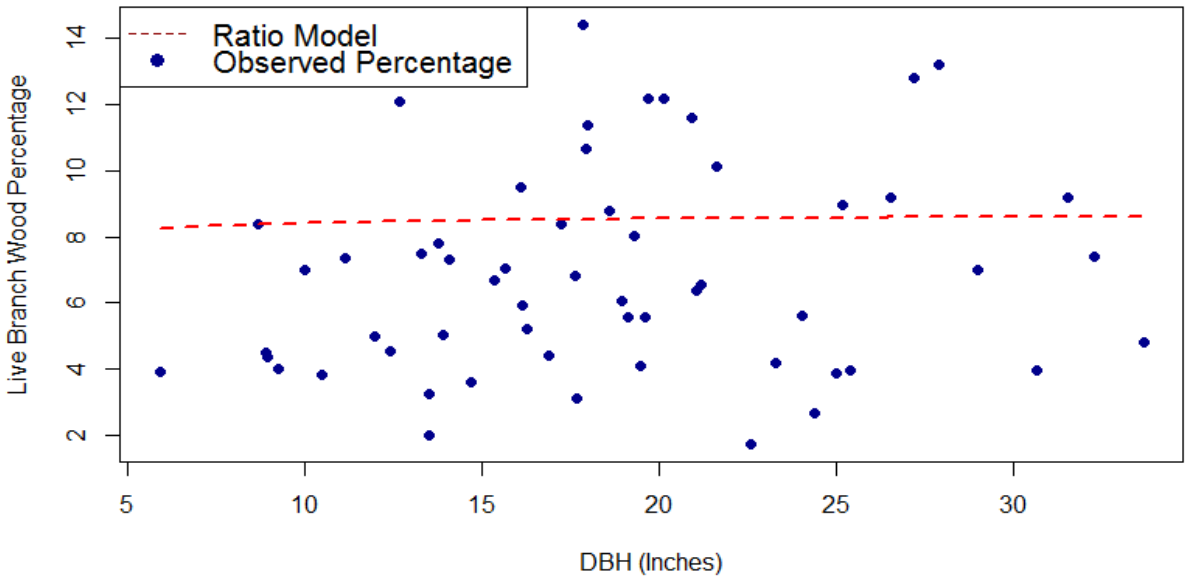

Figure 3.8.2 - Ratio live branch wood model overlaid onto observed values in relation to DBH..

The final model for estimating the percentage of dead branch wood from the total aboveground biomass model is as follows:

$$ln(\boldsymbol{Dead\ Branch\ Wood\ Percentage}) = -0.30 + \frac{14.99}{DBH}$$

Where **Dead Branch Wood Percentage** = Percentage of the total aboveground biomass composed of dead branches their attached bark,
DBH = Diameter at Breast Height (in.).

Standard errors and p-values for the intercept and the coefficient of the original model are displayed below in *Table 3.8.3.*

Table 3.8.3 – Ratio dead branch wood model predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	-0.30	0.46	0.516149
DBH^{-1}	14.99	6.83	0.032463

Model Pseudo R-Squared is 0.063, meaning this model explains 6.3% of the variability observed. Root Mean Squared Error (RMSE) is 1.34. The intercept is not significant at an alpha (α) of 0.05. *Figure 3.8.3* displays the ratio dead branch wood model and observations in relation to DBH.

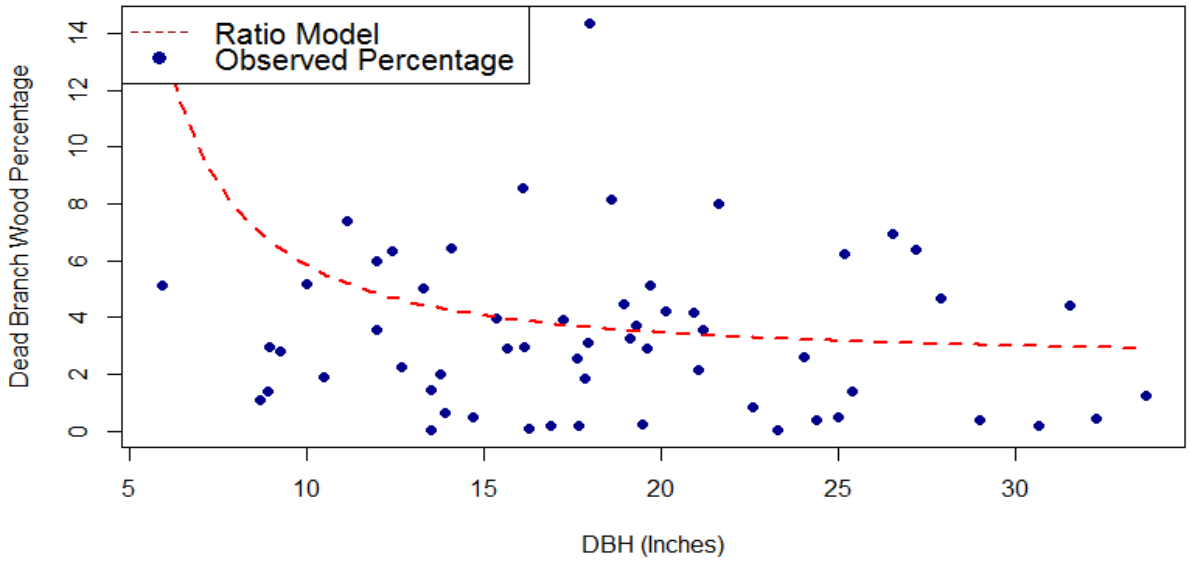

Figure 3.8.3 - Ratio dead branch wood model overlaid onto observed values in relation to DBH.

The final model for estimating the percentage of bark from the total aboveground biomass model is as follows:

$$ln(\boldsymbol{Bark\ Percentage}) = 2.36 + \frac{-1.49}{DBH}$$

Where **Bark Percentage** = Percentage of the total aboveground biomass composed bark attached directly to the stem of the tree,
DBH = Diameter at Breast Height (in.).

Standard errors and p-values for the intercept and the coefficient of the original model are displayed below in *Table 3.8.4*

Table 3.8.4 –Ratio bark model predictors, their coefficients, their standard errors, and their p-values.

Predictor	Coefficient	Standard Error	p-value
Intercept	2.36	0.06	$2e^{-16}$
DBH^{-1}	-1.49	0.83	0.077564

Model Pseudo R-Squared is 0.038, meaning this model explains 3.8% of the variability observed. Root Mean Squared Error (RMSE) is 0.16. DBH is not significant at an alpha (α) of 0.05. Figure 3.8.4 displays the ratio bark model and observations in relation to DBH.

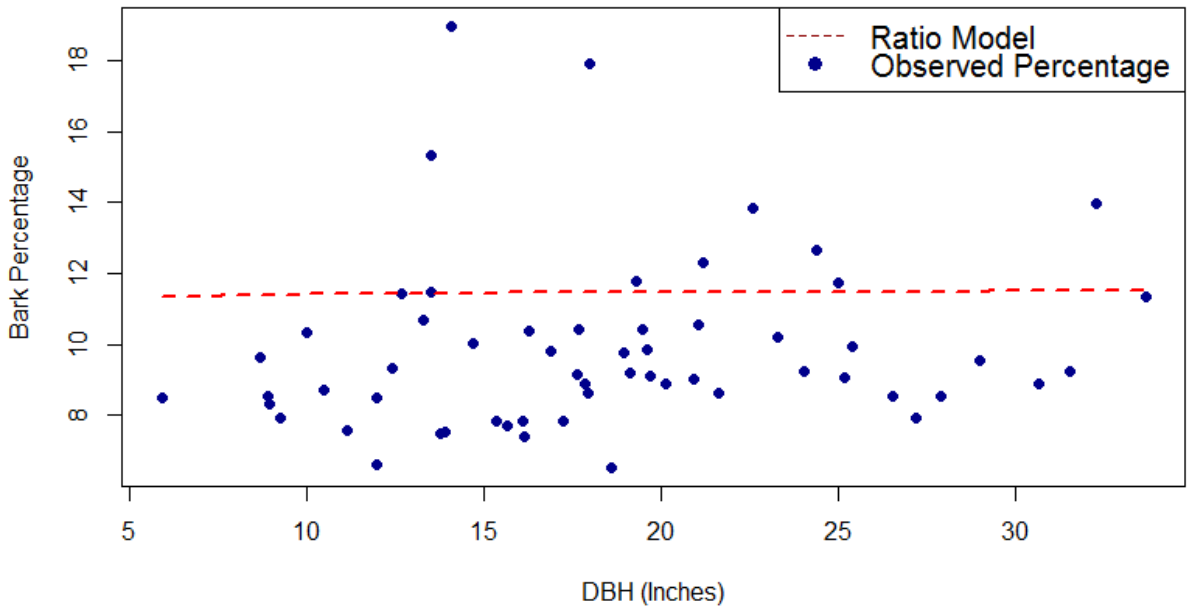

Figure 3.8.4 - Ratio bark model overlaid onto observed values in relation to DBH.

Chapter 4. Discussion and Model Comparisons:

Chapter 4.0 Complex Models Compared to Single Predictor Models

Typically, models produced for aboveground biomass of trees utilize the DBH of the tree as the only predictor, such as the models produced by Gholz (1979), Harrison (2007), and Nay & Borman (2014), among others. The benefits of using a single predictor model include simplicity, as well as the speed and ease with which the necessary field data may be collected. These model types have been widely used for the estimation of tree aboveground biomass.

