AN ABSTRACT OF THE THESIS OF

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Title: Evaluation of a Prototype NIR System for Douglas-fir Wood Density Estimation.

Abstract approved:

Glen E. Murphy

Forest products companies in the U.S. face vigorous competition from other wood producers around the world and other industries (steel, aluminum, plastics, composites). To be competitive, forest companies need to control costs, sort and allocate logs to the most appropriate markets, and recover more value at time of harvest. Interest in log sorting based on internal wood properties is increasing.

Wood properties, such as stiffness and density, are now being considered by log buyers. Assessing these properties in-forest and in real-time will be a challenge for log supply managers. The utility of near infrared (NIR) technology for measuring wood density is showing promise in laboratory conditions. The rationale behind this study was to evaluate NIR under conditions that are similar to

field harvesting operations to estimate log density. Douglas-fir wood samples (110 disks) were collected from the McDonald-Dunn forest and processed in the OSU Oak Creek laboratories. Processing conditions were organized to simulate a harvester processor environment by using a chainsaw, and then channeling the chips with a chute to concentrate chips to move past an NIR sensor. This apparatus was intended to mimic a sensor system fitted to a harvester head.. A rugged Prospectra D^2 NIR sensor was used to collect spectral data.

The generated spectra were analyzed in two forms, as raw data (without any transformations) and a transformed data (2^{nd} derivative). Then, four types of calibration models were applied to predict log density: (1) models that used tree parameters only as a predictor (the simple model), (2) models that used NIR absorbance data and Partial Least Squares (PLS) analysis procedures , (3) models that used NIR absorbance data and Multiple Linear Regression (MLR) analysis procedures, and (4) models that used a mix of NIR absorbance data and tree parameter data and MLR analysis procedures. The goal of the models was to use the NIR data to predict the density of the log that has been cut.

Model results were also obtained for validation (full cross validation) and calibration sets. Data analysis suggests that correlations for calibration sets (R) were high, but when validation was applied there were large drops in R values. The best fit model was the simple model, the model that did not include NIR data as predictors.

Our interpretation of why the simple model was the best fit is that there is great variability of wood characteristics across the stem section, that there was morphological problems associated with how we presented the samples, and that we used a narrower spectral range of NIR compared to the range used in earlier studies.

Evaluation of a Prototype NIR System for Douglas-fir Wood Density Estimation

by
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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.

Maria Francisca Belart Lengerich, Author

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Dedicated to my brother, Genaro Andres

EVALUATION OF A PROTOTYPE NIR SYSTEM FOR DOUGLAS-FIR WOOD DENSITY ESTIMATION

CHAPTER 1

INTRODUCTION

Douglas-fir is an important commercial timber species in many parts of the world. In the United States 7.3 percent (~ 14.3 million ha) of the country's 196 million ha of non-reserved timberland is presently occupied by Douglas-fir. In Canada the area stocked with Douglas-fir is slightly less than one-third (~ 4.5 million ha) of that in the United States. In Europe this species is highly significant in plantation forests, especially in France and Germany (330,000 and 134,000 ha, respectively). In the southern hemisphere it is also well represented, with New Zealand, Chile and Australia being the countries with the greatest presence of the species (Hermann and Lavender, 1999).

Timber resources in the Pacific Northwest have gradually shifted from unmanaged old growth to intensively managed young growth. As younger stands are harvested, wood quality is negatively affected in comparison to old growth wood because of the presence of a higher proportion of juvenile wood, which in turn affects properties such as strength and dimensional stability (Gartner 2005).

Douglas-fir timber must compete against timber produced from other tree species and, in some markets, against substitute materials such as steel, aluminum, plastic and concrete. Competition is making the wood market more complex and demanding (Acuna and Murphy, 2006a). For Douglas-fir, significant quality attributes for wood products include density, microfibril angle, fiber length, lignin content, ring width, knot size and distribution, grain angle, and coarseness, color, etc. (Gartner 2005).

Wood density is one of the most important physical characteristics for wood products because it is an excellent predictor of strength, stiffness, hardness and pulp yield (Megraw 1986, Haartveit and Flæte, 2006). These wood properties have a high influence on the quality of the final product, for example trees with high density and low microfibril angle are desirable for providing stiff and strong structural lumber, while trees with high density and low lignin are required for high pulp yields (Jones, 2006).

