

THE USE OF SITE AND STAND CHARACTERISTICS TO PREDICT STIFFNESS IN
STANDING SMALL DIAMETER INLAND DOUGLAS-FIR

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Carl D. Morrow

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Major Professor: Thomas Gorman, Ph.D.

Authorization to Submit Thesis

This thesis of Carl Morrow, submitted for the degree of Master of Science with a major in Forest Products and titled "The Use of Site and Stand Characteristics To Predict Stiffness in Standing Small Diameter Interior Douglas-fir," has been reviewed in final form. Permission, as indicated by the signatures and dates given below, is now granted to submit final copies to the College of Graduate Studies for approval.

Major Professor _____ Date _____

Thomas Gorman

Committee

Members _____ Date _____

Armando McDonald

_____ Date _____

Russell Graham

Department

Administrator _____ Date _____

Thomas Gorman

Discipline's

College Dean _____ Date _____

Bill McLaughlin

Final Approval and Acceptance by the College of Graduate Studies

_____ Date _____

Margrit von Braun

Abstract

Thinning operations in the Inland Northwest often target small diameter inland Douglas-fir (*Pseudotsuga menziesii* var. *glauca*). The high operational costs associated with their removal demand that land managers find the highest value market for the small diameter material. Structural lumber and roundwood, specifically machine stress rated (MSR) products, may provide a higher value market for forest managers. The objective of this study was to develop models to predict the stiffness of standing trees using standard inventory and readily available GIS measurements. Prior knowledge of the stiffness would allow forest managers to layout and market timber sales to manufacturers of MSR lumber and roundwood products.

Standing stress wave measurements were taken for 274 small diameter Douglas-fir trees in western Montana. Stand, site, and soil measurements collected in the field and remotely through GIS data layers were used to model dynamic modulus of elasticity (MOE) in those small diameter trees. The best fit linear model developed resulted in an adjusted $R^2=0.51$ and used: Mean Annual Increment⁻¹, total tree height, and GIS based soil bulk density. Logical models were also developed to predict membership in dichotomous dynamic MOE categories with 70%-85% correct classification for the three models presented here. The inverse relationship between soil bulk density and dynamic MOE could be explained by soil-tree moisture interactions. The critical variables that for the basis of the models presented here suggest that more transferable process based models for MOE may be possible.

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Introduction

In the interior Northwest, Douglas-fir (*Pseudotsuga menziesii* var. *glauca*) is often a prime candidate for thinning operations in overstocked stands. Douglas-fir can potentially occupy a greater variety of habitats than any other western tree species, from low elevation grasslands to the lower reaches of the timberline, across varied habitat types and disturbance regimes (Burns and Honkala, 1990). The introduction of fire suppression and harvesting regimes has altered the species compositions in western forests, and Douglas-fir has come to dominate many of these stands where it was historically only a small component. While Douglas-fir is successful in occupying these stands, it is more prone to root disease, insect attack, and dwarf mistletoe leading to increased forest health issues (Byler and Gorve 1990). Corrective management such as thinning can be used to maintain forest health, or return species compositions to historic conditions. These thinnings are often targeted at overstocked stands where most of the timber harvested consists of small sawlog sized with small end diameters less than eight inches.

Financial considerations for thinning demand that markets for small logs must be found to best capture their value. Handling of small logs greatly increases harvesting and handling costs, and requires forest managers to find the highest value market for their small logs. Prior studies in the properties of coastal Douglas-fir (*Pseudotsuga menziesii* var. *menziesii*) from suppressed stands have been promising. Prior studies (Green et al. 2005) have found that small diameter Douglas-fir harvested from the Hayfork ranger District in the Shasta-Trinity National Forest in Northern California provided excellent yields of high quality structural material when sawn to dimensional lumber. The use of

small diameter trees as structural roundwood may be a more efficient use of the resource (Wolfe and Murphy 2005) and recent publications have shown there is potential for using existing mechanical grading systems to assess small diameter logs for structural use (Green et al. 2008). Rising petroleum costs has led to interest in the use of timber residues both for direct combustion and the potential for biofuels production.

It would be of great service for forest managers and lumber manufacturers to have a quantitative prediction of wood quality with regards to the structural properties of roundwood or lumber sawn from a given tree or stand. Prior knowledge of the structural quality of wood on a given sale could help forest managers market that timber to structural lumber/roundwood manufacturers. The use of a stress wave speed measurement in conjunction with tree density measurement has been suggested as a means to that end. Stress wave speed measurements on standing trees have been shown to provide reasonable estimates of the modulus of elasticity (MOE) of wood from those tree. Literature reported by practitioners of this method suggests that these stress wave measurements can account not only for the varying MOE in clear sections between trees, but also the morphology within the trees (Grabianowski et al. 2006, Chauhan and Walker 2006, Wang et al. 2007).

The inclusion of stress wave and specific gravity measurements in a stand assessment program could be regarded as prohibitive because of the added time and expense involved with their capture. The primary objective of this study was to develop a model using standard forest inventory data in combination with remotely sensed data to reduce the need for further acoustic testing for mixed age stands of suppressed small diameter

Douglas-fir. The identification of high quality stands before harvest could add value for both the landowner and purchaser. Models were also developed to assess the improvement in predictive power as the variables moved from the office (GIS based- “remote”) to the roadside (general stand variables- “drive-by”) to intensive inventory type measurements. The study was limited to small diameter (<12” dbh) Douglas-fir stands in the Trapper Bunkhouse area within the Darby Ranger District of the Bitterroot National Forest in western Montana (Ravalli County, MT) . The Trapper Bunkhouse region is complex landscape of roughly 23,000 acres sandwiched between the Selway-Bitterroot Wilderness area to the west and state and private property adjacent to the Bitterroot River to the east. Biotic and human influences have led to overstocked suppressed stands in which Douglas-fir is a large component and thinning projects are underway to improve stand health and reduce fuel loads.

Literature Review

Until recently, models for wood quality have focused on predicting the branching behavior of trees and annual ring characteristics to predict product yield and end use suitability. No predictive models for the MOE of suppressed small diameter Douglas-fir are currently available. More recent models have been developed to predict the MOE of certain other species using stand and site characteristics. Models for predicting forest productivity over broad landscapes may serve as a template for the development of wide scale wood quality prediction models.

Simple visual inspection has been and continues to be a common method to predict wood quality. An experienced sawyer/forester/scaler uses visual cues from the bark and form of the tree to determine the best use of the logs from that tree. Log grading criteria represent the first standardized attempt at predicting wood quality. Although researchers have compared log grades to lumber grade yield (Matson and Rapraeger 1950, Grantham and Hunt 1963, Barbour and Parry 2001) these log grading rules include diameter limits that would lump most logs from small diameter trees into the lowest log grade (NLRAG, 2006) Much research has focused on the growth and occlusion of knots as a means to predict product yield and value. Studies on the effects of silvicultural practices such as planting density and thinning (Grah 1961, Maguire et al. 1991) on knot size and occlusion have given way to process and empirically based models to predict internal knot characteristics (Makela and Makinen 2003, Moberg 2001). Valuation of stands using knots as a determining factor for visual and MSR grades have also been proposed (Fahey 1980, Fahey et al. 1991).

Wood density has been used as a measure of wood quality. Two of the most relevant avenues of wood density research to this paper would be the effects of silvicultural practices and the effects of climate on tree ring characteristics. Treatments to promote growth must either: promote retention and development of foliage to increase photosynthetic capacity or improve the availability of limiting nutrients and water. Thinning may accomplish both and has been shown to have either no effect (Megraw and Munk, 1974) or slight increase (Josza and Brix, 1989) in wood density for coastal Douglas-fir. With respect to needle retention, conflicting studies have shown increases in density in trees afflicted with the defoliating disease Swiss Needle Cast in the Pacific

Northwest (Johnson et al. 2005) and decreases in density with declining vigor in Dutch Douglas-fir stands (De Kort 1993). Fertilization and irrigation relieve nutrient and water deficit, and have been shown to temporarily reduce wood density in red pine and Douglas-fir (Zahner et al. 1964, Brix 1972, Josza and Brix 1989) by promoting a delayed transition from earlywood to latewood production. Climate has been shown to be a factor in wood density with the most dramatic effects at the margins of specie's range (Adams and Kold 2004, Savva et al. 2003). The timing of precipitation, soil water demand, and monthly temperatures have been associated with changes in tree ring characteristics such as percent latewood and overall ring density (Roberston et al. 1990, Bower et al. 2005). These findings have led a French team of researchers to propose that increased wood density is an adaptation by Douglas-fir families to better survive drought events (Dalla-Salda et al. 2009).

