AN ABSTRACT OF THE THESIS OF

Jorge Luis Delgado Trejo for the degree of Master of Science in Sustainable Forest Management presented on June 19, 2015.

Title: Using Acoustic Measurements and Inventory Data to Estimate Stiffness in Standing Douglas-Fir Trees.

Abstract approved:

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Kevin D. Boston

Total US lumber production in 2011 was 77.9 million cubic meters. Its primary use was for housing and construction. There is a growing concern that the structural properties for wood are being reduced as trees are harvested at much younger ages as the wood supply shifts from older to younger forests. Goal of this study is to promote the inclusion of wood properties, density and Modulus of Elasticity (MOE) in pre-harvest inventory of Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco). Hitman ST-300, a non-destructive method based on acoustic velocity, was used to estimate MOE. Results from Pearson correlation showed a highly significant relationship between MOE with density (.405), acoustic velocity (.860) and DBH (-.327). A linear model was fitted to estimate MOE as function of acoustic velocity. Slope and intercept are significant for this model (p-value <.001) with an R^2 of .739. A second linear model was fitted including acoustic velocity and DBH as predictor variables. Slope and intercept are significant for this model (p-value <.001) with a R^2 of

.768. Both models were compared obtaining an increase of.017 when DBH was included in the regression. Monte Carlo simulation was used to determine the impact of a subsample of density with acoustic velocity to determine MOE. It was found that an optimal sample size of ten percent when MOE was estimated using acoustic velocity and wood density cores. Using acoustic, non-destructive, evaluation along with these models can help to operationalize the collection of wood properties that can support the primary log supply chain. It also provides a significant opportunity for foresters to know the condition of the forest and its properties early in the supply chain management.

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Using Acoustic Measurements and Inventory Data To Estimate Stiffness In Standing Douglas-Fir Trees

by
Jorge Luis Delgado Trejo

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APPROVED:

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Jorge Luis Delgado Trejo, Author

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1. Introduction

Wood has been used since ancient times as the source for fuel, tools and shelter. Being a renewable material, its uses continue to grow. Howard and Westby (2013) estimated total lumber production (hardwood and softwood) in the US at 77.9 million of cubic meters (33 billion board feet). Softwood represents 79 percent of the total lumber production in the US 2011 and 79 percent Oregon produced 9.8 million m^3 (4.1 billion board feet) is from Oregon (Oregon Forest Resources Institute, 2015). The primary use of lumber has been in single family homes with 63.5 percent of the lumber consumed for housing, 24.3 percent for new construction and 39.2 percent for improvement of existing house units (Howard and Westby, 2013).

There is an effort to build larger structures using wood. In Scandinavia, architects are using wood in novel methods. One example of this is wood city in Helsinki; it is a project that combine commercial and residential buildings. These new residential buildings will be the tallest wooden buildings in Finland with some reaching eight-stories (Stora Enso, 2014). Thus, wood is being placed in more demanding structural uses and a variety of engineered wood products are being developed to meet these needs. This include laminated veneer lumber, oriented strand board, cross laminated timber, glued laminated timber (Glulam), among others. In addition, there is an increasing demand for machine stress grade lumber. It combines visual assessment of knots, and other defects, with a non-destructive bending test to estimates stiffness (Erickson et al. 2000). With the development of engineered wood products, it is becoming increasingly more important to understand the wood properties to allocate logs to most appropriate manufacturing facilities to generate the products that will meet these needs.

Mechanical and physical properties of structural engineered products depend on the interactions between the qualities of the resource, the wood properties, the manufacturing process, and their applications (Lam 2001). Much of the current practice is to judge wood quality according to its visual characteristics; this includes number and size of knots and branches (Husch et al. 1982). Wood quality measurements; include: density, stiffness (modulus of elasticity), microfibril angle, dimensional stability, among others. (Walker 1998, Amishev and Murphy 2008). However, there is a growing concern that the structural properties for wood are being reduced as the wood supply shifts to younger forests. (Amishev and Murphy 2008). Thus, various wood quality measurements will need to be incorporated into operational inventories to allow the improved characterization of the resources that will allow for raw material be allocated to the most appropriate manufacturing plant that will produce the best values.

Wood density (the ratio between wood mass and its volume) is the most common wood property used to describe wood, as it provides an index to many other properties (Walker et al. 1993). It is an important physical property because is a good indicator of many mechanical properties (Leon, 2010). Typical values for western United States species are: Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) 480 Kg/m^3, Hemlock (*Tsuga spp.*) 450 Kg/m^3, ponderosa pine (*Pinus ponederosa*) 400 Kg/m^3, radiata pine (*Pinus radiata*) 420 Kg/m^3 (USDA, 2010)

Modulus of Elasticity (MOE) is the second most prominent wood property. It is the resilience of the wood to deformation when a load is applied. Elasticity implies that deformations produced by stress are recoverable after loads are removed (USDA. 2010, Navia, 2006, Rocha, 2012). High values are desirable to avoid bending of window frames, walls or door frames when loaded. Values for common species are: Douglas-fir 13.6 GPa, western hemlock 11.3 GPa, ponderosa pine 8.9 GPa, radiata pine 10.2 GPa (USDA, 2010).

Today, there are non-destructive methods capable to predict MOE without altering wood end-use capabilities. One of the methods is acoustic testing, a promising method that measure acoustic velocity on trees or logs and allow us to predict MOE due to velocity is related with the modulus of elasticity and density. In this study, Hitman ST300® is used to measure the acoustic velocity of stress-waves in standing trees taking it directly on the lower bole portion of the stem (Paradis et.al. 2013; Tsehaye et. al. 2000; Wang, 2012).

In the future, the wood supply will be coming from younger forest or fast growing plantations and the desirable wood properties from older timber may become scarce (Filipescu 2014). Thus, there is a need to be able to predict the wood qualities better as part of the pre-operational inventory to improve the performance of the forestry supply chain. Logs that have the desirable wood properties need to be identified early in the supply chain and allocated to mills making products where those wood properties may add the most value to the final products.