However, the drawbacks of having a single-predictor model are many. These models are not capable of effectively distinguishing between trees of the same DBH when a multitude of other landscape, stand, or tree level variables may be substantially different. These discrepancies can be substantial, as shown by the inferior performance of the component models produced in this study when DBH was utilized as the only predictor. Models which include more predictor variables than just DBH account for much more variation among trees growing under different conditions.

Multi-variable models are more complex, and do require more field work in order to collect the necessary information other than DBH, unless these other variables are already included in a typical forest inventory. The predictor variables determined to be useful for total aboveground biomass, slash, and component biomass prediction are likely to be reasonably easy to measure in most applications. For instance, predictor variables commonly included in each complex model such as total height, DBH:QMD ratio, relative density, crown ratio, and TPA all take minimal effort to assess.

To visualize the benefits that may be obtained by using complex models, See *Figures 4.0.1* through *4.0.7,* which display the ability of each of the complex models to capture more variation than their respective DBH-only model.

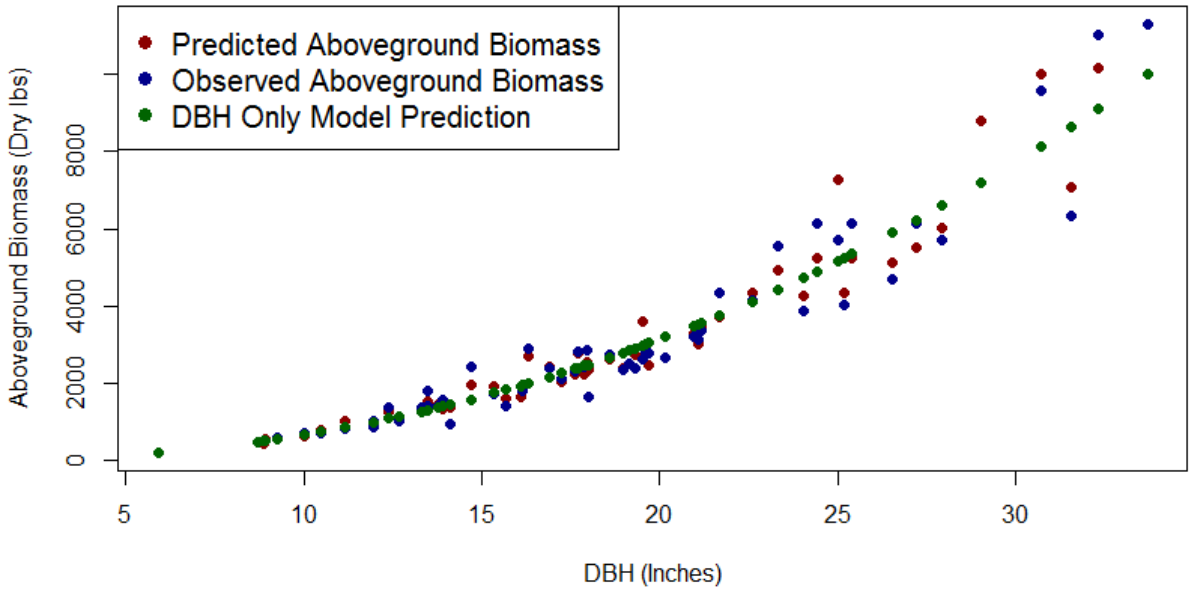

Figure 4.0.1 - Total aboveground biomass full model predictions compared to DBH-only total aboveground biomass model predictions in relation to DBH.

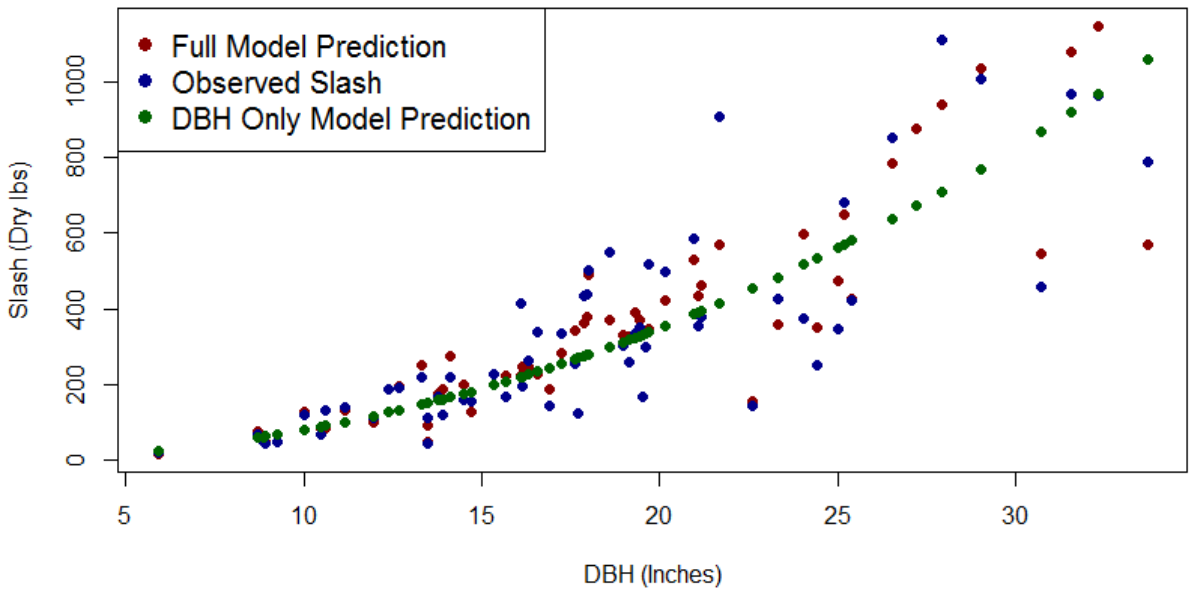

Figure 4.0.2 - Slash full model predictions compared to DBH-only slash model predictions in relation to DBH.

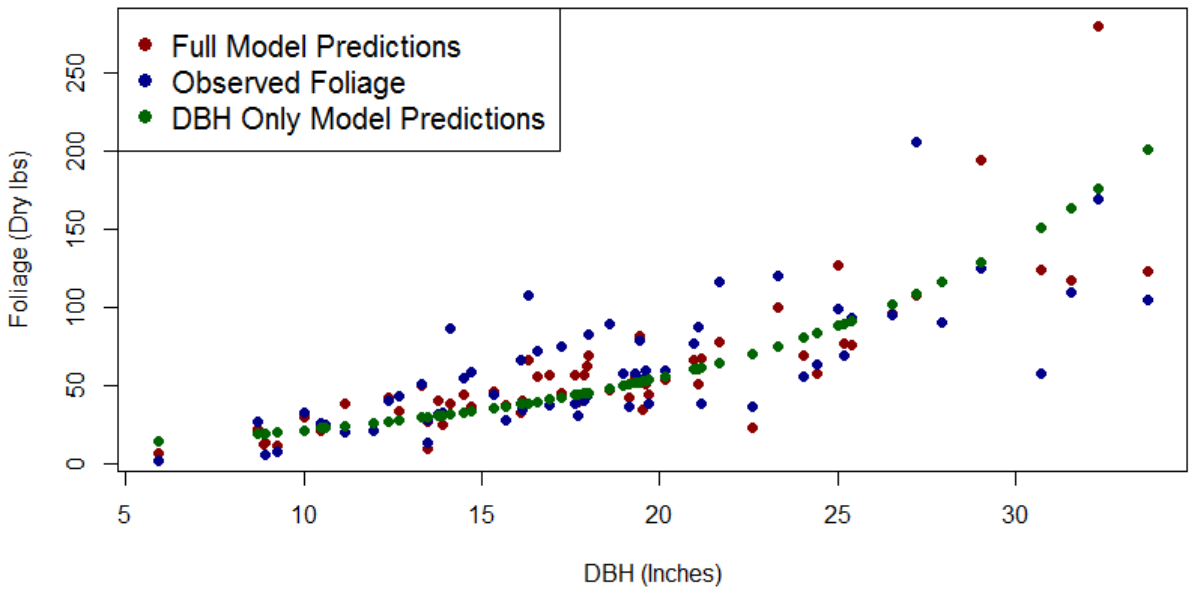

Figure 4.0.3 – Foliage full model predictions compared to DBH-only foliage model predictions in relation to DBH.