Models to predict MOE in standing trees have been proposed for several species. The average MOEs of boards cut from Black spruce (*Picea mariana*) in eastern Canada were modeled using stand and tree measurements in plantation and even-aged naturally regenerated stands (Lei et al. 2005, Liu et al. 2007). The models developed had similar goodness-of-fit measures with R^2 values of 0.55 and 0.56 respectively. MOE in plantation grown radiata pine (*Pinus radiata*) were well modeled ($R^2=0.96$) using a combination of stand variables and soil variables across forested sites in New Zealand (Watt et al. 2008).

The development of productivity models may serve as a template for the development of wood quality models. Basic tools such as Site Index (SI) (average height of dominant or

codominant trees at a given age) are available, and may be developed for a given stand on an empirical basis, but have limited transferability to new stands. Soils based models for forest productivity have been proposed and the variables of interest run the gamut of soil characteristics leading one researcher to conclude that the complexity of forest ecosystems “, does not lend itself to one-size-fits-all soil property ratings.” (Schoenholtz et al. 2000) Predictive models for productivity such as the Forest Vegetation Simulator (FVS) have been developed using stand and general habitat type information to model growth on a stand or tree level. Experience has shown that adaptations to the stock FVS model may be necessary to encompass local stand, species, or environmental conditions (Lacerte et al. 2004, Lacerte et al. 2006) limiting the geographical scope of any one incarnation of FVS. Process based models have been developed that combine stand variables (age, size, stand density, etc.), climatic information, soil variables relating to water and nutrient availability, and tree physiology to predict productivity in terms of Mean Annual Increment (MAI) (Landsberg and Waring 1997, Landsberg et al. 2003) and SI (Swenson et al. 2005). Process based models are attractive because they offer reasonable accuracy using a combination of existing data for soils and climate, previously researched tree responses to environmental variables, and adjustable parameters for transfer between species (Landsberg and Waring 1997, Landsberg et al. 2003, Swenson et al. 2005). A satellite based measurement of leaf area has been shown in one study to provide estimates of SI and annual increment in Douglas-fir and ponderosa pine on par with the previously mentioned process model (Waring et al. 2006). Although the resolution was somewhat coarse, both the process model and satellite derived model were able to provide useful prediction of SI and annual increment when referenced against

over 5000 Forest Service inventory plots in Oregon (Swenson et al. 2005, Waring et al. 2006).

The use of Time of Flight (TOF) stress wave measurements has been reported as a nondestructive method to predict wood quality in a standing tree. A TOF measurement uses synchronized accelerometers embedded in the stem of a tree to measure the velocity of an induced stress wave through that tree. Research suggests TOF measurements of velocity are adequate to predict MOE and demonstrate sensitivity to changes in tracheid length, juvenile wood, microfibril angle, and the presence of defects such as knots and reaction wood (Grabianowski et al. 2006, Wang et al. 2007, Chauhan and Walker 2006).

Methods

Field Measurements

Field measurements were conducted during a six day period in early August 2007 in the Trapper Bunkhouse Area (TBA) on the Darby Ranger District of the Bitterroot National Forest in Ravalli County, Montana. The TBA was chosen as the study area because of its geography, history, biology, and current management. The TBA is very close to the town of Darby, Montana with all the accompanying wildland-urban interface issues and the area has good road access to stands from the Bitterroot River valley up to about 7000 feet in elevation. Before logging commenced in the late 19th century, the region's forests were predominantly ponderosa pine stands grown in the presence of frequent disturbance from fire. The combination of high grading ponderosa pine and the exclusion of fire have led to dense stands of small diameter Douglas-fir typical of the Inland Northwest with high

rates of infection from: dwarf mistletoe, various diseases, and boring insects. A cessation of logging on Forest Service timber lands has led to the departure of large sawmills in the region. Local post-and-pole and specialty mills still buy some logs but most of the Darby Ranger district is too far from a large pulp mill to make harvesting small logs economical. The Darby District has recently proposed thinning operations on about 6,000 acres of the TBA. Forest managers on the district are eager to see if higher value markets exist for their small diameter Douglas-fir.

Stand Selection

The initial sampling strategy for this study was to measure small diameter Douglas-fir at 16 different elevation/crown closure conditions.

Table 1. Initial Sampling Matrix for Small Diameter Douglas-fir

Elevation (ft)	Number of Small Diameter Trees to be Sampled			
	Percent Crown Closure on Plot			
	10%-25%	25%-40%	40%-60%	60%-100%
4200-4900	24	24	24	24
4900-5600	24	24	24	24
5600-6300	24	24	24	24
6300-7000	24	24	24	24

Stand selection was performed using a copy of the Forest Service's Potential Vegetation Type (PVT) Classification of Western Montana and Northern Idaho (USDA Forest Service, Northern Region 2004) overlain with road and elevation layers using ArcGIS 9.1. The PVT is a series of GIS layers generated from digital analysis of satellite images, soils information, and other GIS databases combined with field plots developed to assess current stand conditions. The algorithms employed by the PVT classify stands based on tree dbh, percent crown closure, and vegetation type, and delineate stand boundaries

based on those classifications. The Forest Service has determined 4 categories for percent crown closure (percent of canopy occupied by trees) in the PVT: Low (10%-24.9% crown closure) Low-Moderate (25%-39.9% crown closure), Moderate-High (40%-59.9% crown closure), and High (60%-100% crown closure).

Seedling transfer guidelines are general rules used by foresters and silviculturists to determine how far a given seed source can be used removed from its origin, and still maintain an acceptable survival and growth rate. Elevational seed transfer guidelines for this portion of Montana suggest segregating seed sources above or below 5000 ft (Franc 1991) but for Central Idaho and southeastern Washington acceptable transfer zones are only ± 330 ft and ± 350 ft respectively (Rehfeldt 1983, Randall and Berrang 2002). In an attempt to more finely sample the potentially different populations, a narrower set of elevation ranges were employed than those prescribed by Franc. The elevations available for sampling were limited by the Bitterroot River valley floor (4200 ft) and road access at upper elevations (7000 ft). For the sake of simplicity, the elevations sampled were: 4200-4900 ft, 4900-5600 ft, 5600-6300 ft, and 6300-7000 ft. All sites sampled were located on “favorable” aspects: generally north to east facing. The stands meeting these criteria were targeted during field data collection. All stands sampled were naturally regenerated.

Historic surveys of specific gravity in Douglas-fir in Ravalli County indicated a range of values from 0.35 to 0.53. With no prior knowledge of the ranges of MOE that would be encountered, the variation in historical specific gravity was used to establish a sample size. Assuming the full range of specific gravities could be found in any given elevation/crown coverage condition; a sample size of 24 small diameter trees per

elevation/stand density combination was established as a goal. The total initial sampling goal was 384 small diameter Douglas-fir trees.

Field Data Collection

Stands meeting the various elevation/crown coverage criteria were identified using the PVT before field work commenced. In the field, data collection proceeded as follows: Plot center was located such that discontinuities such as roads, large openings, or other nonforested areas were not part of the plot and the stand conditions were consistent.

Inventory data collected at each plot included:

- A point sampled plot was established using a 10, 30, or 40 BAF lens to capture between 3 and 7 trees per plot for the basal area measurement. These measurements of basal area included large trees and trees of other species in addition to the small diameter Douglas-fir of interest in this study.
- Crown closure measured with a spherical densitometer to verify percent canopy cover from GIS
- Total number of trees in plot
- Latitude/Longitude of plot center with a GPS
- DBH and total height of all trees in the plot (broken top heights were estimated)
- Slope (%) and aspect(deg) at plot center

These measurements were selected because they represent fairly standard cruise data and give a representation of the stand in the vicinity of the plot. No measurements of defect or merchantability were collected. The percent cover measurement from the densitometer and elevation recorded by the GPS were used to assign the plot to a percent cover/elevation sampling combination.