2. Objectives

The objective of this study is to promote the inclusion of wood properties, density and MOE in pre-harvest inventory. The goal will be to develop various analytical techniques to will allow for these wood properties to be predicted from easy to measure variables such as diameter and from the acoustic velocity from the standing trees and predict the desired wood properties. Although these are based on a sample from one stand, we believe that they demonstrate the potential to capture and include wood properties to support the inclusion of wood properties in the primary supply chain.

3. Literature Review

Non-destructive evaluation (NDE) are those techniques that allow the evaluation of material properties without producing damages to subject matter (Amishev and Murphy, 2008). Nowadays, there are several NDE that have been developed and they are frequently used to estimate mechanical wood properties such as MOE and microfibril angle. Some of this NDE can be classed into two groups the first one is based on microwaves like SilvaScan-2®, Near Infra-Red (NIR) spectroscopy, and the second group based on acoustic velocity like Fakoop Microsecond Timer, IML Hammer® and the tool used in this study the HITMAN® (Amishev and Murphy 2008; Paradis et al. 2013; Merlo et.al., 2008; Chauhan and Walker 2006).

Acoustic technologies like Fakoop and Hitman are well-established and support the allocation of logs to uses, based on its acoustic values they produce. Their use has been accepted for the forest products industry (Wang et al. 2007; Paradis et al. 2013;). According to Amishev and Murphy, (2008) the information provided by acoustic tools have been used to sort logs for veneer uses, they found a correlation of 0.52 between acoustic velocity and mill veneer recovery. Johnson and Gartner (2006) used acoustic testing in four 20-years old Douglas-fir progeny tests in the Coast Range of northern Oregon, to estimate heritability MOE and basic density. They found that heritability Index for MOE and density were 0.55 and 0.59 respectively. Also overall mean for MOE and density was calculated obtaining 8.55 GPa, and 415 Kg/m^3 respectively.

Paradis et al. (2013) investigated the use of Hitman ST300 to identify the stands to supply raw material for the production of machine stress-rated lumber. Three hundred thirty-three trees were measured from an uneven-age black spruce stand in the North Shore region of Quebec in Canada. A multiple linear regression model was developed describing mean tree MOE as a function of acoustic velocity squared and DBH. Coefficient of determination R^2 was 0.41. Similar studies completed by Mora et al. (2009) and Lui et al. 2007 found higher values of explained variance with values of 0.65 in *Pinus taeda* and 0.55 in black spruce with acoustic velocity and tree diameter and MOE. In addition, they found that acoustic velocity could be affected by the insertion depth of Hitman probes.

Acuna and Murphy (2006) selected 119 Douglas-fir trees from 17 second growth stands in the Coast and Cascade range of Oregon, collecting 400 disk to obtain wood density. They used a stepwise multiple regression analysis to estimate wood density values, using as explanatory variables height (along the tree where the disk were collected), average diameter of each disk including the bark, elevation of the site, density at 0 m above the base, and the aspect of the tree where the sample were taken. Overall, the mean density was 0.404; this is lower than reported values for Douglas-fir (0.450). Among all the variables used in their model, only height was significant at explaining density. The linear model explain 25.9 percent of the variation of log density. As expected, mean density values decrease when the wood disk were taken higher in the stem as the proportion of juvenile wood increased.

Lachenbruch et al. (2010) studied the relationship of density, microfibril angle, and acoustic velocity with stiffness in Douglas-fir. One hundred eighty-three trees were sampled from 17 stands that were older than 20 years with no silvicultural treatments in the past seven years were used in their study. These, stands are located in western Cascade and Coastal range of Oregon. From each stand, 7-12 dominant or codominant trees were sampled by removing small clear sections of mature wood. The samples were dried to a 12 percent moisture content. Using Silvascan, density was estimated 0.526 g/cm^3 and microfibril angle in 14.6 degrees. Using direct measurements, they obtain density was 0.553 g/cm^3, acoustic velocity 5443 m/s, and MOE 11533 MPa. Modulus of elasticity was correlated with density 0.762 and with velocity 0.680 (Lachenbruch et al. 2010). They predicted the MOE values using density and velocity as the independent variables and their model produce significant slope. The model explained 73.3 percent when density and velocity^2 were used. MOE was better predicted when both variables were used than by either one alone (0.578 for density and 0.460 for velocity) (Lachenbruch et al. 2010).

Wang et al. (2005) studied the relationship between acoustic velocity measurement on standing trees and the acoustic velocity measured in butt logs of five softwood species (sitka spruce (*Picea sitchensis*), western hemlock (*Tsuga heterophylla*), jack pine (*Pinus banksiana*), ponderosa pine, and radiata pine). A total of 352 trees were evaluated, stand age varies from 8 to 25 years in radiata pine, spruce and hemlock stands are uneven-aged, meanwhile jack pine and ponderosa pine have 40 and 43 years respectively. A linear model was fitted using the acoustic velocity on logs as the independent variable and acoustic velocity measured on trees as the dependent variable. The model explained a large amount of the variability with a coefficient R^2 of 0.993 for sitka spruce, 0.845 for western hemlock, 0.710 for jack pine, 0.830 for ponderosa pine, and 0.900 for radiata pine. Positive relationship between tree velocity and DBH was found in ponderosa and radiata pine and they suspect that this relationship will be also found in other species.

4 Methods

Data were collected from a second growth Douglas-fir stand with mixed ages located in the McDonald-Dunn Forest. The mean age is 70-75 years, and has been commercially thinned on three occasions. A subset of the stand was used in this study that included 510 trees. Each tree had the DBH, height, acoustic velocity, and wood core from an increment bore collected.

Hitman ST300 was used to measure the acoustic velocity for the lower portion of the tree bole. Carter et al. (2005) explained Hitman's functioning, "Transmitter and receiver probes are driven through the bark into the outer wood of the lower stem. They are vertically aligned along the stem approximately 1.3 meters apart. A laser guided ultrasound rangefinder measures the exact distance between the probes. An acoustic wave is imparted into the tree stem through the transmitter probe by a hammer blow. The receiver probe picks up the acoustic signal passing through the tree and determines the time-of-flight of the acoustic wave. The distance and time are sent by wireless communication to a PDA (personal digital assistant) that calculates the acoustic velocity and also allows the user to enter other tree and stand data" This process was repeated three times for each tree measured (Figure 1).