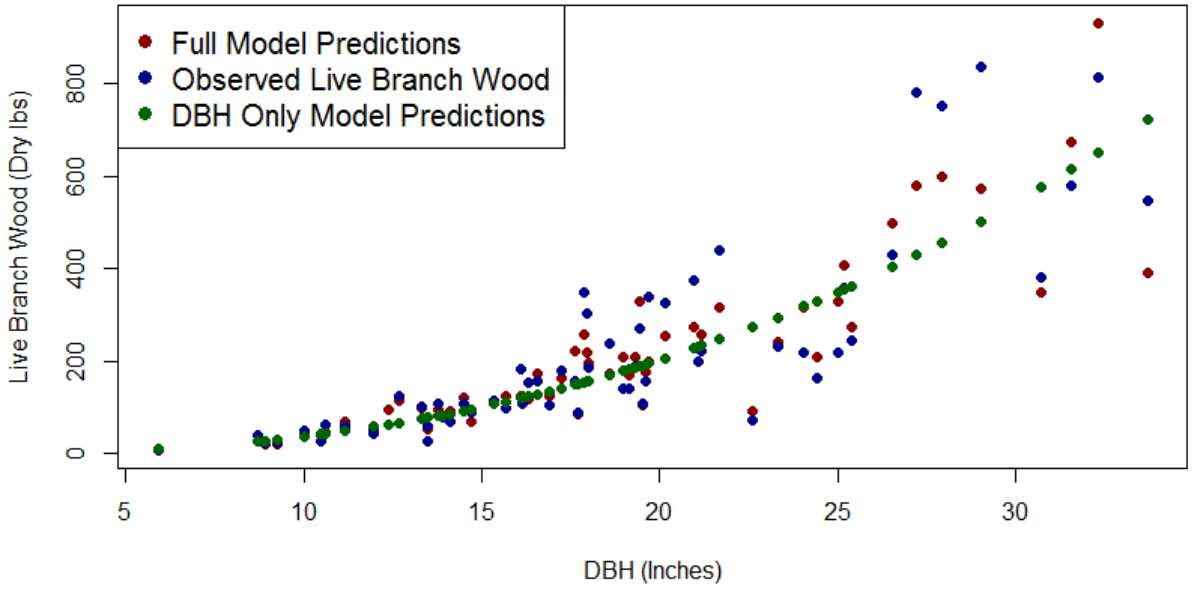

Figure 4.0.4 – Live branch wood full model predictions compared to DBH-only live branch wood model predictions in relation to DBH.

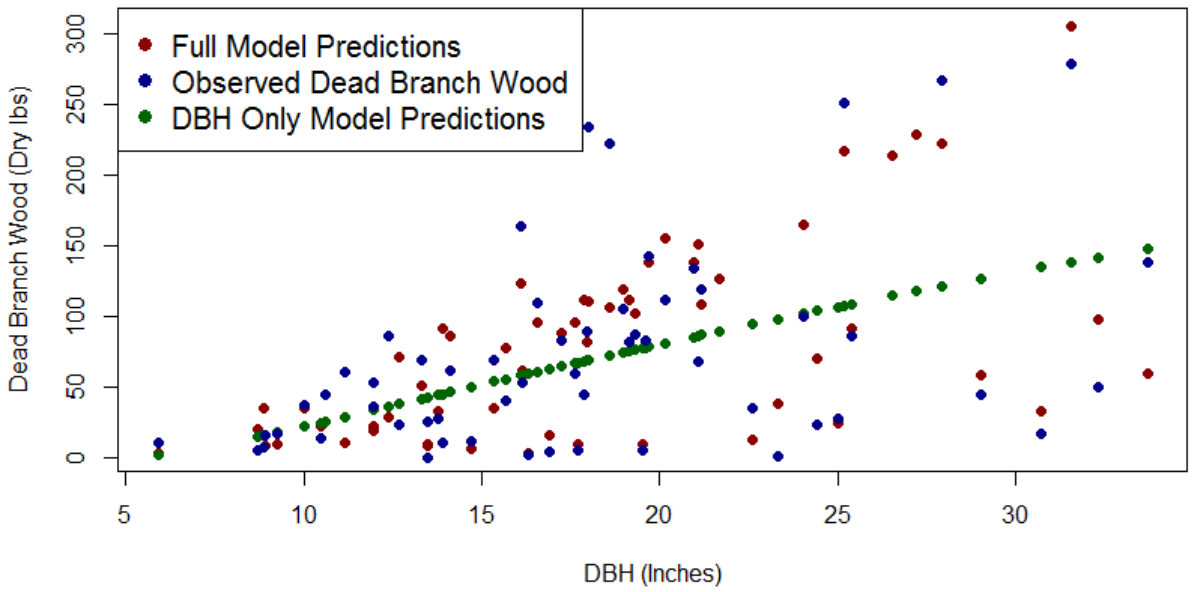

Figure 4.0.5 – Dead branch wood full model predictions compared to DBH-only dead branch wood model predictions in relation to DBH.

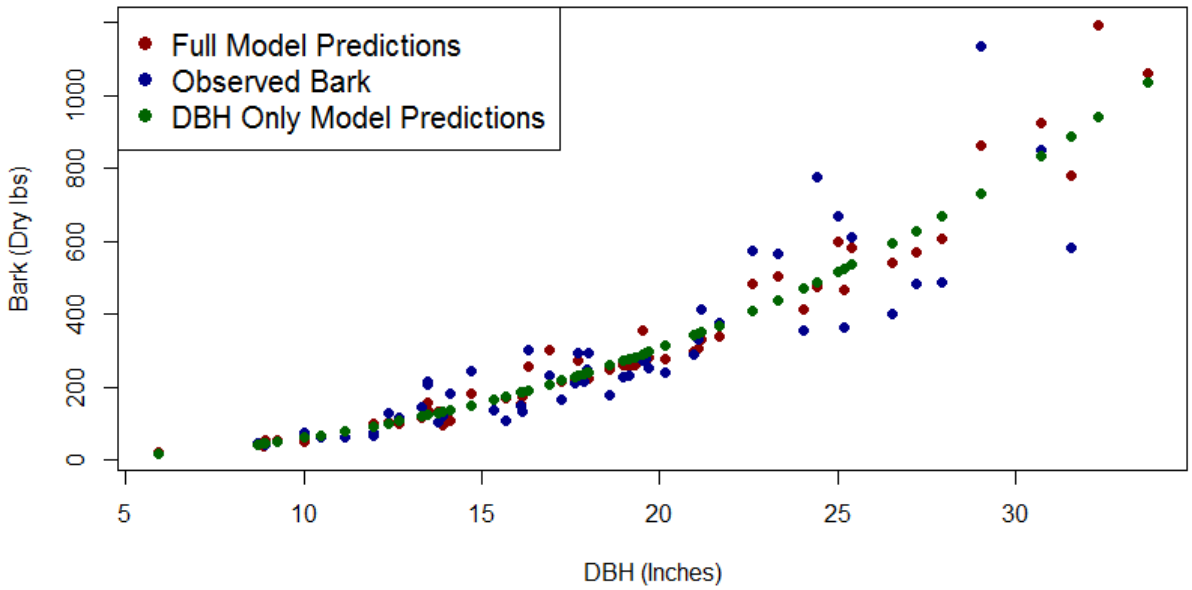

Figure 4.0.6 –Bark full model predictions compared to DBH-only bark model predictions in relation to DBH.

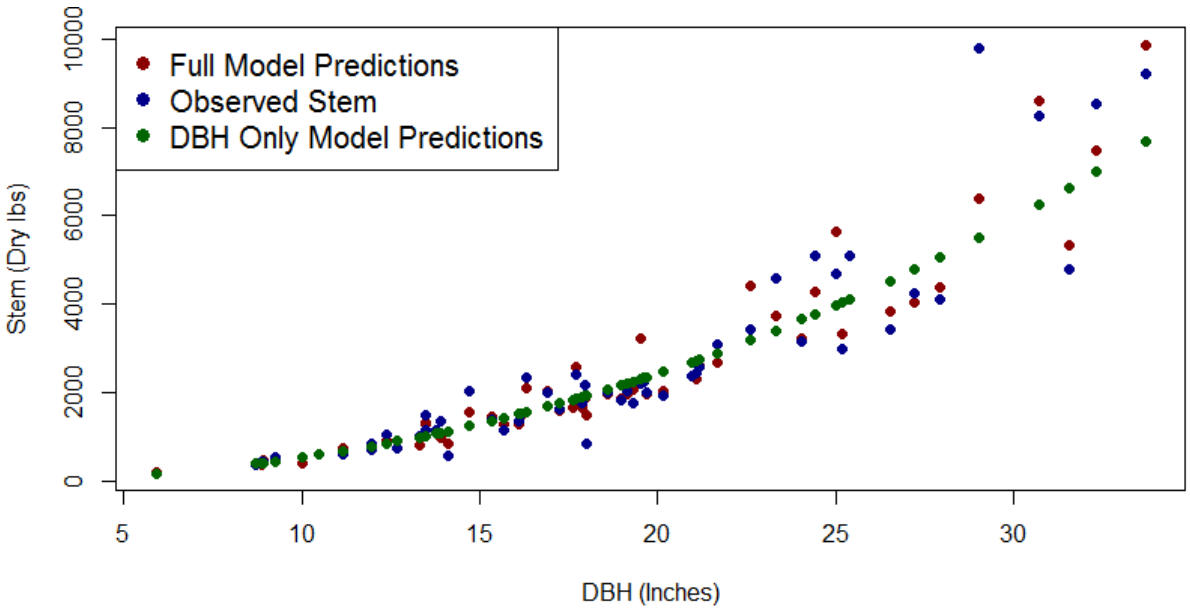

Figure 4.0.7 –Stem wood full model predictions compared to DBH-only stem wood model predictions in relation to DBH.

Chapter 4.1 Total Aboveground Biomass Model Discussion

The model for total aboveground biomass has a wide array of interesting applications, especially suited towards climate change scientists and industrial forest managers. Total aboveground biomass can be utilized in determining the overall carbon sequestration in an entire stand, landscape, or region, and can also inform forest managers about the biomass they can expect under different conditions throughout their holdings.