Of the Douglas-fir between 4.0 in and 12.0 in dbh on each plot: the largest, the smallest, and one closest to 8.0 in were sampled for the following characteristics:

- A standing stress wave speed measurement taken from the uphill side above any gross defect such as: scars, sweep, or mistletoe/growth defects. Stress wave measurements were taken using Fibre-Gen's Director ST-300.
- A clear 0.5" increment core was extracted as close to 4.5 ft as possible from the same face from which the standing stress wave was measured (uphill side or first clear face)
- Length of green increment core
- Percent live crown
- Length of branch free bole

The stress wave and core measurements were taken to determine the trees' dynamic MOEs. The percent live crown and branch free bole length were taken as measures of competition. No more than four plots were established in any stand, and plots within the same stand were spaced at least 200 ft apart.

Lab Measurements

The increment cores were returned to the Department of Forest Products lab at the University of Idaho. The specific gravity on a green volume basis was determined for each core, and the trees' ages at breast height were determined using a dendrochronometer. Tree age was divided by DBH to calculate the inverse of Mean Annual Increment (MAI⁻¹) for the trees.

Remotely Sensed Data

GPS locations of the plot centers were overlain on several GIS data layers. Mapping was performed using ArcGIS 9.1. The GIS data layers were:

- Potential Vegetation Type (PVT) Classification of Western Montana and Central Idaho (2004)-USDA-USFS: Dominant vegetation, tree size, and percent crown coverage for each plot was extracted. The categorical class values (ie: 1 = small tree, 2 = medium tree, 3 = large tree, etc.) were linearized to reflect their correlation to dynamic MOE.
- SSURGO Soil Map 647-USDS-NRCS: Soil properties from the USDA-NRCS soil survey were extracted for each plot location. The soil properties were given as associated soil groups, and converted to a weighted average of soil properties encountered in soil layers above obstruction and across the mapping unit. The resulting indices were :Organic Matter (OM) Index(% organic matter by weight), pH Index (pH), Sand Index (% sand by weight), Silt Index(% silt by weight), Clay Index (%clay by weight), Cation Exchange Capacity (CEC) Index (milleq per 100 grams), Bulk Density (BD) Index(lb dry basis per cubic inch at .33 bar moisture tension), and maximum observed root depth(cm). The Indices in essence represent the soil properties one would expect if the O, E, A, B, and C soil layers were excavated and thoroughly mixed. For example, if a soil type had a Silt Index value of 20% that would mean that if all the soil above undifferentiated parent material were mixed, an average sample would contain 20% sand. The indices were also weighted according to the prevalence of each soil type within a mapping unit, therefore, soils with greater distributions within the mapping unit had greater influence on the final index value for that mapping unit
- The preliminary geologic map of the Nez Perce Pass 30' x 60' quadrangle - Montana Bureau of Mines and Geology: underlying parent materials for the plots were extracted.

- Wetness index-USDA-USFS: LIDAR measures of soil wetness were taken during the spring and during the summer. The index measured the relative drying for each mapping unit during that period.

Calculations

An estimation of the standing tree dynamic MOE was made by combining the squared stress wave speed with an estimated green bulk density based on the increment core specific gravity. The wood bulk densities were calculated using an assumed moisture content of 35%:

$$\text{Dynamic MOE} = \frac{\rho}{g} V^2 \quad (\text{Eqn. 1})$$

$$\text{Where: } \rho = 0.036 \left(\frac{\text{lb}}{\text{in}^3} \right) \times (\text{specific gravity}) \times (1.35)$$

$$g = 386 \left(\frac{\text{in}}{\text{s}^2} \right)$$

$$V = \text{stress wave velocity} \left(\frac{\text{in}}{\text{s}} \right)$$

Stand Density Index (SDI) was calculated for the plots using two methods:

Reinke's even aged SDI

$$\text{Log } SDI = \log N + 1.605 \log D - 1.605 \quad (\text{Eqn. 2})$$

Where: N = number of trees per acre

D = diameter of tree of average basal area (in)

And the summation method (Long and Daniel 1990) for uneven aged stands:

$$SDI = \sum tph_i (DBH_i / 25)^{1.6} \quad (\text{Eqn. 3})$$

Where tph_i = trees per acre for i^{th} diameter class (cm)

DBH_i = midpoint of the i^{th} diameter class (cm)

Statistics

Statistical analysis was performed using SAS and SPSS. Theoretical and analytical models were developed to predict the dynamic MOE of trees sampled during the field research. The data were divided into two subsets. The calibration data set was built from one randomly selected tree from every plot. The remaining trees formed the test data set. Models were built using the calibration data set (84 samples), and once the best performing models were identified, the test data set (164 samples) was used to test the fit of the models. A complete list of variables can be seen in Appendix A.

Initially all variables were regressed individually with Dynamic MOE. Those variables with potential for predictive ability were assessed to see if transformations or rearrangements to the variables would improve predictive ability. For example, when tree age was regressed against Dynamic MOE, an increasing trend was for trees up to about 130 years of age. Trees older than 130 years all had similar distributions of Dynamic MOE. Therefore, a modified variable was created that assigned a value of 130 years for any tree older than 130 years. Categorical variables were likewise plotted against Dynamic MOE, and assigned class values such that they reflected the linear increase/decrease in Dynamic MOE from class to class. The new class values provided variables more suited for linear regression. The use of multiple datasets allowed for more

aggressive transformations of the variables in the model building phase. Transformations that performed well using the calibration subset were applied to the test subset during the model testing phase, essentially testing the models with a new dataset. This tactic was used to reduce the opportunity for overfitting the models.

Theoretical models were developed by stepwise regression on the calibration dataset, initially within variable categories (Remote, Stand level, Plot level) then in combination. The models shown in the results section of this paper represent a few of the best performing models from the analysis based on their goodness-of-fit. It should be noted that samples with missing values for variables used in the model are excluded by SAS in the model building process. These exclusions led to slight differences in the samples on which the models were built. The models built using a combination of all variable categories (Remote, Stand, Plot) had the most samples excluded. The model results reported in the results section therefore represent the first attempt to winnow the most viable models from the larger collection.

The development of logical models stemmed from a stepwise discriminant function analysis (DFA) performed using SAS showing that BD Index was the most useful variable for separating trees with high and low Dynamic MOE. The logical models were built using DFA and visual analysis to determine which variables best grouped the trees in dichotomous categories (ie above or below 1.5E6 psi, above or below 1.8E6 psi, etc.) and the cutoff values for those variables. The models were built using the smaller calibration data set, and once the models were finalized, tested using the larger test data set.

Results

During the course of the fieldwork, it became apparent that the lowest percent crown coverage conditions indicated by the GIS data layers were not found on the ground. Final minimum mapping cell for the PVT was about 300 ft, and the lowest coverage on north or east aspects were actually very dense clumps of trees surrounded by rock or other nonforested areas. The trees in these low coverage stands were growing very close together, not open grown as one would expect in a stand with low levels of crown closure. This led to the combination of the two lowest crown coverage classes. This finding was especially true in stands at higher elevations and is reflected in the absence of trees sampled in the lowest crown closure class and highest elevation range. Fifteen trees were excluded from the analysis because they fell in areas that the PVT determined to be grass or shrub dominated, 4 trees were excluded because of damaged increment cores, and 3 trees were excluded for missing data. The final distribution of small diameter Douglas-fir sampled was as follows:

Table 2. Distribution of small diameter Douglas-fir sampled by elevation and percent crown coverage

Elevation (ft)	Number of small diameter DF sampled		
	Percent Coverage on Plot		
	10%-40%	40%-60%	60%-100%
4200-4900	6	33	27
4900-5600	21	27	34
5600-6300	18	18	23
6300-7000	0	18	24

A complete list of variable descriptions is included in Appendix A, but below is shown a synopsis of tree characteristics:

Table 3. Synopsis of small diameter Douglas-fir field measurements

Tree Variable	Average ^a
Percent Crown Closure (%)	57 (33)
Basal Area on Plot (ft ²)	116 (47)
DBH (in)	8.7 (25)
Total Tree Height (ft)	46.7 (27)
Percent Live Crown (%)	63 (35)
Mean Annual Increment ⁻¹ (yrs/in DBH)	8.9 (39)
Stress Wave Speed (ft/s)	13624 (13)
Specific Gravity	0.45 (7)
Age at Breast Height (yrs)	75 (39)
Dynamic MOE (psi)	1548716 (29)
Clear Height (ft)	0.5 (0)(0) ^b

^a Numbers in parenthesis are coefficient of variation in percent

^b Values in parenthesis are median and mode for severely skewed distribution

Given the average age of 75 years and average height of 47 feet, many of the trees sampled during this research were severely suppressed. The slow diameter growth coupled with the relatively short average height implies that these trees were essentially stagnant. More than 30 trees were over 100 years old at breast height with the tallest measuring 87 feet. The maximum and minimum specific gravities measured (0.346 to 0.530) matched records from the 1965 Western Wood Density Survey (USDA 1965) for Ravalli County almost exactly (0.35 to 0.53) and the average is in-line with expected values.

Field data was collected on 18 different typed soils defined by the NRCS soils map. A summary of the physical properties of the soils is given in Appendix B. The introduction of soils data to the data set was done after the field sampling was completed meaning there was no systematic sampling across soil types or soil characteristics.

Theoretical and analytical models were developed to predict dynamic MOE in the small diameter Douglas-fir trees. Theoretical models were built to test improvement in predictive power as the variables moved from remotely sensed, to stand based, to plot variables as well as a best fit model for all variable types. Table 4 shows some of the theoretical models developed by James Evans, David Kretschmann, and Cheryl Hatfield of the Forest Products Laboratory. The models in Table 4 were built using the smaller calibration data subset.

Table 4. Selected theoretical models developed

Variable Types	Variables					R ²
Remotely Sensed Variables	Recoded Coverage Class ^a	Wetness Index ^b	Categorical BD	pH Index ^b	Sand Index ^b	0.48
Stand based Variables	BD Index ^b	Wetness Index ^b	Elevation	Silt Index ^b		0.45
Inventory Variables	% Foliage	Foliage length	DBH	Clear Ht		0.39
	% Foliage	Foliage length	DBH			0.36
	Age Max 130 ^c	MAI ¹				0.45
	Categorical BD	MAI ¹	Total Height	Recoded Remote tree size ^d		0.64
Combinations	Categorical BD	MAI ¹	Total Height			0.62

a. Recoded Coverage Class – Remotely measured coverage class values were linearized to reflect increase in dynamic MOE across classes

b. Index Values – See Remotely Sensed Data section of page 12 for explanation

c. Age Max 130 – Age for all trees was capped at 130 years, trees older than 130 years were passed the value of 130 yrs

d. Recoded Remote Tree Size – Remotely measured tree size class values were linearized to reflect increase in dynamic MOE across classes

The stand based variables were able to account for the lowest amount of variation in the samples. The remotely sensed and the plot variables were able to account for the same amount of variation, but half as many plot variables were needed. When the variables from the three classes were combined; MAI¹, Categorical BD (where BD Index > 91 lb/cuft = 0, BDIndex < 91 lb/cuft = 1) and Total Height were able to account for 62% of the variation in the samples. The addition of the recoded remotely sensed tree size rendered only a modest increase in the R² of the model. It should also be noted that the variables on which the study was designed (elevation and percent coverage) were of

limited use in the prediction of dynamic MOE. For economy's sake, the discussion below will focus on the final model proposed in Table 3.

As an intermediate step, the model was rerun such that all the data points in the smaller calibration subset were used (not excluded by SAS). The resulting model had an adjusted $R^2 = 0.550$. To test the model's fit with a new dataset; a model was built using MAI⁻¹, Total Height and Categorical BD Index with the larger Test data subset. The results are given in Table 5.

Table 5. Regression results from MAI⁻¹, BD Group, and Total Height using larger test subset of data

	R-Square	Adj R-Square	Root MSE	Mean Dynamic MOE (psi)	
	0.493	0.483	318016	1531217	

Model	Sum of Squares	DF	Mean Square	F Value	Pr > F
Regression	1.57E+13	3	5.24E+12	51.80	<.0001
Residual	1.62E+13	160	1.01E+11		
Total	3.19E+13	163			

Source	Univariate SS	Univariate F Value	Type III SS	Type III F Value	Pr > F
MAI ⁻¹	8.93E+12	62.98	6.45E+12	63.80	<.0001
Total Height	5.18E+12	31.41	3.09E+12	30.55	<.0001
Cat. BD Index	6.24E+12	39.40	2.14E+12	21.16	<.0001

Parameter	Unstandardized Coeff.	Std. Error	Standardized Coeff.	t	Pr > F
Intercept	384773	117774		3.27	0.0013
MAI ⁻¹	61302	7675	0.46	7.99	<.0001
Total Height	11381	2059	0.32	5.53	<.0001
Cat. BD Index	281894	61284	0.272	4.60	<.0001

The drop in R^2 from Table 4 to Table 5 (0.62 to 0.483) represents the affects of the truncated sample size imposed by SAS in Table 3 (over-optimistic goodness of fit), the

introduction of the new test data subset, and the introduction of an Adjusted R^2 value.

Although the goodness of fit dropped approximately 12% from the Calibration to the Test data subset, it still was able to account for about half of the variance present in the Test data subset.

MAI¹ accounted for the most variance, followed by total height and BD Index. This can be seen in the Type III Sum of Squares for the individual variables and the Standardized Coefficient in Table 5. The Type III Sum of Squares is a measure of the variance accounted for by the inclusion of the variable in question after the other variables have been entered and reflects the unique contribution of that variable to the performance of the model. MAI¹ accounts for more than twice as much variance as Total Height, and three times as much as BD Index. The Standardized Coefficient is another measure of the importance of individual variables. The Standardized Coefficient reflects the relative influence of the variables if each was mean centered and divided by its standard deviation. With the variables all on the same standardized scale, meaningful comparisons of their influence can be made. MAI¹ has a Standardized Coefficient of 0.46, followed by Total Height with a Standardized Coefficient of 0.32, and lastly BD Index with a Standardized Coefficient of 0.27. The Standardized Coefficients again indicate that MAI¹ is the most influential variable followed by Total Height and BD Index.

The final proposed model was built using both subsets of data, and the results are shown below in Table 6.

Table 6. Final Proposed Model Using Both Data Sets

F Value Model	R-Square	Adj R-Square	RMSE	Mean Dynamic MOE
85.915	0.515	0.509	309504	1548716

Parameter	Unstandardized Coeff.	Std. Error	Standardized Coeff.	t	Pr > F
Intercept	437398	91183		4.797	<.0001
MAI ⁻¹	60473	5977	0.465	10.117	<.0001
Total Height	10685	1611	0.304	6.633	<.0001
Cat. BD Index	302677	48358	0.295	6.259	<.0001

The final model would therefore be:

$$\text{Dynamic MOE} = 437398 + 60473 * \text{MAI}^{-1} + 10685 * \text{Tot. Ht.} + 302677 * \text{Cat. BD Index}$$

With an adjusted R² value of 0.509, the model accounts for just over half of the variance in the combined sample sets. From the standardized coefficient values in Table 6, MAI⁻¹ was the most influential variable followed by total height and categorical BD Index. The Root Mean Squared Error (RMSE) for the final model was 309504 psi

Figure 1 below shows the fit of the final model developed using both data sets with the Dynamic MOE measured for those trees. The darker 95% confidence lines represent the predicted value \pm RMSE \times 1.96.