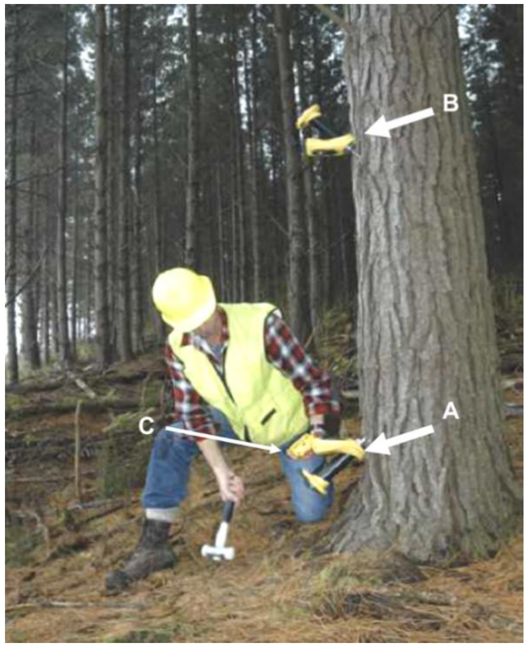

Figure 1. Measurement of acoustic velocity with the Hitman ST300. (A) Transmitter probe (B) Receiver probe (C) Personal digital assistant (Fibre-gen.com, 2015).

As Hitman assumed that density is constant, a tabulated value for green density for different seasons is usually used to account the changes in moisture content (Paradis et al. 2013; Achim et al. 2010). Auty and Achim (2008) citing Sandoz (1993) and Carter et al. (2005) suggest that fresh-cut density should be used to account for small variations in the cell wall. In addition, tree diameter was also found to have a positive relationship with velocity and therefore, it has an influential impact on MOE estimation (Chauhan and Walker 2006; Paradis et al. 2013) these considerations are taking account for this study.

Wood density was computed weighting wood core mass and the volume was computed by water displacement; later density is compute by the ratio of mass divided by its volume (Williamson and Wieamann 2010). Thus, having the density and the velocity for each tree, dynamic MOE for each tree can be computed using the following equation (1) (Wang, 2012; Tsehaye, 2000; Paradis et al. 2013):

$$MOE_D = V^2\rho \tag{1}$$

Where,

MOE_D = dynamic modulus of elasticity

V = average acoustic velocity from Hitman measurements

ρ = wood sample density

As one of the objectives of this study is to combine the use of the acoustic tool (Hitman ST-300) and inventory data to predict wood properties that can be difficult or expensive to measure on every tree. Therefore, different relationships were being explored among the inventory and acoustic variables. A number of alternative models were tested, those models include variables such as total height, basal area, but they were discarded because height is difficult to measure for every tree and basal area is a function of diameter.

The first step was to develop a linear model that estimates MOE as a function of acoustic velocity and DBH (equation 2).

$$MOE_D = b_0 + \ b_1 Velocity + b_2 DBH \tag{2}$$

Where,

MOE_D = dynamic modulus of elasticity

Velocity = average acoustic velocity from Hitman measurements

DBH=Diameter at the breast height in meters.

The second linear model is a simplification of the first linear model (Equation 3) but in this case using just velocity as variable because MOE is directly proportional to Velocity when a tabulated wood density is use in equation (2).

$$MOE_D = b_0 + \ b_1 Velocity \tag{3}$$

MOE_D = dynamic modulus of elasticity

Velocity = average acoustic velocity from Hitman measurements

4.1 Monte Carlo Simulation

Monte Carlo methods encompass several techniques that use random numbers and probability distributions to approximate solutions to quantitative problems (Temesgen, 2015). Monte Carlo simulates the full sampling process many times (hundreds or thousands times). At each iteration, the process selects randomly a certain number of sampling units according to a sampling intensity. Then, estimation are made for the rest of the population based on a model fitted with the selected sample. The outcome is a probability distribution of the overall value of the system calculated through the iterations of the model (Yadav and Ramasubramanian 2011).

In forestry, Monte Carlo methods has been used by Temesgen et al. (2011) to simulate different sampling strategies to estimate tree foliage biomass in Douglas-fir and ponderosa pine stands. They found that systematic sampling with ratio estimation is the most efficient sampling to estimate foliage biomass in both species.

In this study, the purpose of the Monte Carlo simulation to explore the potential to reduce the number of wood density samples needed to calculate reliable dynamic MOE. Therefore, a random sample of wood density are taken from the population of 510 trees (Table 1) to determine the sample size needed to support the characterization of the resources.

Table 1. Sample intensities for Monte Carlo Simulation and number of trees that it represents.

Sample (%)	# Trees
1	5
1.5	8
2	10
2.5	13
3	15
5	26
7	36
10	51
12	61
15	77
17	87
20	102
25	128
30	153
35	179
40	204
45	230
50	255
55	281
60	306

Then, five hundred iterations were performed at each sampling intensity and the values were used to estimate the dynamic MOE with a subsample of population (Equation 4). With this sub-sample of wood density and velocity as the predictor variables and dynamic MOE as the response variable, a linear regression will be developed (Equation 4);

$$MOE_D = b_0 + \ b_1 Velocity + b_2\ \rho \tag{4}$$

Where,

MOE_D = dynamic modulus of elasticity

Velocity = average acoustic velocity from Hitman measurements

ρ = wood sample density

The performance of the estimator is measured using the following performance measures as described by Temesgen et al. (2008)

$$Bias = \frac{1}{500} \sum_{i=1}^{500} (MOE_i - \widehat{MOE}_i) \tag{5}$$

Mean squared error MSE (equation 6)

$$MSE = \frac{1}{500} \sum_{i=1}^{500} (MOE_i - \widehat{MOE}_i)^2 \tag{6}$$

Root Mean Squared Error (equation 7)

$$RMSE = \sqrt{\frac{1}{500} \sum_{i=1}^{500} (MOE_i - \widehat{MOE}_i)^2} \tag{7}$$

The goal is to find the lowest bias and variance from the various sample sizes. The optimal sample size can be determinate by a significant change in the values of MSE or RMSE or graphically by the point where the curve stabilized and produce a straight line (Temesgen et.al. 2008; Poudel et.al. 2015; Temesgen et.al. 2011).