The predictors and the signs of their coefficients included in the model for total aboveground biomass appear appropriate. DBH and total height are general indicators of the overall size of the tree, and their positive correlation with total aboveground biomass is directly demonstrable. Crown ratio was positively correlated with total aboveground biomass, and is indicative of more live branches present on the tree. A higher crown ratio also indicates more sun exposure and less crown recession, meaning that living branches may have the time to get large and accumulate substantial biomass. TPA is a measure of the density of the stand and was negatively correlated. Trees growing in denser stands experience more competition for resources such as light and water, limiting their individual biomass accumulation.

The 45 pound (1.4%) average underestimation bias of the model is quite low, and lends confidence to the model's ability to accurately predict the total aboveground biomass of a tree over a wide range of variables. It is important to note that this particular model, in contrast to the others produced in this study, remains exceptionally accurate for larger trees. This suggests that the model could potentially even be extrapolated accurately on trees larger than the range of the dataset utilized for the model.

Example prediction intervals for 3 DBH's representing small, medium, and large trees are presented in *Table 4.1.1* to demonstrate the variability in precision of the model among trees of

different sizes. This variability is important to take into account depending upon the size of the tree(s) being assessed. Predictions are calculated when all other predictor variables are set to their mean value.

Table 4.1.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the total aboveground biomass model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

DBH (Inches)	Lower Prediction (lbs)	Prediction (lbs)	Upper Prediction (lbs)	Interval Size (lbs)
10	688	936	1272	584
20	2251	2985	3958	1707
30	4358	5884	7945	3587

Comparing the model predictions to the total aboveground biomass model produced by Harrison (2009) illustrates some interesting differences. It is apparent in *Figure 4.1.1* that the Harrison total aboveground biomass model most closely fits both the predictions and the observations up to about 21 inches DBH. However, after this point, the Harrison model appears to under-predict for larger trees.

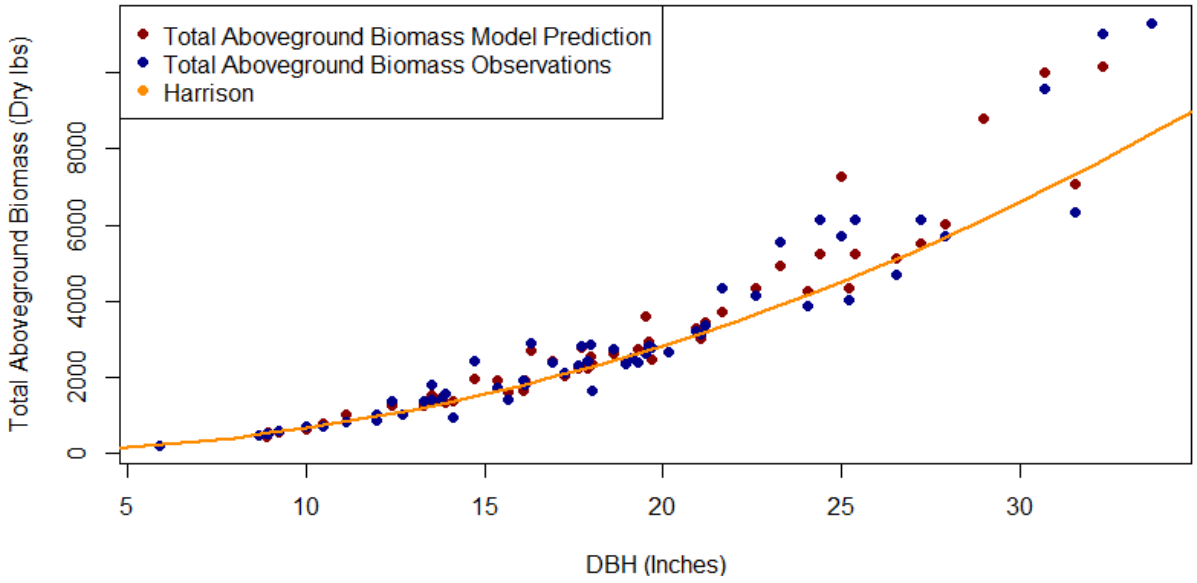

Figure 4.1.1 – Total aboveground biomass model predictions and observations compared to the Harrison model.

Overall, the sum of the individual component models (Foliage, live branch wood & bark, dead branch wood & bark, stem bark, and stem wood*)* match very well with the predictions of the total aboveground biomass model. It is apparent in *Figure 4.1.2* that the model predictions match especially well at smaller overall aboveground biomass totals, in the 0-4000 dry pound range. Above this amount of biomass, the individual component model predictions are less precise. However, even the largest variation is slight, indicating that the individual component models and the total aboveground biomass model are in reasonable consensus. The Aboveground biomass model and the individual model sums had a pseudo R2 value of 0.951. Similarly, as shown in *Figure 4.1.3*, the sum of the individual components match well with the observations of total aboveground biomass, with the majority of variation occurring in trees weighing above about 4000 dry pounds. The sums and the observations had a pseudo R2 value of 0.939.

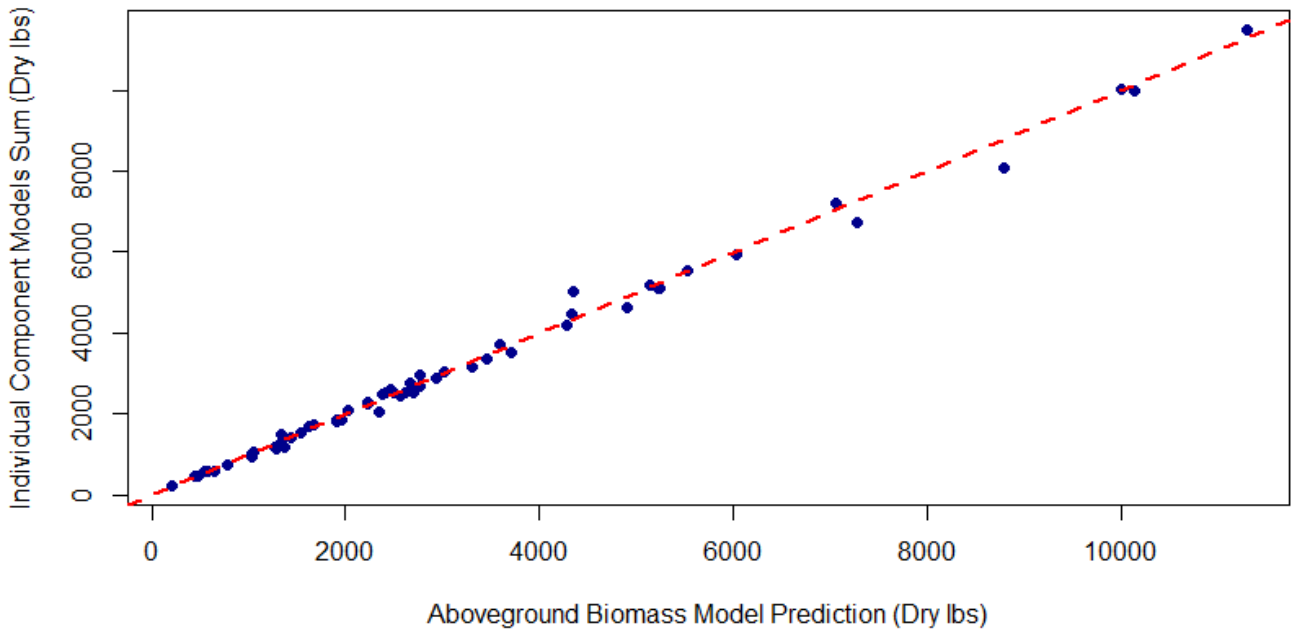

Figure 4.1.2 - Sum of the individual component models (Foliage, live branch wood, dead branch wood, bark, and stem wood) compared to the total aboveground biomass model predictions, with a dashed red line of slope 1 overlaid. Points to the right of (below) the red line indicate over-predictions, points to the left of (above) the red line indicate under-predictions.