Wood density is a widely variable characteristic; there is variation between trees within a stand and also within the same tree (Josza and Middleton, 1994). Density is lower in juvenile wood, near the pith and in early wood. In Douglas-fir wood density may also be affected by environmental conditions such as elevation. It has demonstrated to be a very plastic species (Cown and Parker, 1979). Silvicuture also has a strong effect on wood density. Heavily thinned stands respond with

greatly increased latewood density and this offsets the persistent low earlywood density because of the augmented radial growth (Harris 1985).

Optimally matching wood quality to markets can mean cutting logs for very specific end uses and classifying them into several categories or "sorts" to improve product uniformity, productivity and profitability along the seedling to customer supply chain. Log makers have to adhere to a set of rules referred to as log specifications. These specifications can significantly affect the values generated for both forest owners and log processing industries. They also ensure that the logs will fulfill mill requirements for a given product. In markets where there are many customers, there can be many log grades. As an example, a paper on New Zealand log markets reported thirty eight (38) log grades, twenty for domestic market and the rest for export markets (NZIF, 2005). As another example, in central Georgia some companies have up to fifteen different (15) log grades (Amanda Hamsley, University of Georgia, pers. communication).

Optimally matching wood to markets produces a big challenge for log distribution to processing centers. In some markets, the log mix is transported to the mill and once there, classified in the log yard. If logs do not meet specification they can be (1) reclassified and sent to another mill, adding transportation costs to the operation, (2) cut into other log products, producing efficiency problems, or (3) accepted and processed in the mill, leading to less than satisfactory mill outputs. Some wood markets are beginning to include internal wood properties in their log

specifications. New sensor systems are being developed to help classify logs based on these internal wood properties (Andrews 2002, Dickson et al. 2004, Young 2002).

Traditionally, wood quality is determined in laboratory conditions using destructive methods, which can be expensive and time consuming. However, there are some non-destructive methods, such as acoustics and Near Infrared spectroscopy (NIR), which can be both time and cost effective. Another advantage of these methods is that some instruments have already been developed for use in the forest or could be adapted for that purpose.

NIR has a number of advantages that make it an ideal tool for characterizing biomass. These include minimal sample preparation, rapid acquisition times, and non-contact, non-destructive spectral acquisition (Kelley *et al*. 2004a). Some commercial spectrometers are also lightweight, easy to operate and economic.

Several authors have investigated the use of NIR to predict wood properties. In 2002, Schimleck *et al.* used NIR to estimate wood stiffness in laboratory conditions. Correlations between laboratory determination of modulus of elasticity and predicted by NIR were higher than 0.9 for the species tested. Kelley *et al.* (2004a) combined NIR with multivariate analytic statistical techniques to predict mechanical and chemical properties of solid wood, based on a “full” spectral range (500 nm – 2400 nm) and a reduced spectral range (650 nm – 1150 nm). Their

results indicated that correlation coefficients remained high even though the spectral range was reduced. This analysis indicated that lightweight and economical equipment for NIR measurements could be used.

Later, Acuna and Murphy (2006b) confirmed that oven dry wood density can be predicted from measurements of green and dry wood chips using Near Infrared (NIR) technology and these measurements possibly could be used as the basis for sorting logs into several density categories. They noted, however, that further research was required before NIR technology could be cost effectively applied in "real-time" forest harvesting operations. A limitation of their study was that measurements were made under laboratory conditions using chips rotating on a turntable under NIR light with wavelengths ranging from 500 to 2500 nm.

Further research was required to determine whether small, faster, lighter and less expensive industrial-grade spectrophotometers (with a reduced spectral range) could be used to measure density from green chain saw chips ejected as each stem is cut into logs by mechanized harvesting equipment. If so, then spectra and density predictions could be gathered across the log diameter - from bark to pith to bark.

Other raw material producers have begun to use NIR sensors for product segregation and crop management. Some recent applications of NIR on harvesters have been undertaken in agriculture in Europe (Dardenne and Femenias 1999),

USA (Von Rosenberg *et al*. 2000) and Australia (Taylor *et al.* 2005). For example, Taylor *et al.* (2005) have reported the use of NIR as a protein sensor on grain harvesters. GIS have been attached to the NIR sensor in order to map crop nutrient deficiencies. The output from the NIR protein sensor showed strong spatial patterns that were consistent with observed yield variations and what growers expects and have lead to improved crop management decisions.