5. Results

Five hundred ten trees were used in this study to develop methods to incorporate wood properties into an operational inventory. The results will include both the summary statistics and the statistics describing the appropriateness of the analytical models that were developed to estimate dynamic MOE using easily measured variables to support supply chain management.

The descriptive statistics are shown in Table 2 with the distributions presented in Figure 5. DBH appears to be skewed to the left but this is expected, as this is a mixed-age cohort stand.

Table 2. Descriptive Statistics for Dynamic MOE, Velocity, DBH, Wood density

	N=510	Minimum	Maximum	Mean		Std. Deviation
				Statistic	Std. Error	Statistic
MOE (GPa)		7.3728	23.1246	13.0834	.10774	2.43317
Velocity (Km/s)		3.7612	6.3043	4.9709	.0187	.42432
DBH (m)		.1640	1.4000	.5363	0.93	.21064
Wood density (g/cm^3)		.3772	.6932	.5265	.0021	.04938

Figure 2 show the distribution of calculated MOE, Velocity, DBH (m) and wood density, our response and predictor variables used in the study and its theoretical normal distribution.

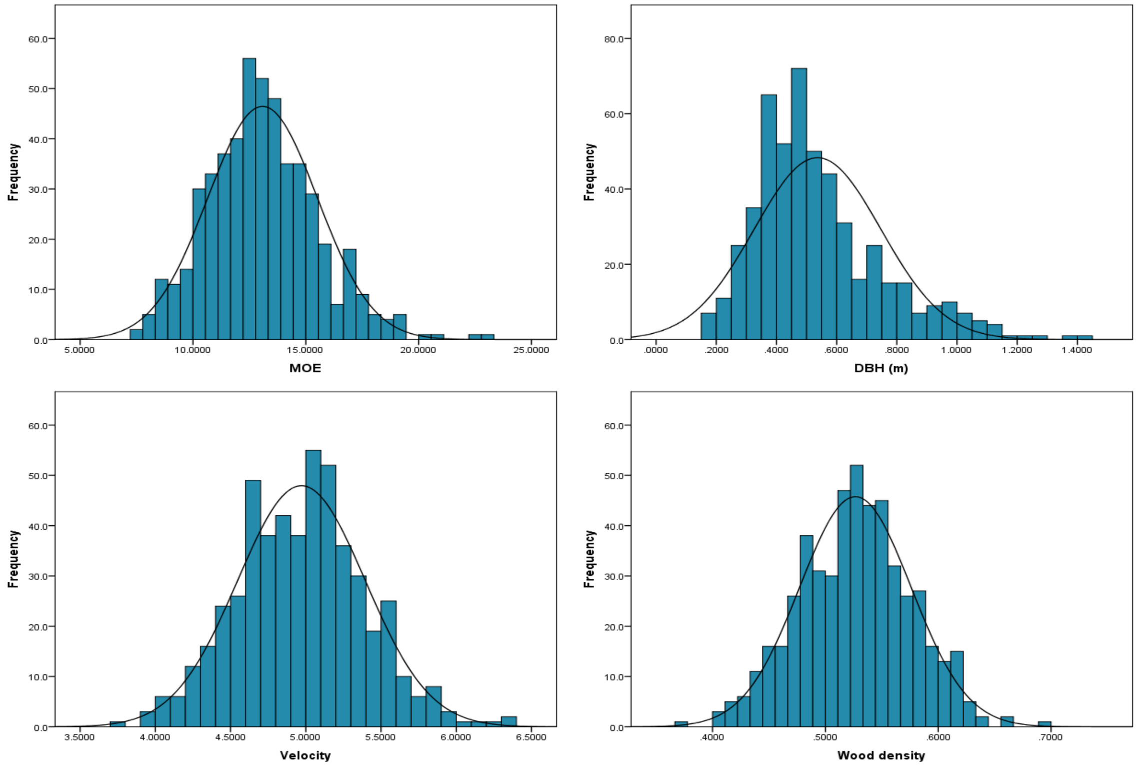

Figure 2. Response and predictor variables distribution. Line represent variable theoretical normality curve.

5.1 Pearson Correlations.

MOE is one of the most important wood property variables due to its importance in many engineered wood applications, where stiffness is an important attribute. Due to its relevance, all variables were analyzed to determine their correlation with MOE. Table 3 shows that acoustic velocity has the highest correlation, 0.860, followed by wood density, 0.405, the third one in order of relevance –or influence- is DBH -0.327. Even though, both basal area and total height (HT) also have significant correlation with MOE, both were left out of the modeling analysis because basal area is a function of DBH and total height may be difficult to obtain for each tree in an industrial scale.

Table 3. Pearson Correlation for study variables.

		MOE	DBH (m)	Velocity	Wood density	HT	Basal area
MOE	Pearson Correlation	1	-.327**	.860**	.405**	-.190**	-.323**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N		510	510	510	510	510
DBH (m)	Pearson Correlation		1	-.548**	.348**	.830**	.974**
	Sig. (2-tailed)			.000	.000	.000	.000
Velocity	Pearson Correlation			1	-.109*	-.408**	-.521**
	Sig. (2-tailed)				.014	.000	.000
Wood density	Pearson Correlation				1	.364**	.304**
	Sig. (2-tailed)					.000	.000
HT	Pearson Correlation					1	.759**
	Sig. (2-tailed)						.000
Basal area	Pearson Correlation						1
	Sig. (2-tailed)						

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

5.2 Modeling analysis

As one of the objectives of the project was to test whether a more easily collected set of variables (i.e. can one avoid collecting density on all trees) can be used to estimate MOE. Several linear models were tested (those include variables as total height, volume, basal area, among others). The first model includes two independent variables DBH and the velocity measurement. The slope for both terms are highly significant with a p-value of .000 and the model explains 76.8 percent of the variation in the dynamic MOE (see Tables 4a,b,c).

Table 4a. Model Summary.