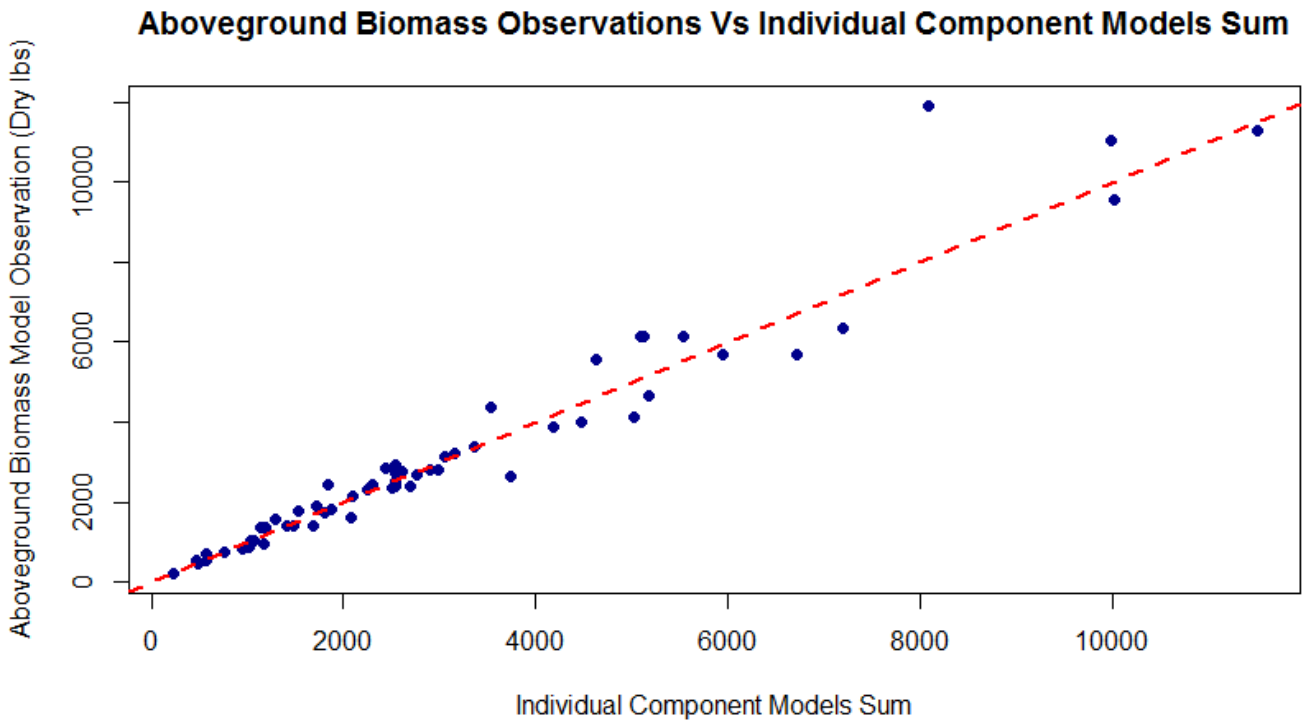

Figure 4.1.3 - Sum of the individual component models (Foliage, live branch wood & bark, dead branch wood & bark, stem bark, and stem wood) compared to the observed total aboveground biomass, with a dashed red line of slope 1 overlaid. Points to the right of (below) the red line indicate over-predictions, points to the left of (above) the red line indicate under-predictions.

Chapter 4.2 Slash Model Discussion

The model for slash is particularly useful for industrial forest managers. Slash piling and disposal is one of the most time-consuming processes of timber harvest and is usually necessary for the re-establishment of the next cohort of trees. Having accurate estimates of slash will provide managers with tools to plan for the machinery and manpower necessary for a given harvest site. It may also be valuable information with regards to site preparation, in determining if a broadcast burn or other such site preparation treatments may be feasible based upon the amount of slash expected.

The predictors and the signs of their coefficients included in the model for slash appear appropriate. DBH is a general indicator of the overall size of the tree, and typically larger trees will have more live branches, dead branches, and foliage compared to a smaller tree grown under the same conditions. Crown length was positively correlated with slash, and is indicative of more live branches present on the tree. DBH:QMD ratio was positively correlated and is indicative of a tree being larger than its neighbors, meaning that the tree likely had access to more sun and therefore was able to grow more branches and foliage. Relative density is a measure of the density of the stand and was negatively correlated. Trees growing in denser stands experience more competition for resources such as light and water, limiting their individual branch and foliage growth. Elevation and Latitude were both negatively correlated with slash, which goes against the typically expected relationship for coastal Douglas-fir. This may be due to higher elevations and latitudes being associated with more severe weather events and higher snow loads which may impact the retention of crown. For latitude, it may also be due to the lower angle of the sun causing more shading due to neighboring trees, in turn leading to sparse crowns with smaller branches.

The 13 pound (3.6%) average underestimation bias of the model is quite low, and lends confidence to the model's ability to accurately predict the slash yield of a tree over a wide range of variables. It is important to note that the model typically becomes less precise for larger slash estimates. This is likely due to the greater variability in the crowns of larger, older trees, which have had time to develop greater differences than in smaller, younger trees.

. Example prediction intervals for 3 DBH's representing small, medium, and large trees are presented in *Table 4.2.1* to demonstrate the variability in accuracy of the model among trees of different sizes. This variability is important to take into account depending upon the size of the tree(s) being assessed. Predictions are calculated when all other predictor variables are set to their mean value.

Table 4.2.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the slash model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

DBH (Inches)	Lower Prediction (lbs)	Prediction (lbs)	Upper Prediction (lbs)	Interval Size (lbs)
10	69	119	203	134
20	191	315	520	329
30	330	557	941	611

Chapter 4.3 Foliage Model Discussion

The model for foliage has a wide array of interesting applications, specifically suited towards ecologists, climate change scientists, and industrial forest managers. Foliage can be thought of as the source of the productivity of a tree, as the foliage is where all photosynthesis occurs in Douglas-fir. This model could therefore be applied to a stand as a way to measure the overall productivity of a stand over a certain area. The sum of this foliage estimation from all living trees in a stand could also be utilized in such a way as to determine the portion of the site resources that the trees are utilizing. A higher amount of foliage over a given area may indicate more of the sunlight is taken up by the trees and be directly related to the types natural regeneration that may occur or the composition of understory species.

The predictors and the signs of their coefficients included in the model for foliage appear appropriate. DBH is a general indicator of the overall size of the tree, and typically larger trees will have more foliage compared to a smaller tree grown under the same conditions. Crown ratio was positively correlated with foliage, and is indicative of more live branches present on the tree. A higher crown ratio also indicates more sun exposure and less crown recession, meaning that living branches may have time to grow and accumulate substantial biomass. Somewhat counterintuitively, height of crown base was shown to be positively correlated with foliage. This may be due to older, larger trees having large amounts of foliage despite having crowns that begin high on the tree. In this way, height of crown base acts as a surrogate for age, in synergy with live crown ratio. TPA is a measure of the density of the stand and was negatively correlated. Trees growing in denser stands experience more competition for resources such as light and water, limiting their individual biomass accumulation. Latitude displayed a negative relationship

with foliage, which was unexpected. This may be due to the lower angle of the sun causing more shading due to neighboring trees, thus in turn leading to sparse crowns.

The 1 pound (1.3%) average underestimation bias of the model is quite low, and lends confidence to the model's ability to accurately predict the foliage of a tree over a wide range of variables. It is important to note that the model typically becomes less precise for larger foliage estimates. This is likely due heteroscedasticity of the data, and the greater variability in the crowns of larger, older trees, which have had time to develop greater differences than in smaller, younger trees.

Example prediction intervals for 3 DBH's representing small, medium, and large trees are presented in *Table 4.3.1* to demonstrate the variability in accuracy of the model among trees of different sizes. This variability is important to take into account depending upon the size of the tree(s) being assessed. This table's intervals differ from the other models in that individual example trees of the varying DBH's were used. Values of predictors included in the foliage model are set to those of each example tree, as using the mean values did not create an accurate representation of the model's variability as tree DBH increased.

Table 4.3.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the foliage model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. This table's intervals differ from the other models in that individual example trees of the varying DBH's were used. Values of predictors included in the foliage model are set to those of each example tree, as using the mean values did not create an accurate representation of the model's variability as tree DBH increased.

DBH (Inches)	Lower Prediction (lbs)	Prediction (lbs)	Upper Prediction (lbs)	Interval Size (lbs)
10	11	29	75	64
20	22	53	131	109
30	47	119	305	258

Comparing the foliage model predictions to the foliage models produced by Gohlz (1979), Harrison (2009), and Nay & Borman (2014) illustrate some interesting differences. It is apparent in *Figure 4.3.1* that the Harrison foliage model most closely fits both the predictions and the observations. This makes sense, as half of the data utilized in the development of this model comprised the dataset which Harrison utilized for his model. Both the Gohlz and the Nay & Borman models fit the predictions and observations decidedly less well, with both of the models fitting reasonably well up to about 15 inches DBH and then increasing far above most of the predictions and observations.

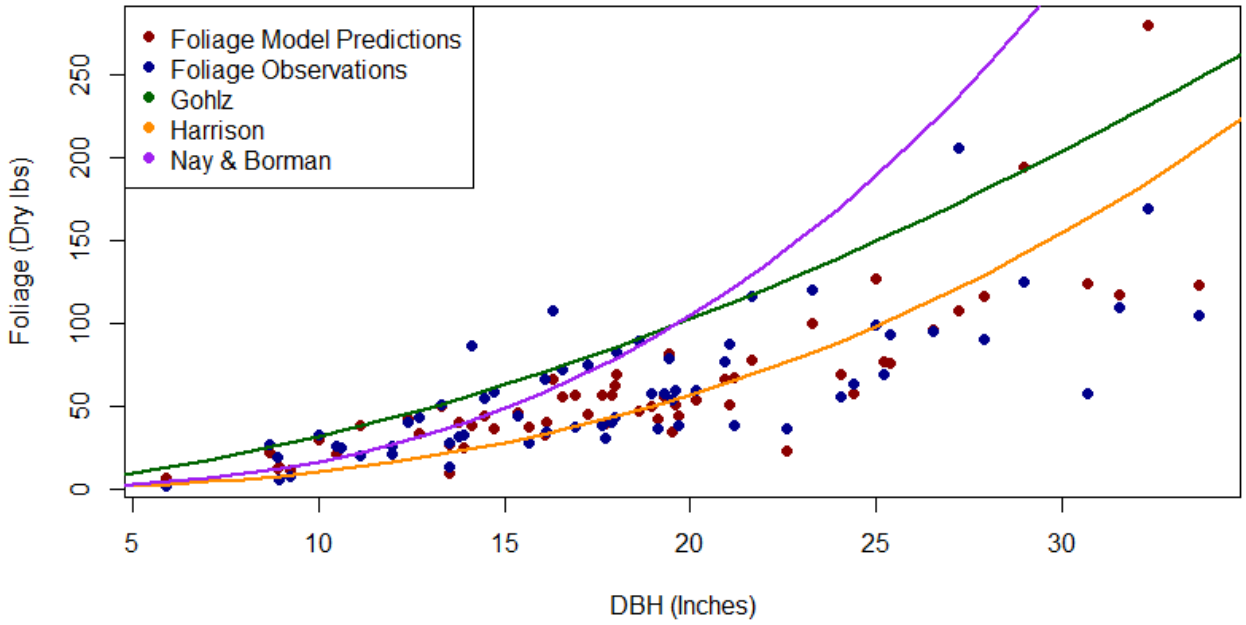

Figure 4.3.1 – Foliage model predictions and observations compared to other models.