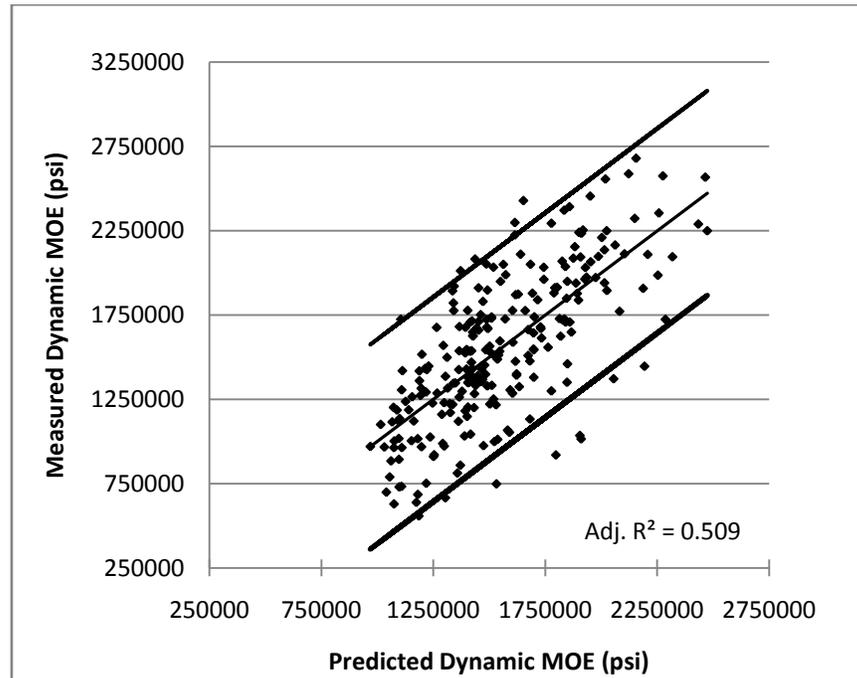


Figure 1. Model Fit for Both Data Sets with 95% Confidence Intervals

The inverse of Mean Annual Increment (MAI^{-1}) seemed to be a significant predictor of dynamic MOE. Figure 2 shows a comparison of the average dynamic MOE by MAI^{-1} classes with one standard deviation error bars for each group:

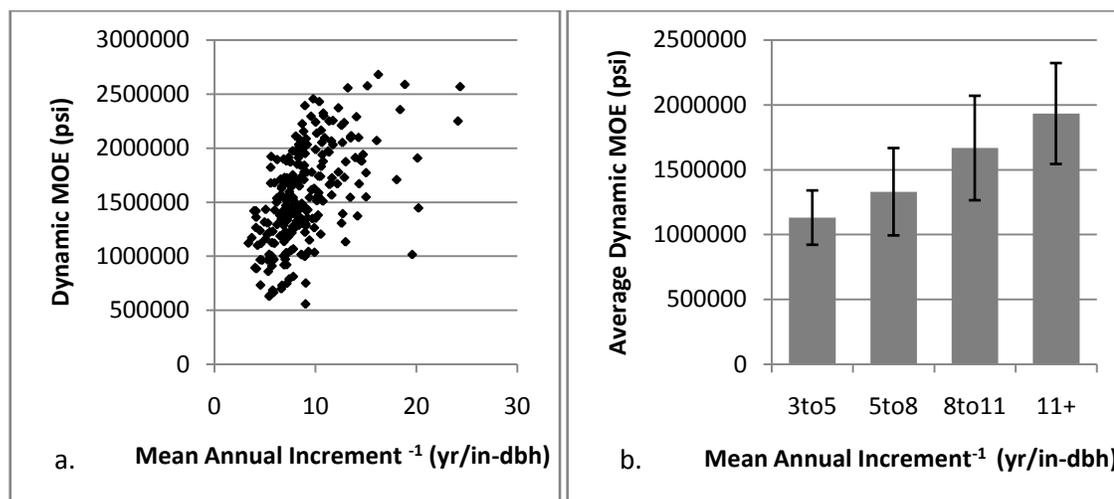


Figure 2. Mean Annual Increment⁻¹ and Dynamic MOE (a) Average Dynamic MOE Mean Annual Increment⁻¹ Class (error bars represent one standard deviation) (b)

MAI^{-1} seemed to be positively correlated with the dynamic MOE value measured for the trees. As can be seen in Figure 2(a), there is an increasing trend in dynamic MOE with increasing MAI^{-1} but little difference in dynamic MOE in trees with a MAI^{-1} values greater than 11 yr/in-dbh. Dunnett C comparison of means for the categories shown in Figure 2(b) showed that the four MAI^{-1} classes had significantly different average dynamic MOE with $P < 0.05$ for all comparisons.

Tree Height was chosen as significant predictor of dynamic MOE in these stands. Tree age would seem a more likely variable to be chosen in the model building process, but as seen in Table 7 below, tree height is virtually uncorrelated with MAI ($r=0.083$) with a moderate correlation to Dynamic MOE ($r=0.398$) while tree age was highly correlated

with MAI ($r=0.7$). From a statistical perspective, tree height's independence from MAI made it a more useful predictor than tree age and may act as a surrogate for tree age.

Table 7. Pearson Correlations for selected tree variables

	% Coverage	BAF on Plot	Age at BH	Tot Ht	MAI ⁻¹	DMOE
% Coverage	1.000					
BAF on Plot	0.615	1.000				
Age at BH	0.145	0.149	1.000			
Tot Ht	0.186	0.083	0.559	1.000		
MAI ⁻¹	0.200	0.196	0.751	0.057	1.000	
DMOE	0.261	0.292	0.579	0.398	0.550	1.000

Figure 3 illustrates the poor correlation between Total Height and MAI⁻¹ (a) and positive correlation between Total Height and Dynamic MOE (b).

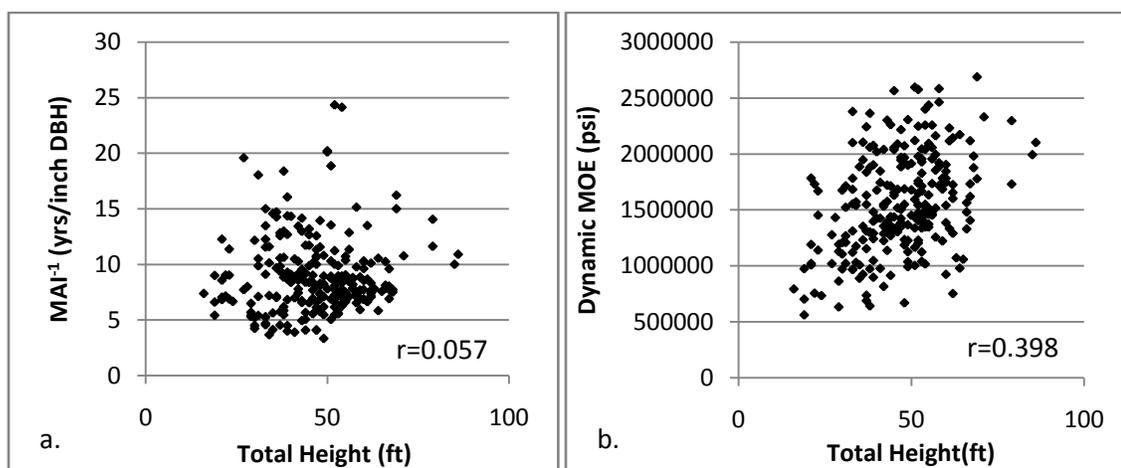


Figure 3. Graph depicting lack of correlation between Total Height and MAI⁻¹ (a) Correlation between Total Height and Dynamic MOE (b)

Statistical analysis performed to develop a theoretical model indicated that one of the most valuable variables captured during this research was the BD index. The analysis suggests that soil bulk density was negatively correlated with the average dynamic MOE for the trees sampled. Figure 4 shows the clustering of average dynamic MOE measured

in the trees from each soil type(a) and the average dynamic MOE from each soil type plotted against that soil's BD Index(b):