Model	Adjusted R Square	Std. Error of the Estimate
1	.768	1.1720284

Table 4b. ANOVA Summary for the model.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2317.003	2	1158.501	843.374	.000[b]
	Residual	696.441	507	1.374		
	Total	3013.443	509			

a. Response Variable: MOE
b. Predictors: (Constant), DBH (m), Velocity

Table 4c. Coefficients Summary.

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-15.929	.827		-19.270	.000
	Velocity	5.579	.146	.973	38.114	.000
	DBH (m)	2.386	.295	.207	8.093	.000

a. Response Variable: MOE

Residual analysis of this model validate the assumptions needed for regression. Residuals were constant, linear and normality as required to apply the general linear model. The Q-Q graph of the residuals shows that most of the values can be explained by the model, but 21 percent of the cases cannot be explained by the fitted model. Residual versus fitted and scale-location plots (Figure 4) show no correlation between residuals and fitted values, which supports the use of the fitted model. In addition, the residual vs leverage plot shows that there is the possibility of some outlier values that are affecting the prediction power of the regression (Figure 3).

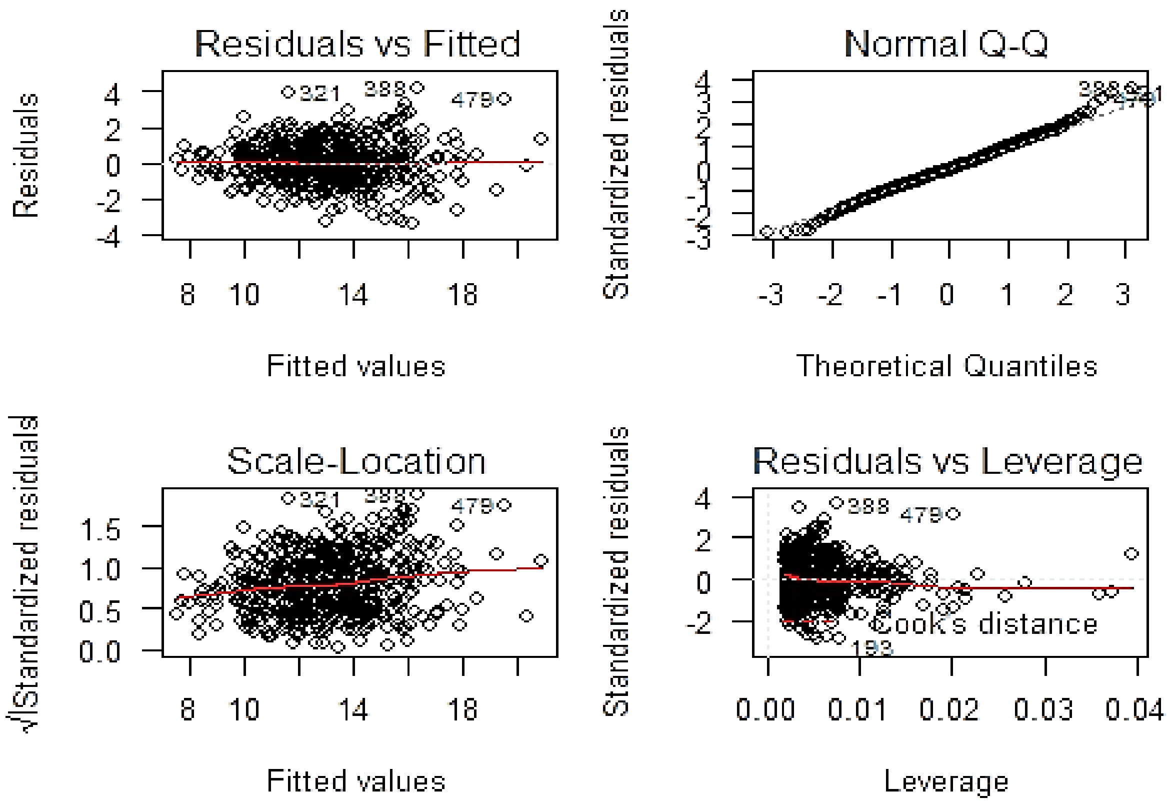

Figure 3. Regression summary Plots

The high correlation value between MOE and velocity (Table 3) makes one think about the possibility of a simpler model that computes MOE using only velocity as the predictor variable. The fitted model was highly significant p-value .000, and an adjusted R^2 of .739 (Table 4a). Thus, another linear model was fitted using the input method to compare if the addition of an extra variable, in this case DBH, improves the prediction power of the model.

Now there are two models:

Model 1: $MOE = -11.421 + 4.930\, Velocity$

Model 2: $MOE = -15.929 + 5.579\, Velocity + 2.386\, DBH$

Slope and intercept are significant (p-value .000) for model 1 (Table 5b) Figure 5 show the regression plots and indicates that model 1 has no pattern or trend on the residuals as seen in scale-location and residual plots. Q-Q plot show that most of the values (74 percent) are explained with the model fitted. Additionally, the assumptions required for the linear model are also validated (Figure 4). Furthermore, the Leverage plot that indicate the possible presence of outlier values and its possible source will be discussed in the next section.