Chapter 4.4 Live Branch Wood & Branch Bark Model Discussion

Live Branch biomass typically comprises the bulk of slash yield in timber harvest operations, and is therefore important for the same reasons that slash is. Additionally, use of forest biomass for biofuel or other energy uses is likely to rely heavily upon the live branches, making estimation of live branch biomass essential for biofuel production estimates.

The predictors and the signs of their coefficients included in the model for live branches appear appropriate. DBH is a general indicator of the overall size of the tree, and typically larger trees will have more live branch wood compared to a smaller tree grown under the same conditions. Crown length was positively correlated with live branches, and height of crown base was negatively correlated. These relationships are indicative of more live branches present on the tree, more sun exposure, and less crown recession, meaning that living branches have time to grow and accumulate substantial biomass. Relative density is a measure of the density of the stand and was negatively correlated. Trees growing in denser stands experience more competition for resources such as light and water, limiting their ability to develop large branches and causing the death of branches sooner. Latitude displayed a negative relationship with live branches, which is unexpected. This may be due to the lower angle of the sun causing more shading due to neighboring trees, leading to sparser crowns with fewer and/or thinner branches.

The 8 pound (3.9%) average underestimation bias of the model is quite low, and lends confidence to the model's ability to accurately predict the live branch wood weight of a tree over a wide range of variables. It is important to note that the model typically becomes less precise for larger live branch wood estimates. This is likely due to the greater variability in the crowns of larger, older trees, which have had time to develop greater differences than in smaller, younger trees.

Example prediction intervals for 3 DBH's representing small, medium, and large trees are presented in *Table 4.4.1* to demonstrate the variability in accuracy of the model among trees of different sizes. This variability is important to take into account depending upon the size of the tree(s) being assessed. Predictions are calculated when all other predictor variables are set to their mean value.

Table 4.4.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the live branch wood model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

DBH (Inches)	Lower Prediction (lbs)	Prediction (lbs)	Upper Prediction (lbs)	Interval Size (lbs)
10	23	38	65	42
20	122	198	322	200
30	310	518	865	555

Comparing the live branch wood model predictions to the live branch models produced by Gohlz (1979), Harrison (2009), and Nay & Borman (2014) illustrate a consensus among the models. It is apparent in *Figure 4.4.1* that all of the models closely fit both the predictions and the observations. There is some discrepancy with the models after about 23 inches DBH, but this is expected due to the increased heteroscedasticity of the data at larger values.

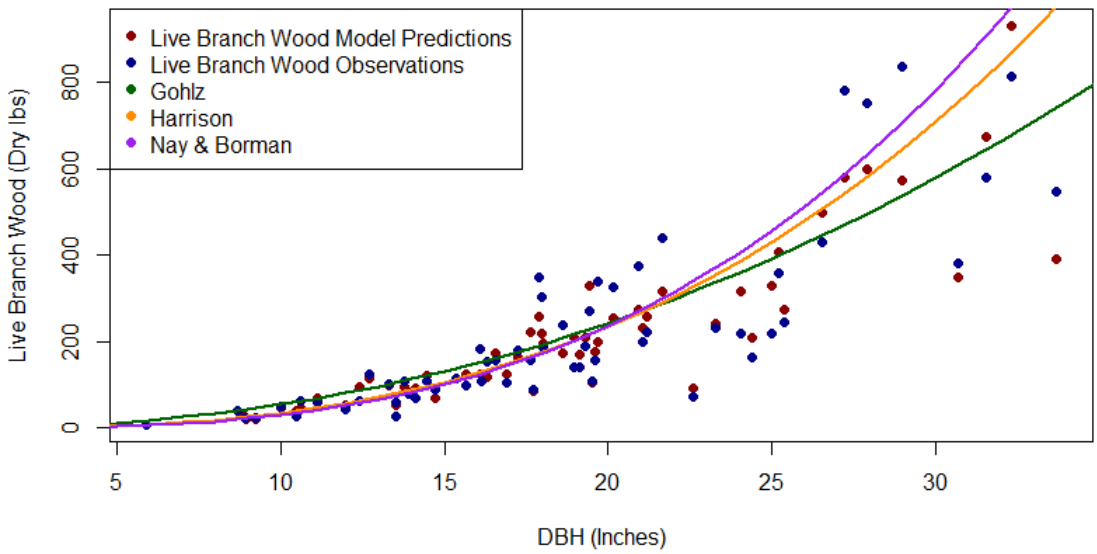

Figure 4.4.1 – Live branch wood model predictions and observations compared to other models.

Chapter 4.5 Dead Branch Wood & Branch Bark Model Discussion

Dead branch biomass has potential to be useful in predictions of gross primary production, and in predicting the input of woody detritus into the forest aside from the typical instances of entire trees falling over.

The predictors and the signs of their coefficients included in the model for dead branches appear appropriate. DBH is a general indicator of the overall size of the tree, and typically larger trees will grow larger branches compared to a smaller tree grown under the same conditions. When these large branches eventually die, they become larger amounts of dead branch biomass. DBH:QMD ratio was positively correlated and is indicative of a tree being larger than its neighbors, meaning that the tree likely had access to more sun and therefore was able to grow larger branches before these branches died. Crown ratio was negatively correlated with dead branches. This is indicative of crown recession, meaning that living branches have died. Interestingly, height of crown base was negatively correlated with dead branches. This may be due to trees with more receded crowns having had more time for their dead branches to be shed from the tree, thus again, acting as a surrogate for age and/or density moderating the effects of live crown ratio.

The 7 pound (8.1%) average underestimation bias of the model is low, and lends confidence to the model's ability to accurately predict the dead branch wood weight of a tree over a wide range of variables. Note that the model typically becomes much less precise for larger dead branch wood estimates, especially as the observations and predictions appear to diverge into two groups as seen in *Figure 4.5.1*. Greater variability in the crowns of larger, older trees, which have had time to develop greater differences than in smaller, younger trees, is the suspected cause, but no strong indication of bifurcation was found.

Example prediction intervals for 3 DBH's representing small, medium, and large trees are presented in *Table 4.5.1* to demonstrate the variability in accuracy of the model among trees of different sizes. This variability is important to take into account depending upon the size of the tree(s) being assessed. Predictions are calculated when all other predictor variables are set to their mean value.

Table 4.5.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the dead branch wood model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

DBH (Inches)	Lower Prediction (lbs)	Prediction (lbs)	Upper Prediction (lbs)	Interval Size (lbs)
10	5	16	104	99
20	12	81	213	201
30	33	143	331	298

Comparing the dead branch wood model predictions to the dead branch wood models produced by Gohlz (1979) and Harrison (2009) illustrates some interesting differences. It is apparent in *Figure 4.5.1* that the Harrison model most closely fits an upper distribution of predictions and observations, while the Gohlz model most closely fits a lower distribution. The trees composing each of these two distributions were examined among variables such as crown class, stand density, and age to determine if bifurcation of the data was occurring, but no strong indication of bifurcation was found.

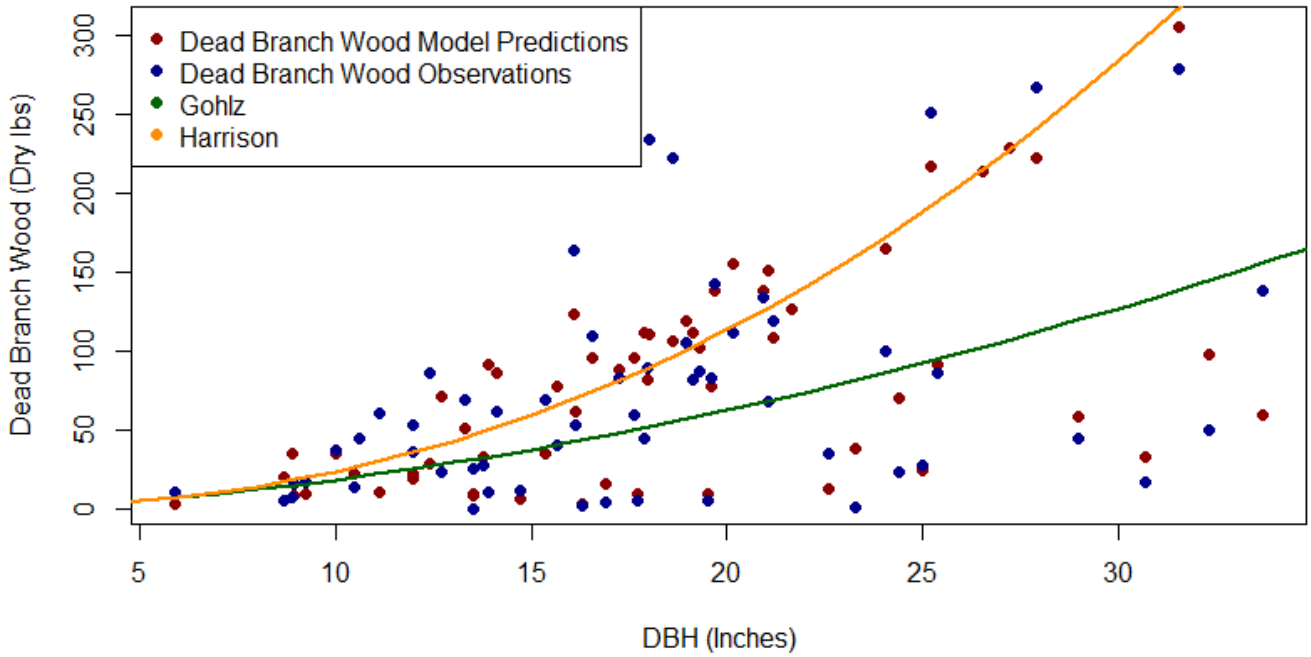

Figure 4.5.1 – Dead branch wood model predictions and observations compared to other models.