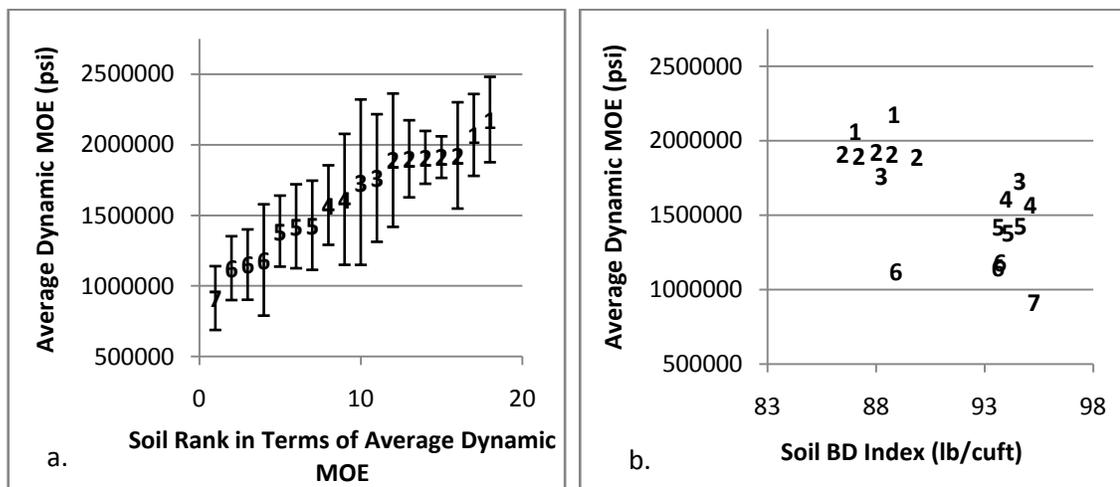


Figure 4. Results of clustering for average DMOE for the soils (error bars represent 1 standard deviation) (a) Comparison of average DMOE and BD Index for each soil (b)

In Figure 4b, trees on soils with lower BD Index had higher average dynamic MOE values with the exception of one soil in group 6. These aggregations led to the development of a categorical BD Index variable used in the analytical model in which $BD\ Index < 91\ lb/cuft$ were assigned the value 1 and the $BD\ Index > 91\ lb/cuft$ were assigned the value 0. Although not shown here, models using BD Index as a continuous variable performed identically to those using BD as a categorical variable.

Analytical models were also built to predict memberships in dynamic E categories. Again, the models were built with the smaller calibration sample set and then tested with the larger test subset. The results from the test subset are reported here. The following methods were developed to identify trees with dynamic MOE: above 1.5×10^6 psi, above

1.8 X10⁶ psi, and below 1.1 X10⁶ psi. In all three analytical models, the bulk density of the soil was the most important factor for selection.

The three columns on the right side of Table 8 are measures of success for a given model. For example: Rule 1 of the model to predict trees with dynamic MOEs above 1.5 X10⁶ psi selects all trees on soils with BD Index below 91 lb/cuft. For those tree selected: 82% actually had dynamic MOEs greater than 1.5 X10⁶ psi, 39% of all trees with dynamic MOEs greater than 1.5 X10⁶ psi were selected, and trees with dynamic MOEs greater than 1.5 X10⁶ psi represent 51% of the total sample.

Table 8. Rules for selection of trees meeting given criteria

Model Criteria	Rule #	Rule	Percentage of selected trees meeting criteria (%)	Percentage of trees meeting criteria selected (%)	Percentage of trees overall meeting criteria (%)
Trees with MOE > 1.5X10 ⁶ psi	1	BD Index < 91 lb/cuft	82	39	51
	2	add soils BD Index > 91 lb/cuft and elevation > 5900ft	72	73	51
Trees with MOE > 1.8X10 ⁶ psi	1	BD Index < 91 lb/cuft and remotely measured crown closure % = High	72	60	29
Trees with MOE < 1.1X10 ⁶ psi	1	BD Index > 91 lb/cuft add sites with pH < 5 and add sites with pH> 6 and trees with % coverage < 30%	71	34	18

Discussion

The measurement of dynamic MOE used in this study was driven by two factors: measured stress wave speed and specific gravity (Eqn. 1). Changes in stress wave speed were able to account for substantially more variance in dynamic MOE than specific gravity, therefore it is not surprising that the variables selected to predict dynamic MOE were more closely correlated with stress wave speed than specific gravity. Table 9 shows

Pearson correlations for the main variables present in the final model as well as stress wave speed and specific gravity.

Table 9. Correlation between selected model variables and elements of dynamic MOE

	Dynamic MOE	Stress Wave Speed	Specific Gravity	MAI ⁻¹	Total Height	BD Index
Dynamic MOE	1.000					
Stress Wave Speed	0.962	1.000				
Specific Gravity	0.542	0.321	1.000			
MAI ⁻¹	0.550	0.492	0.370	1.000		
Total Height	0.398	0.375	0.296	0.057	1.000	
BD Index	-0.445	-0.391	-0.313	-0.222	-0.205	1.000

MAI⁻¹ had the highest correlation with Dynamic MOE, stress wave speed, and specific gravity. Slow growth has been shown to be associated with higher wood density (Johnson et al. 2005), especially when coupled with elevated latewood percentages in the annual rings. Slow growth combined with increasing latewood proportions could likewise be associated with higher stress wave speed because of the increased proportion of high stiffness latewood. DBH was negatively correlated with stiffness in even aged black spruce stands (Lei et al. 2005, Liu et al. 2007) indicating that slow growth was associated with higher stiffness in that study as well. Slow growth associated with high levels of competition for light between trees may also be correlated to fewer and smaller diameter branches, which result in higher stress wave speed.

The use of tree height was another logical choice for the theoretical models of dynamic MOE because it may have acted as a surrogate for tree age. Tree height was moderately well correlated with tree age up to approximately 130 years. Trees older than 130 years were essentially the same height as 130 year old trees i.e. in these suppressed stands, the

trees grew very slowly after reaching 130 years. The average age of trees sampled during this research was 75 years, but there were 20 trees less than 30 years old. We would expect the influence of juvenile wood and high microfibril angle to be greatest in those younger trees and expect decreasing influence in older trees, but not linearly into perpetuity. Trees sampled showed a trend of increasing dynamic MOE with tree age, up to approximately 130 years at which point there was no further increase in dynamic MOE. Tree height may function as a substitute for a capped age variable for these suppressed trees.

The selection of soil bulk density as an important variable presented a more complicated interpretation of the data. While soil bulk density may be influential in many tree-soil interactions, its role in plant available moisture seemed to be the most likely avenue of influence. The concept of Least Limiting Water Range (LLWR) (da Silva et al. 1994, Schoenholtz et al. 2000) states that for a given soil bulk density there exists a range soil moisture contents between which a plant can extract water from the soil. The upper limit of the range is either the moisture content at which roots are deprived of oxygen or the field capacity in a saturated soil and the lower limit of the range is the moisture content at which the soil is too hard for roots to penetrate or the wilting point. Increasing soil bulk density is associated with a narrowing of the limits. Da Silva gives examples of sandy loam soils that exhibit drastic reductions in the amount of available water with a 20% increase in bulk density. Figure 5 portrays a slightly exaggerated example of the LLWR concept. In very low bulk density soils, field saturation point and wilting point are limiting. As bulk density increases, lack of oxygen due to filled pore space (upper limit) and the moisture content at which root penetration is limited (lower limit) are limiting.