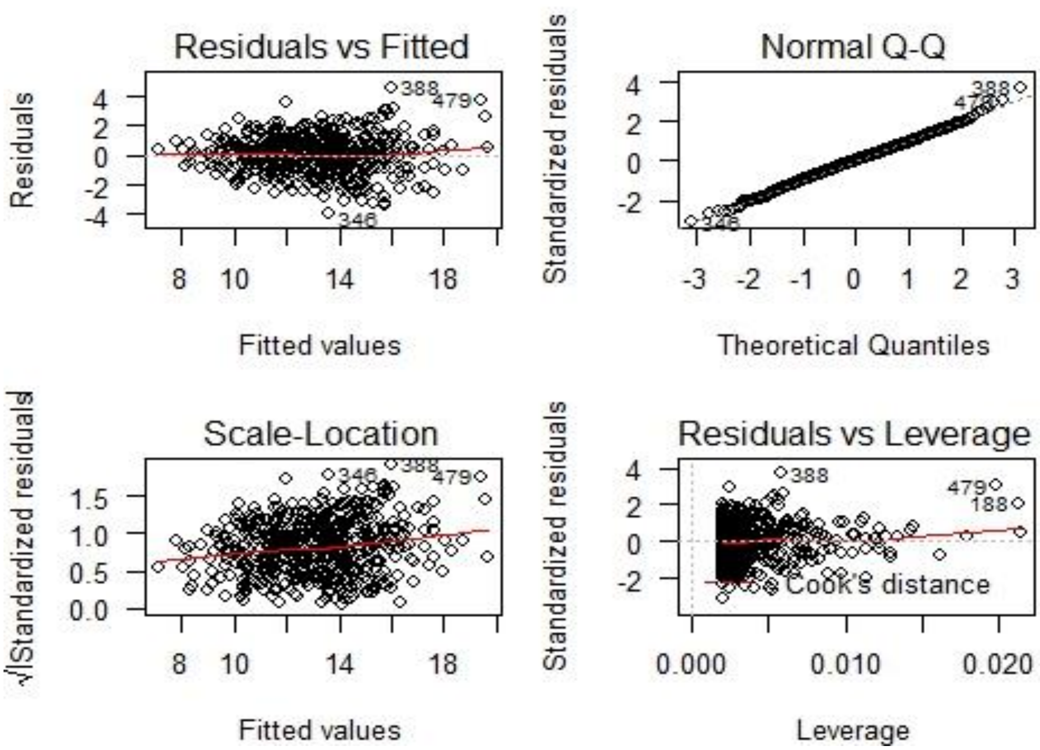

Figure 4. Regression summary Plots for model 1.

5.3 Comparing the use of one variable model vs the two variable model

All terms in the regression for both models are significant (Table 5b). The inclusion of DBH into the model 1 improves adjusted R^2 from .739 to .769 (Table 5a). In addition, adding DBH into the model reduced residual mean square error in .174, this represents a reduction of 11 percent (Table 5b).

Table 5a. Model Summaries.

Model	Adjusted R Square	Std. Error of the Estimate
1	.739	1.2442142
2	.768	1.1720284

Table 5b. ANOVA Summary for both models.

	Model	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2227.024	1	2227.024	1438.582	.000[b]
	Residual	786.419	508	1.548		
	Total	3013.443	509			
2	Regression	2317.003	2	1158.501	843.374	.000[c]
	Residual	696.441	507	1.374		
	Total	3013.443	509			

a. Response Variable: MOE

b. Predictors: (Constant), Velocity

c. Predictors: (Constant), Velocity, DBH (m)

Table 5c. Coefficients Summaries for both models.

		Unstandardized Coefficients		Standardized Coefficients		
	Model	B	Std. Error	Beta	t	Sig.
1	(Constant)	-11.421	.648		-17.614	.000
	Velocity	4.930	.130	.860	37.929	.000
2	(Constant)	-15.929	.827		-19.270	.000
	Velocity	5.579	.146	.973	38.114	.000
	DBH (m)	2.386	.295	.207	8.093	.000

a. Response Variable: MOE

The relevance of having both DBH and velocity variables in the model was also confirmed by the confidence interval ellipse (Figure 5), which produce a pairwise confidence region at 95 percent for a linear model fit.

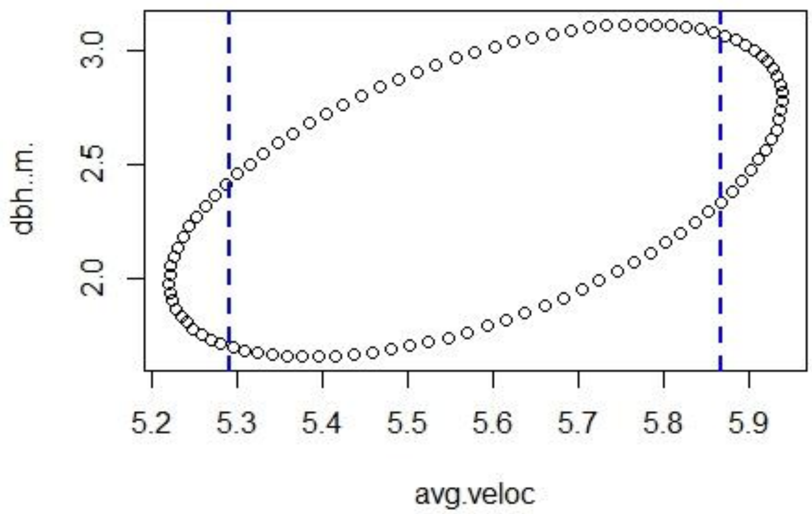

Figure 5. Confidence ellipse for model 2. Blue lines represents the confidence interval for model 2

5.4 Monte Carlo Simulation

Since density is such an expensive variable to collect as each core must be taken, labeled, dried, weighted and immersed in water to compute the density. It was hoped that its collection could be minimized when computing the dynamic MOE. What is the sampling size of density needed to estimate the dynamic MOE in the stand? Twenty sample intensities from one to 60 percent of the population were used in a Monte Carlo simulation. Each sample had 500 iterations and the mean MOE was calculated (Figure 6).