Chapter 4.6 Stem Bark Model Discussion

Stem bark is a valuable secondary forest product with a range of potential uses and markets. One such popular application of bark is known as “beauty bark” which is employed widely in landscaping and horticulture. Bark is also widely used as an ingredient in many potting soils. Bark is also useful for generation of electricity, and many new mills employ co-generators to power their mills.

The predictors and their coefficients included in the model for stem bark appear appropriate. The positive coefficient on DBH, (a general indicator of the overall size of the tree) reflects that typically larger trees will be dominant over their neighbors and have more carbohydrates available to dedicate to bark growth compared to a smaller tree grown under the same conditions. Interestingly, DBH:QMD ratio was negatively correlated. DBH:QMD ratio is indicative of a tree being larger than its neighbors. This negative relationship may be due to DBH:QMD ratio’s positive correlation with DBH, and may serve to temper the effects of DBH in the model. Further tempering the effect would be the greater discrepancy between DBH and QMD.

The 11 pound (3.5%) average underestimation of the model is quite low, and lends confidence to the model’s ability to accurately predict the bark of a tree over a wide range of variables. It is important to note that this particular model stays reasonably precise for larger bark estimates. This indicates that the model could likely be utilized effectively for stands of mature, large trees.

Example prediction intervals for 3 DBH’s representing small, medium, and large trees are presented in *Table 4.6.1* to demonstrate the variability in accuracy of the model among trees of different sizes. This variability is extremely important to take into account depending upon the

size of the tree(s) being assessed. Predictions are calculated when all other predictor variables are set to their mean value.

Table 4.6.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the bark model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

DBH (Inches)	Lower Prediction (lbs)	Prediction (lbs)	Upper Prediction (lbs)	Interval Size (lbs)
10	28	46	76	48
20	197	318	513	316
30	601	989	1,625	1,024

Comparing the bark model predictions to the bark models produced by Gohlz (1979), Harrison (2009), and Nay & Borman (2014) illustrate some interesting differences. It is apparent in *Figure 4.6.1* that all of the models fit well up to about 20 inches DBH. After this point, the Gohlz and Nay & Borman models each begin to fit towards the high end of the predictions and observations, while the Harrison model begins to fit towards the low end of the predictions and observations.

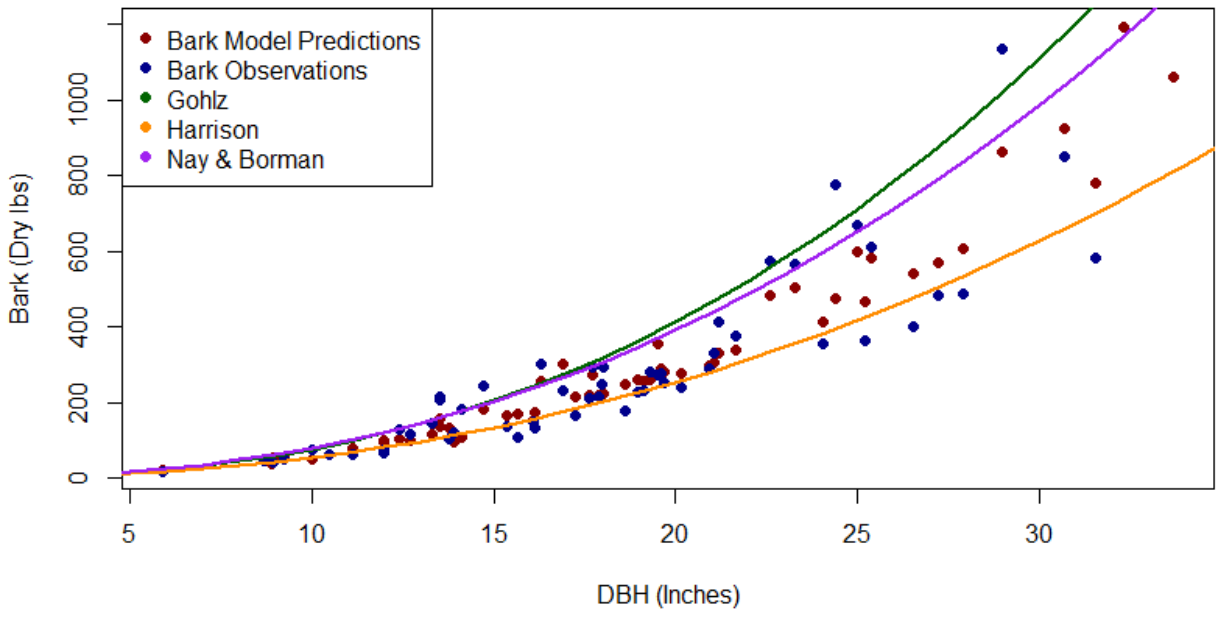

Figure 4.6.1 – Bark model predictions and observations compared to other models.

Chapter 4.7 Stem Wood Model Discussion

The model for stem wood is of particular interest for industrial forest managers. Stem wood, or timber, is the primary forest product of industrial forestland. This model could therefore be applied to a stand as a way to measure the overall timber productivity of industrial timberlands. Another potential use is for wildlife and natural regeneration in the production of large trees which have the potential to serve as snags and nurse logs at the end of their lives. It may also have a large impact on payment through programs such as carbon credits, as the stem is the primary long-term carbon sink of the tree.

The predictors and the signs of their coefficients included in the model for stem wood appear appropriate. DBH and total height are general indicators of the overall size of the tree, and their positive correlation with stem wood is directly demonstrable. Latitude was positively correlated, which may indicate slower growth rates at more northerly latitudes resulting in denser wood that sequesters more biomass. Interestingly, DBH:QMD ratio was negatively correlated. DBH:QMD ratio is indicative of a tree being larger than its neighbors. This negative relationship may be due to DBH:QMD ratio's positive correlation with DBH, and may serve to temper the effects of DBH in the model. Further tempering the effect would be the greater discrepancy between DBH and QMD.

The 44 pound (1.8%) average underestimation bias of the model is quite low, and lends confidence to the model's ability to accurately predict the stem wood of a tree over a wide range of variables. It is important to note that this particular model stays exceptionally precise for larger stem wood estimates. This indicates that the model could likely be used effectively for stands of mature, large trees, and potentially even used effectively on trees greater than the range of the dataset utilized for the model.

Example prediction intervals for 3 DBH's representing small, medium, and large trees are presented in *Table 4.7.1* to demonstrate the variability in accuracy of the model among trees of different sizes. This variability is extremely important to take into account depending upon the size of the tree(s) being assessed. Predictions are calculated when all other predictor variables are set to their mean value.

Table 4.7.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the stem wood model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

DBH (Inches)	Lower Prediction (lbs)	Prediction (lbs)	Upper Prediction (lbs)	Interval Size (lbs)
10	345	530	813	468
20	1,676	2,405	3,450	1,774
30	3,871	5,827	8,770	4,899

Comparing the stem wood model predictions to the stem wood models produced by Gohlz (1979), Harrison (2009), and Nay & Borman (2014) illustrate some interesting differences between the models. It is apparent in *Figure 4.7.1* that all of the models fit well up to about 20 inches DBH. After this point, the Gohlz, Harrison, and Nay & Borman models all fit the predictions and observations decidedly less well, with all of the models beginning to deviate. This is potentially due to the increased heteroscedasticity of the data for larger trees.

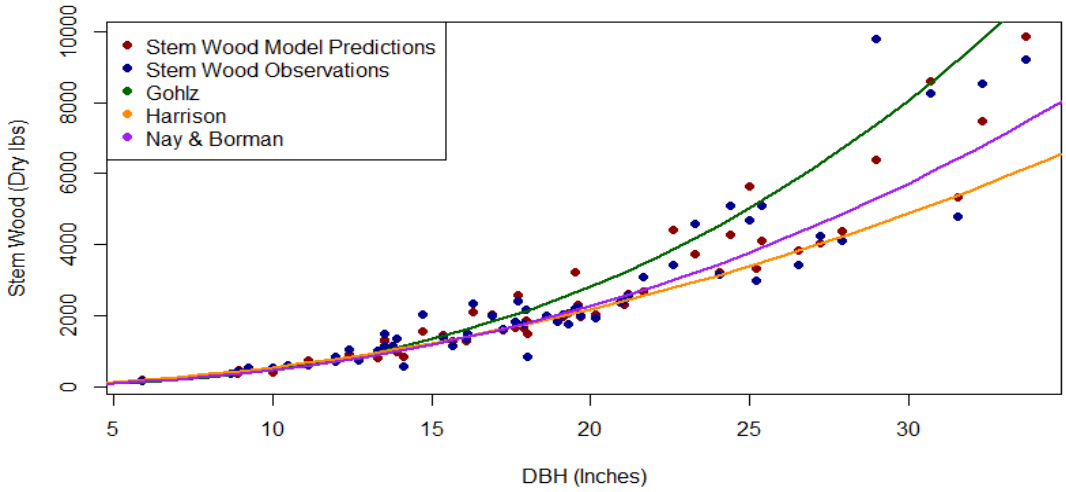

Figure 4.7.1 – Stem wood model predictions and observations compared to other models.