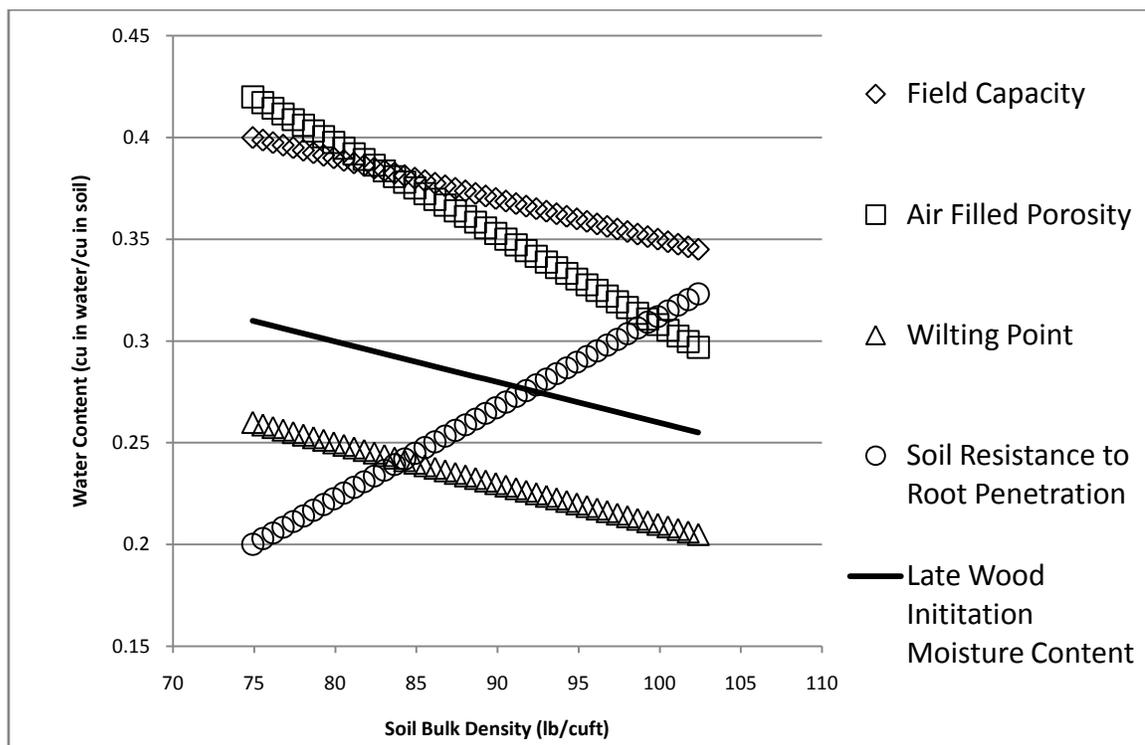


Figure 5. Illustration of LLWR concept

Within the framework of LLWR, bulk density could influence specific gravity of a given tree both directly within the tree, and indirectly through inter-tree competition. Irrigation and drought have been shown to influence the date of initiation and duration of the latewood production period (Zahner et al. 1964, Brix 1972, Josza and Brix 1989). A tree in lower bulk density soil may have an extended window of available water after the onset of latewood production, leading to higher latewood proportions in the annual rings and higher specific gravity. From a stand level perspective, if low bulk density sites have more water available, they might be able to support higher stocking levels with prolonged stem exclusion phases. The increased competition for sunlight could lead to shorter crowns with limited needle retention. Johnson found increasing latewood percentages and

density with decreasing needle retention in Douglas-fir afflicted with the defoliating disease Swiss needle cast.

Within the framework of LLWR, bulk density could influence stress wave speed. Within individual trees, higher proportions of high stiffness latewood produced on low bulk density sites could lead to elevated stress wave speeds. As with specific gravity, if lower bulk density sites permitted higher stocking, fewer and smaller knots would be produced in the lower bole of the tree. We would expect trees with fewer knots to register higher stress wave speeds.

Using BD Index as a variable likely has limitations in its utility to model dynamic MOE. BD Index was derived from a weighted average of soil data from a NRCS soil map. Within each mapping unit of the soil map, there were often several soil series listed with differing soil profiles and distributions within the soil mapping unit. BD Index was weighted to reflect the density, the depth, and the distribution of different soil series within one mapping unit. BD Index represented a very coarse estimate of average bulk densities found at a given location, and was not spot checked in the field for this research. As seen in Figure 4b, trees on two relatively narrow ranges of BD Index were sampled: the low BD Index group ranges from 86–90 lb/cuft while the high BD Index group ranges from 93-95 lb/cuft. The bulk density values are clustered such that there was little difference in regressions using the categorical or continuous values for BD Index. The bimodal distribution of bulk densities forces the assumption of the linear influence of BD Index for the range of 86 to 95 lb/cuft. In addition to the limited range of values sampled, the trees on the low BD Index sites were on average: older, taller, and more slowly

grown. Graphical analysis of trees on high and low bulk density sites showed that the trend between total height, MAI^{-1} , and Dynamic MOE remained fairly consistent between the two bulk density groups but again showed that trees on low bulk density sites had consistently higher Dynamic MOE values for a given height/ MAI^{-1} combination.

The findings of this study are likely restricted to the region in which the data was collected and the range of stand and soil conditions collected therein. Although relationships between soil moisture and stress wave speed were not found in the course of this research, specific gravity has been shown to vary with drought severity at the margins of a species' range (Adams and Kold, 2004). Variables such as MAI^{-1} and total height may prove to be transferable, but soil bulk density may not be an important variable in areas where soil moisture is more or less limiting. Site history was not incorporated into the sampling procedure except to avoid stands that were clearly planted or had received treatments that might bias measurements of stand density. Finally, there was no accounting for genetic differences within and between plots. The assumption made in this study was that the stands were naturally regenerated with local seed sources after the last harvest or disturbance, but no effort was made to quantify differences in populations.

The analytical and logical models presented in this paper could offer forest managers in the Bitterroot Valley additional information as to the quality of timber growing in their suppressed Douglas-fir stands. Managers could combine inventory data with soils maps to inform boundary and marketing decisions. Sale boundaries could be established that would capture sites with potential for high Dynamic MOE trees. The identification of

sites with potential for high Dynamic MOE trees could be targeted for more intensive measurements. Using the analytical model, they may be able to develop an estimate of the distribution of Dynamic MOE for a given sale in the same manner that volumes are calculated, reducing the uncertainty for parties interested in purchasing the sale. The research presented here suggests that a 95% confidence interval for a given prediction encompasses about $\pm 600,000$ psi using the analytical model. This interval seems high but with no quantitative alternative, it would still inform the buyer and seller's decisions. It may be more practical to use less strenuous confidence intervals and one-sided distributions of Dynamic MOE to determine cut-off values. In addition to the analytical model, the logical models suggest that relatively simple rules can result in selections of sites with >70% yield of 1.5×10^6 psi and 1.8×10^6 psi trees. Sites with potential for lower Dynamic MOE would still be of interest for pulp, fuel, and nonstructural applications such as post and pole manufacture.

An interesting development for future study was the utility of using only remotely sensed variables. In Table 4 the best fit models using only remotely sensed variables were able to account for nearly half of the variance in the Test data subset. The logical models to select trees with Dynamic MOEs greater than 1.5×10^6 psi and 1.8×10^6 psi used only remotely sensed variables and were able to identify stands in which >70% of the small diameter trees in those stands met the selection criteria. These findings indicate that considerable information about the Dynamic MOE of suppressed Douglas-fir may be available using combinations of existing vegetation, soil, and topographical GIS information.

Future testing involving destructive sampling is needed to verify the models developed in this study. The measurements on which this study is based were nondestructive Time of Flight measurements taken through the lower bole of the trees. Experience has shown that TOF measurements are not perfect, but short of destructive testing, they are a reasonable starting point for model building of this type. Expanding the scope of the testing to southern and western aspects as well as other suppressed Douglas-fir stands in the inland Northwest would help improve the models presented here.

Conclusions

In this study, several analytical and logical models were developed to predict the Dynamic MOEs of small diameter suppressed Douglas-fir in the wildland-urban interface west of Darby, Montana. The models were built using fairly standard inventory data and existing GIS data layers. The final analytical model proposed incorporated the inverse of Mean Annual Increment (MAI^{-1}), total tree height, and a remotely collected soil bulk density measurement and resulted in an adjusted $R^2 = 0.509$. MAI^{-1} and total tree height were positively correlated to Dynamic MOE. Bulk density of the soils was inversely related to the Dynamic MOEs of the trees found on them and proved to be an important variable for the prediction of Dynamic MOE in both the analytical and logical models. The logical models for locating trees with Dynamic MOEs greater than 1.5×10^6 psi and 1.8×10^6 psi were able to identify stands in which more than 70% of the sampled trees met their respective criteria using existing GIS data layers. The soil-water-root interaction defined by the Least Limiting Water Range concept may provide an explanation for the importance of soil bulk density in this study.