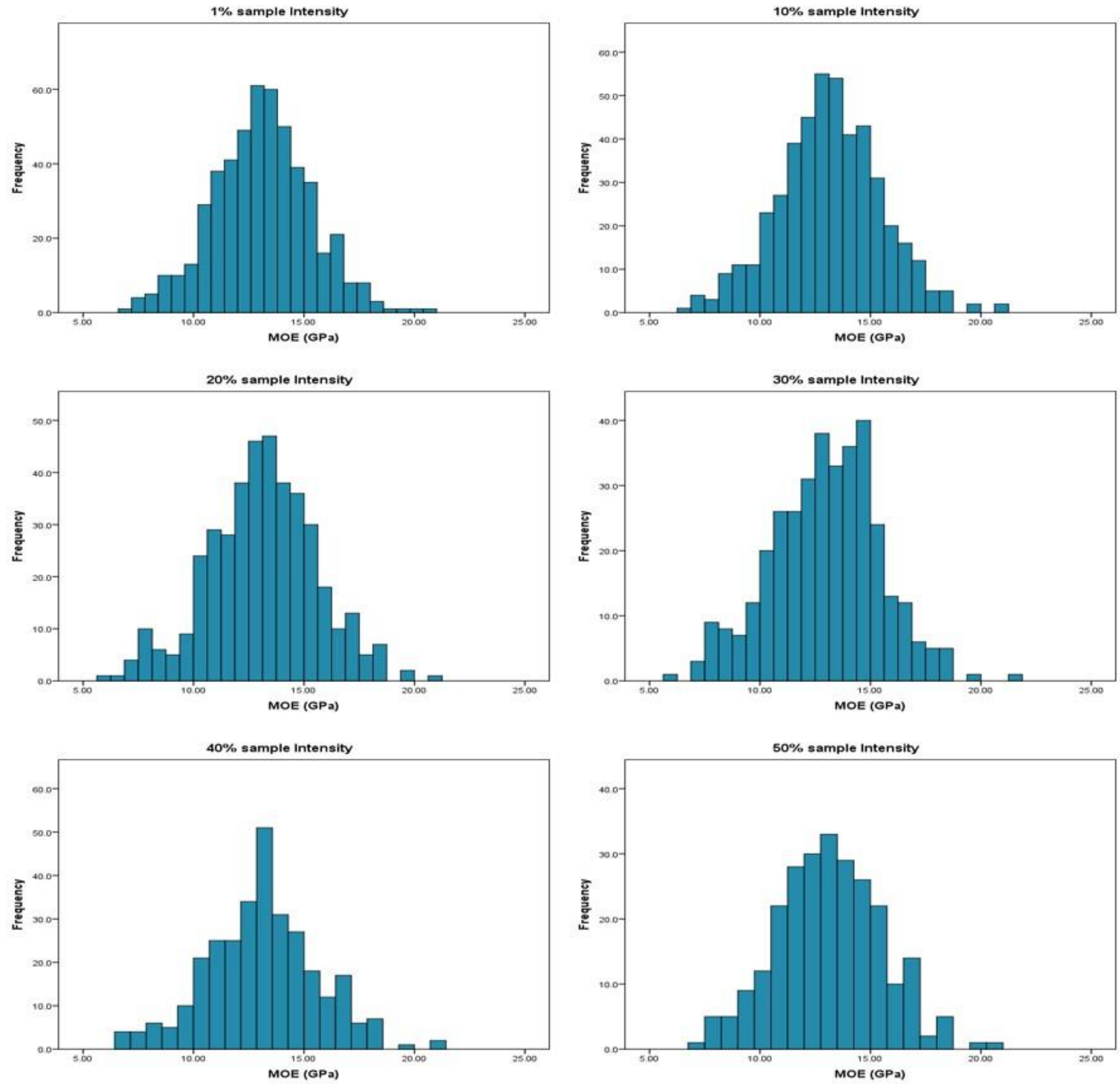

Figure 6. Distribution of iteration means per sampling intensity.

The bias and root mean square errors (RMSE) values were computed for estimated dynamic MOE from the samples. The absolute bias values range from 0.0003 to 0.0631, these low values indicate that the predictor used in this simulation makes accurate predictions (Table 6).

Table 6. Monte Carlo Simulation Summary variables per sampling Intensity.

Sampling intensity %	BIAS	MSE	RMSE	MEAN
1	0.03610	0.1249	0.35340	13.1265
1.5	0.024644	0.1037	0.322090	13.00334
2	0.018659	0.0925	0.304098	13.00373
2.5	0.009825	0.0883	0.297097	13.13666
3	0.012490	0.0837	0.289358	13.11202
5	0.008076	0.0741	0.272250	13.08662
7	0.007528	0.0702	0.265036	13.17628
10	0.003857	0.0670	0.258922	13.09133
12	0.003028	0.0659	0.256688	13.00699
15	0.001377	0.0642	0.253355	13.10147
17	0.002156	0.0639	0.252704	13.07007
20	0.001219	0.0629	0.250827	13.07036
25	0.001398	0.0624	0.249781	12.96586
30	0.000591	0.0615	0.248029	13.06039
35	0.000654	0.0611	0.247111	13.09574
40	0.000509	0.0606	0.24620	13.2014
45	0.000278	0.0605	0.246012	12.99049
50	0.002250	0.0611	0.247164	13.04720
55	0.001564	0.0602	0.245317	13.19156
60	0.001725	0.0605	0.245970	13.07846

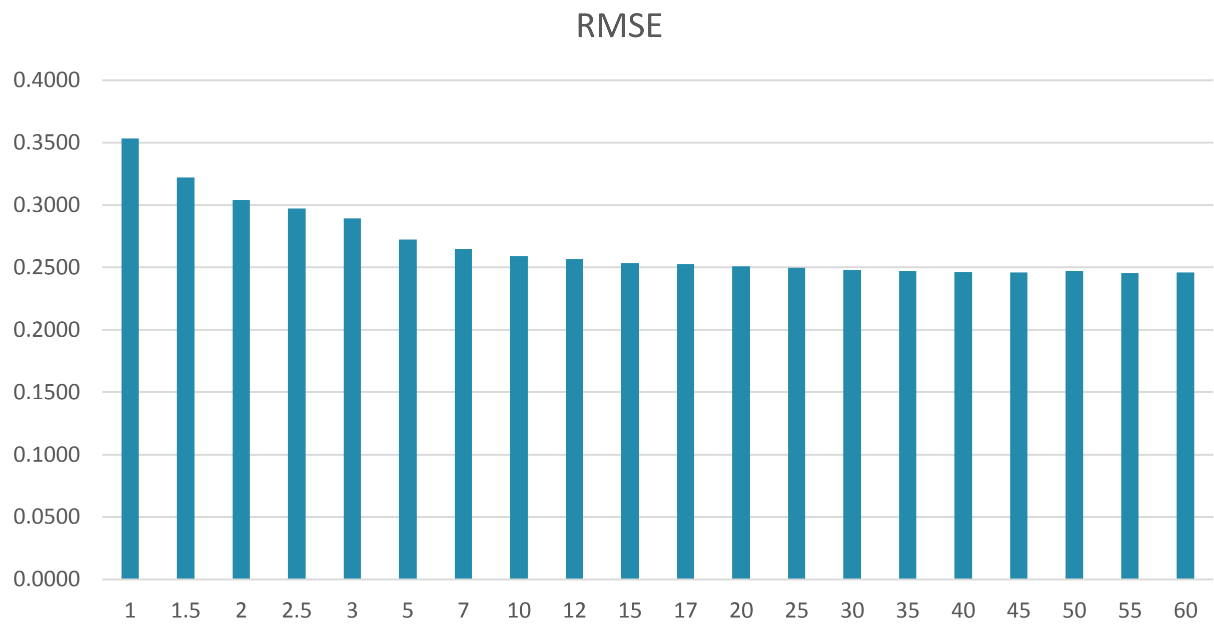

Figure 7. Root Mean Square Error by sampling intensity.