Chapter 4.8 Component Ratio Models Discussion

Jenkins (2003), used ratio models for the biomass components of the tree. This involved regressing models that predict the ratio of each component biomass to the total aboveground biomass. In many situations this technique makes good sense, as it is undeniable that each of the components of the tree, and their development, are intertwined rather than independent of one another. For instance, as the live branches of the tree change in overall amount or proportion, so too will the foliage, dead branches, bark, and the stem of the tree. When modeling the allometric components independently of one another, as was done in this study, this inter-relatedness of the components is not necessarily accounted for as explicitly as in a ratio model.

The ratio models fit in this study use DBH as their sole predictor variable, as in Jenkins (2003). This method did not take advantage of the full suite of factors intentionally varied in the study. This left a great deal of variation unaccounted for by using DBH-only equations and likely was the cause of their insignificance. DBH was chosen as the only predictor in the ratio method in this study, since DBH was the only predictor variable that appeared in every one of the allometric component models modeled independently. A total aboveground biomass model using DBH as the only predictor was utilized for the ratio method. Jenkins (2003) used an inverse transformation of DBH and a logarithmic transformation of the proportion was used to develop equations which would approach asymptotic limits for large trees. For the same reasons, the component ratio equations created here utilize these same transformations.

There are several important qualifications to make for the ratio models produced from this dataset. In general, they were inferior to the independently modeled components. None of the ratio models produced were significant at alpha (α) = 0.05, other than for dead branch wood. Furthermore, the adjusted R^2 values indicated that the ratio models explained almost none of the

variation present in the data. This means that the ratio models are no better than using a simple average proportion as the prediction.

The insignificance of the ratio models are likely due to several causes. The first is the use of DBH as the only predictor, and the second is the limited range in DBH sizes within the data. The dataset had a minimum DBH of 5.9 inches, and the youngest tree sampled was 39 years old. This leaves a large gap in the small and young end of the dataset, and means that the values presented in the ratio models, especially the intercepts, may not necessarily accurately represent trees younger than 39 and/or smaller than 5.9 inches in DBH. Moreover, on the other end of the dataset range, none of the components for the range of trees analyzed in this dataset appear to approach any asymptotes. This may in part be due to the lack of trees older than 120 years and larger in DBH than 33.7 inches within this dataset. For a species such as coastal Douglas-fir which can reach ages in excess of 1,000 years and DBH's well in excess of 120 inches, this dataset does not necessarily represent an age or diameter range which can justifiably represent physiological limits of the species (Sillett et Al., 2018).

The ratio models may have performed better if different approaches had been taken. Use of the full model to predict the total above ground biomass, and/or incorporating some of the other tree, stand, and landscape level variables in the ratio models may have improved the performance of these models significantly.

Chapter 5. Conclusions

The various combination and component aboveground biomass models produced in this study provide a truly diverse array of potential applications. These models have the capacity to inform land managers, researchers, and scientists pursuing topics ranging from wood productivity to climate change to wildlife management. These models have illuminated some interesting and valuable information regarding the distribution of biomass among aboveground components under varying conditions.

In all models produced in this study, the multi-variable models were significantly better at explaining variation than DBH-only models produced utilizing the same dataset. In addition to this, the total aboveground biomass model suggests that variation in many variables may primarily shift biomass among the aboveground components of the tree, rather than causing an increase or decrease in the overall amount of aboveground biomass. Many generally accepted relationships between variables and aboveground component biomass were supported by the models produced in this study, such as the increase in both overall aboveground biomass and component biomass as DBH of the tree increased. Other general relationships were also shown to be valid in this study, such as higher stand density decreasing biomass allocation to the crown of the tree. Certain relationships were unexpected, such as height of crown base's positive correlation with foliage. Unexpected relationships such as these may illuminate interesting, previously undescribed patterns in the development of trees. This relationship may be indicative of a tree reaching up above its neighbors, or may simply be due to older, larger trees having large amounts of foliage despite having crowns that begin high on the tree. It was also shown that older, larger trees have substantially more variation among both their total aboveground biomass and their component biomass than younger trees, perhaps because they have had far more time to

experience the multitude of events such as storms, fires, and tree-falls which lead to more heterogeneous trees and stands.

It is essential when producing equations such as these to clearly state the limitations of the models produced. One such limitation of the study is the reliability of the equations towards the ends of the range of the data. For instance, all of the trees of approximately 10 inches in DBH were all intermediates, and all of the trees of approximately 30 inches in DBH were dominant. Therefore it is prudent to recognize that this potentially prevents the model from making accurate predictions for small dominant trees and large intermediate trees. Similarly, one of the most difficult aspects of this study was the extraordinary variation in older stands used in the dataset. This variation was most often natural, but some of it was due to human management in the form of thinning, despite every attempt being made to ensure sufficient time for the stands to re-capture the space freed by the thinning. Independent of the source of the variation, it impacted the precision of the models on trees of older ages and larger sizes. The dataset was heteroscedastic, so the imprecision of model predictions was greater for the older, larger trees in every one of the models developed in this study. Therefore, the prediction interval for older trees was much greater than that of the younger, smaller trees. In order to more effectively account for the high levels of variation in the older trees, more samples of this age and size-range would be required. This is not to say that the models produced in this study are not useful for older, larger trees. Indeed, these models are capable of taking into account much more variation than their predecessors. Instead, it is simply prudent to recognize the limitations of these equations during their application to use them effectively.

The study covered a large portion of the range of coastal Douglas-fir, but it may be valuable to determine if the relationships between the variables assessed in this study are

consistent throughout the range of coastal Douglas fir, as it extends far beyond the range of latitude present in the dataset utilized for this study, into southern Oregon, northern California and southern British Columbia. Alongside this, it may be valuable to determine if these trends also apply to other commercially valuable species in the maritime Pacific Northwest. Of particular interest may be species such as Western hemlock, as it often occurs in both natural and planted mixtures with coastal Douglas-fir.

Another limitation of this study was the lack of soil information and site topography. It was beyond the scope of the study to quantitatively examine the soil and topographic features encountered throughout sampling, because the sample size was too small. A larger sample size is needed to adequately cover the wide range of soil types and topographic formations found throughout the maritime Pacific Northwest. Many site and soil variables, such as the soil structure and aspect, likely had effects upon the aboveground development of the trees sampled in this study. Soil, it's doughtiness, and topography are also well documented to have a drastic effect upon the amount of carbohydrates that a tree dedicates to belowground biomass (Joslin 2000). The allocation of carbohydrates to belowground biomass reduces the amount dedicated to aboveground biomass, likely having some impact upon the overall amount and distribution of biomass among the various aboveground components. Without having measured or estimated the belowground biomass of the samples, this was simply outside of the scope of the study.

The models produced in this study use multiple predictor variables, each with inherent measurement issues of varying degree. Applying these models may lead to greater expense compared to DBH-only models, unless these types of data are already recorded in a managers typical stand inventory. Despite the increased difficulty and expense of prediction variable measurement in some of the models created in this study, these more accurate models are

important for many applications that have found increasing importance in today's changing world. Carbon sequestration has gained newfound relevance in recent decades, with many nations hoping to increase carbon sequestration in forests in order to mitigate the effects of climate change. Additionally, our managed forests in the Pacific Northwest and around the world are being managed more intensively, and by fewer entities, than ever before. Very small differences in models can be multiplicative when determining carbon levels across landscape or regional levels such as those which would be important on a national or global scale. The same can be said for the amounts of industrially important components, such as the stem of the tree, when large landowners look at forest management of their large holdings. Small differences in productivity across large tracts of land may influence a land owner's decision whether to retain their land in timber production or to transition the land to another use. In this way, these small gains in accuracy may be critical for the perpetuity of working forests. Therefore, the small increases in accuracy gained by using models which take more variables such as latitude, tree height, and elevation into account are especially vital and valuable on large scales.

Moving into a world where forests are managed more intensively, managers are encountering a diverse array of new and old problems, goals, and considerations. Oftentimes these forests are managed for multiple purposes concurrently, and the balancing of these objectives requires more accurate information than has been required in the past. These models should be able to provide clear, precise, and accurate estimates to inform managers under a wide array of situations, and facilitate the solving of problems moving into an increasingly complicated and demanding future.

Appendices

(In order of appearance)

Appendix.1 List of Figures:

Appendix.2 List of Tables:

P.59 - Table 4.5.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the dead branch wood model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

P.62- Table 4.6.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the bark model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

P.64 - Table 4.7.1 - Examples of varying 95% prediction intervals for trees of differing DBH in the stem wood model. It is important to understand these varying intervals when applying the equations to trees of differing sizes in order to appropriately use these equations. Predictions are calculated when all other predictor variables are set to their mean value.

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