Process based productivity models exist that incorporate fundamental tree physiology to predict productivity over wide geographical regions. The importance of soil bulk density and remotely sensed data in the empirical models built in this study suggest that process based approaches to modeling wood quality may be possible. These models presented in this paper were based upon a nondestructive Time of Flight measurement through the lower bole of the trees. Future research including destructive testing and expanded sampling regions is needed to verify and improve the models. Soil bulk density may not be a “one size-fits-all soil property rating” but future research should consider tree-soil interactions for broad-scale wood quality models.

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Appendix A

Initial Variable	Description	Variable Classification
BAS_TCC041	Satellite measure of crown closure from PVT - 3 classes	Remote
BAS_TC072	Satellite measure of crown closure from PVT - 4 classes	Remote
BAS_DBH041	Satellite measure of tree DBH from PVT - 3 classes	Remote
BAS_DBH042	Satellite measure of tree DBH from PVT - 4 classes	Remote
OM_Index	Organic matter by % wt from NRCS soil map-continuous	Remote
pH_Index	Soil pH from NRCS soil map - continuous	Remote
Sand_Index	Sand % by weight from NRCS soil map - continuous	Remote
Silt_Index	Silt % by weight from NRCS soil map - continuous	Remote
Clay_Index	Clay % by weight from NRCS soil map - continuous	Remote
CEC_Index	Cation Exchange Capacity (milleq per 100g) from NRCS soil map - continuous	Remote
BD_Index	Soil bulk density (lbs dry weight per cm ³ at .33 bar moisture) from NRCS soil map - continuous	Remote
AWC	Available Water Capacity- continuous	Remote
Wetness Index	Remote spectroscopic measure of relative wetness from USFS. The index compared change in soil wetness from spring to summer - continuous	Drive-by
Geology	Major Geologic formations from Montana Bureau of Mines and Geology - 2 classes	Drive-by
Slope %	Slope measurement at plot center (%) - continuous	Drive-by
Elevation	Elevation derived from GPS unit (ft) - continuous	Drive-by
Dbh	Diameter at Breast Height (in) - diameter to nearest 0.1" taken 4.5' above ground on uphill side - continuous	Drive-by
Tot ht	Total height of tree measured with clinometer to nearest 1.0'. Broken tops estimated - continuous	Drive-by
Foliage length	Length of stem containing branches with live needles (ft) - continuous	Drive-by
% Green Length	Percent of stem with branches with live needles (%) - continuous	Drive-by
Clear Height	Stem distance from the ground to the 1st branch (ft) - continuous	Drive-by
% Coverage	Percent of crown closure measured at plot center with a concave densiometer (%) - continuous	Inventory
BAF Plot	Basal area using point sampling at plot center (ft ² per acre) - continuous	Inventory
Avg SSW	Stress wave speed measurement in standing tree using ST300 (feet per second)- continuous	Inventory
Sp grv	Specific gravity of increment cores on oven dry basis-continuous	Inventory
Age at BH	Tree ring count from pith to bark from increment cores	Inventory

	(years) - continuous	
Essw	Dynamic MOE calculated from stress wave speed measurement and specific gravity standardized to constant moisture content (psi) - continuous	Inventory
Mean Annual Increment ¹	Tree age determined by increment core divided by DBH (rings per inch diameter) - continuous	Inventory
SDI-1	Stand Density Index calculated using Reinke's method (average tree method for even aged stands) - continuous	Inventory
SDI-2	Stand Density iIndex calculated using Long and Daniel's method (additive method for uneven aged stands) - continuous	Inventory

Appendix B

NRCS Soil Designation	# Trees	Avg DMOE	SD DMOE	Family description	OM Index	pH Index	Sand Index	Silt Index	Clay Index	CEC Index	BD Index	Max Root Depth	average AWC
31K56	9	815961	201541	Holter-Whitlash	1.21	4.71	59.29	18.72	22.00	16.43	1.53	126.10	0.080
36D43	3	1004935	222091	Mohaggin-Leighcan-Hun	2.97	5.47	62.34	26.49	7.87	4.79	1.42	140.41	0.070
33B30	21	1052770	341618	Haugan-Kadygulch-Sharrott	1.84	6.25	63.98	20.16	13.68	11.44	1.50	112.75	0.086
61D15	12	1056788	195920	Leighcan-Tolby_Craw fish, complex, breaklands	2.60	5.34	70.12	20.69	6.22	1.36	1.50	87.21	0.047
31B70	54	1212001	257422	Macmeal-Kadygulch_Tolman, complex, dissected mountain slopes	1.88	6.21	59.26	19.08	19.17	15.65	1.51	95.96	0.074
31D15	9	1269304	265113	Tolby-Agneston_C rawfish, complex, dissected mountain slopes, moist	1.90	5.45	73.12	17.85	6.78	4.34	1.50	62.03	0.046
31B15	18	1469188	508182	Totelake-Macmeal-Sharrott families, complex, dissected mountain slopes	2.12	6.14	69.23	18.08	10.54	8.78	1.52	106.95	0.054
32D43	6	1574048	402874	Mohaggin-Tolby families, complex, moderately steep mountain slopes	2.55	5.53	65.11	25.54	6.42	5.18	1.41	131.23	0.064
49D41	9	1686512	421029	Jeru family-Rubble land-Rock outcrop association, trough walls	1.58	5.77	71.13	19.63	5.94	5.35	1.44	157.48	0.062

NRCS Soil Designation	# Trees	Avg DMOE	SD DMOE	Family description	OM Index	pH Index	Sand Index	Silt Index	Clay Index	CEC Index	BD Index	Max Root Depth	average AWC
32B30	12	1275859	281638	Macmeal-Totelake-Sharrott, complex, moderately steep mountain slopes	1.52	6.1	66.6	17.9	13.3	10.6	1.52	99.66	0.060
30B18	45	1356873	318089	Kadygulch-Totelake, complex, steep mountain slopes	1.44	6.0	70.5	20.5	6.92	5.78	1.52	152.40	0.041
30T13	5	1379679	319596	Kloutch family-Rubble land-Rock outcrop complex, steep mountain slopes	1.15	5.4	62.4	26.7	8.81	7.65	1.40	68.58	0.041
30D18	24	1439320	413381	Leighcan family, Steep mountain slopes, moist	2.11	5.3	65.9	22.7	8.03	8.71	1.51	116.84	0.054
31B15	18	1469188	508182	Totelake-Macmeal-Sharrott families, complex, dissected mountain slopes	2.12	6.14	69.23	18.08	10.54	8.78	1.52	106.95	0.054
32D43	6	1574048	402874	Mohaggin-Tolby families, complex, moderately steep mountain slopes	2.55	5.53	65.11	25.54	6.42	5.18	1.41	131.23	0.064
49D41	9	1686512	421029	Jeru family-Rubble land-Rock outcrop association, trough walls	1.58	5.77	71.13	19.63	5.94	5.35	1.44	157.48	0.062

NRCS Soil Designation	# Trees	Avg DMOE	SD DMOE	Family description	OM Index	pH Index	Sand Index	Silt Index	Clay Index	CEC Index	BD Index	Max Root Depth	average AWC
32G43	7	1704478	166847	Leighcan-Mohaggin families, complex, moderately steep mountail slopes	3.38	5.35	63.23	24.66	8.26	1.94	1.42	127.30	0.063
30G43	6	1706067	131224	Mohaggin-Tolby families, complex, steep mountain slopes	3.56	5.60	60.95	27.30	7.56	6.69	1.39	121.02	0.072
30D30	9	1716790	335668	Tolby-Agneston families, complex, steep mountain slopes	1.60	5.17	66.66	16.65	8.45	5.94	1.41	65.74	0.048
44D41	12	1846029	258479	Roman-Priestlake-Lilylake families, complex, moraines	2.15	5.24	70.58	21.17	3.90	2.07	1.39	132.08	0.051
47D13	6	1943267	269770	Roman-priestlake-Jurvannah families, complex, trough bottoms, extremely bouldery	1.47	5.26	73.75	20.15	3.87	2.01	1.42	131.23	0.048