Figure 7 shows the changes in root mean square with increasing sampling intensity. It shows that at a 10 percent sampling intensity results in the most efficient strategy. It is produced when RMS errors stabilized, in this case around 0.250 with small variation when sampling intensity increased more than 10 percent.

6. Discussion

After descriptive statistics were performed there was no missing values in any of the analyzed variables. Computed MOE correlations with density (.405), acoustic velocity (.860) and DBH (-.327) are all highly significant. This relationships was reported in other studies that use acoustic measurements to estimates MOE (Paradis et al. 2013; Amishev and Murphy, 2008; Carter et al. 2005; Auty and Achim, 2008). Acoustic velocity is the most significant variable to explain MOE predictions with a correlation of .860. These results are slightly better than those found by Lachenbruch et al. (2010) reported that density has a higher correlation to MOE than velocity, .762 and .680 respectively for mature Douglas-fir trees. This difference could be due to the forest population subject to study, Lachenbruch et al. (2010) use a mature meanwhile the other is a second growth forest.

A weak inverse trend was found between DBH and MOE. Lower DBH values correspond to high values of MOE, it could be attributable to some variation caused by the probes insertion depth. This trend was also found by Grabianowski et al. (2006) in radiate pine.

Regarding the model fitted, the use of DBH combined with velocity demonstrates a good prediction power with a R^2 of .768. Slope and intercept are significant (p-value .000). In general, R^2 is higher than those reported in similar linear model with the same variables for Black Spruce R^2= .410 (Paradis et al. 2013). For Douglas-fir Lachenbruch reported R^2= .733, but in this case they use density instead of DBH.

Residual and leverage plots shows the possible presence of outlier values, this could be attributable to variation in velocity and DBH. Velocity variation could came from changes in tree moisture content. DBH variation source could be due to the depth insertion of the probes. In addition, Paradis et al. (2013) indicate that is known inclusion of DBH bring some variation in stress waves even if MOE and Density remain constant.

When velocity was used to predict MOE by itself an R^2 of .739 was found, variable and slope were highly significant (p-vales .000) for this model. Although this model obtain good values, an increase of .017 in R^2 was found when DBH is used in the model, with a reduction in 11 percent in residuals MSE means a moderate reduction in the difference between the estimation and the real value. The same trend was shown by Wang et al. (2007); their model reduced prediction variability in velocity and improve prediction power when DBH is include in the regression. Lachenbruch et al. (2010) also found an increase in predictive power when regression model include both velocity and density than when estimation were made based on either variable alone.

After completing the 500 iterations from the Monte Carlo Simulation, all the simulations contain the MOE population mean μ=13.08 GPa in each one of them, no significant skewedness was found. BIAS remain small (0.0003 – 0.0631) indicating the model is able accurately predict MOE from these samples.

Wood density samples are expensive to collect and process for large-scale operational inventories. This study finds the optimal wood density sample size for MOE estimations based on acoustic velocity and tree density, through the Root mean squared error. RMSE shows the expected path of decrease while the sampling intensity increased. The RMSE stabilizes after that 10 percent of sampling intensity is used, which allow one to make valid statistical infer on the population based on that 10 percent.

However, if sampling 10 percent of the population represents a limitation, researcher could appeal to use a smaller sampling intensity of 7 percent without a reduction in the predictability with an RMSE increasing from 0.265 at a 7 percent sample versus a 0.250 at 10 percent sample 0.250.

7. Conclusions

The objective of the study is to promote the inclusion of wood properties density and MOE in pre-harvesting inventories. It was demonstrated that this inclusion is possible and reliable (R^2= .768, when DBH used in the model) in the estimations of Modulus of Elasticity obtained, which becomes a helpful tool during pre-harvest inventory planning. In addition, techniques developed show that is possible to combine wood properties with inventory information to asses wood stiffness.

Modulus of elasticity is well correlated to acoustic velocity with, wood density and DBH. DBH has an inverse trend with MOE, lower DBH values yields to higher values of MOE. Despites this trend on DBH, which is always part of every operational forest inventory, is a helpful variable when combined with acoustic velocity to predict MOE values (R^2= .769). With this model foresters are provided of an equation that require less complex inputs, reduce in the variation of the acoustic velocity measurements, and without doubts an easier way to estimates MOE with variables that are cheaper, easier and less time consuming that wood density. To reduce variation in acoustic velocity measurements and the possible presence of outlier values, probes insertion depth should be controlled by prefixing it according to the specie sapwood characteristics.

Monte Carlo Simulation shows that it is possible to make accurate estimations of MOE with a subsample of density cores. A 10 percent of wood density (cores) appears to be the best sampling intensity. However, one can use an interval between 7 and 12 percent of sampling intensity because of the small differences in RMSE. Using more than 12 percent sampling intensity does not improve in the quality of MOE estimations. Therefore, there is no statistical gain in use a sampling intensity bigger than 12 percent. However, this result is produced from only one stand.

Using acoustic nondestructive evaluation can help to operationalize the collection of wood properties that can support the primary log supply chain. It also provides a significant opportunity for foresters to know the condition or status of the forest and its properties early in the supply chain management. Furthermore, it is an opportunity for Douglas-fir foresters to assess wood quality practically in real time, which will allow them to take the decisions about the best silvicultural treatments to achieve desired quality for a specific end-used.

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