The main goal of this project was to use NIR absorbance values obtained from various known heights in logs as an index of wood density at those locations. The models employed several varied factors: the number of peaks from the spectral data that were included, and breast height diameter (DBH) and the tree diameter and height within the tree at which the material was sampled. Several different models were used, with the overall question of whether there is a basic model to estimate wood density in real time from a minimum amount of information.

The specific objectives of this study were to develop wood density models from a single stand which indicated whether:

- it was possible to make strong prediction models of a sample's specific gravity from external characteristics alone (such as DBH, and/or diameter and height of sampling point).
- correlations could be improved by including data from NIR absorbance spectra collected from green chainsaw chips.

- whether the presence of bark in the saw chips adversely affected prediction power of the models.

CHAPTER 2

LITERATURE REVIEW

In the following section, some background information is provided on wood density, near infrared principles, and the use of technology for harvesting operations. The first section is a brief review of the wood density variation between and within the tree, and the factors that might cause this variation. The second section includes an explanation of how NIR works to characterize the sample and how we relate this information with a variable of interest, all with the aim of building a prediction model. The third section is a brief summary of previous work on technology that has been done by other researchers in order to optimize cost and/or productivity in harvesting operations.

2.1 WOOD DENSITY

Most mechanical and physical properties of wood are closely correlated to specific gravity and density. These terms have distinct definitions although they refer to the same characteristic (Bowyer et al, 2003). Wood density is a simple measure of the total amount of solid wood substance in a piece of wood (Jozsa et al., 1989).

Traditionally, density has been measured based on Archimedes' principle. The green volume (for basic density) is measured by water displacement. Then, mass

of the sample is measured at the appropriate moisture content and density is calculated (Sarampää, 2003).

The strength of wood as well as its stiffness increases with specific gravity. The yield of pulp-per-unit volume is directly related to specific gravity. The heat transmission of wood increases with specific gravity as well as the heat per unit volume produced in combustion. It is possible to learn more about the nature of a wood sample by determining its specific gravity than by any other single measurement. Perhaps it is for this reason that density was the first wood property to be scientifically investigated (Bowyer et al, 2003).

Wood density is a widely variable characteristic; there is variation between trees in a same stand and also within the same tree. Because of the tree growth pattern, we have more early wood and wider rings near the pith in the upper crown region (i.e. less dense wood in the upper section of the tree). If we look at the cross section of the stem, there is an important pith-to-bark gradient. This is a cause of the juvenile wood that occurs during the first 15 to 30 years of growth (Harris, 1985; Josza and Middleton, 1994; Lausberg et al., 1995). This wood is different because it grows under the influence of live branches. In general, this wood has lower density, shorter fibers, larger microfibril angle and lower cellulose content than mature wood (Josza and Middleton, 1994).

In addition, trees that grow faster will have a higher content of juvenile wood and consistently lower density. This is a big issue when pulp companies decide about their silvicultural treatments because they want fast growth but at the same time that means lower pulp yield per tree.

Density uniformity is also an important issue for some end uses such as veneer production. The greatest change in density is found between rings and between latewood and earlywood. In the special case of Douglas-fir, density is high in the darker area of the ring (latewood) and lower in the direction of the next ring (earlywood). Douglas-fir has a great intra-ring density variation (range between 0.25 to 0.85 (g/cm^3)) (Josza and Middleton, 1994). Harris (1969) also reported an extreme contrast between latewood and earlywood finding a maximum range 0.17 to 0.87 g/cm^3 in successive growth layers. On the other hand he also found that earlywood values are quite constant across the stem and average 0.2 g/cm^3.

When Jozsa and Middleton (1994) analyzed the relative density at breast height they found that Douglas-fir has a decrease in density from rings zero to ten (juvenile wood) and then starts increasing until the tree reaches thirty years, then keeps increasing each year but at a slower rate.

When we talk about wood density, we also have to refer to the chemical properties of its components. In general, conifer cell walls have three principal components:

cellulose between 40 and 50%, hemicellulose between 20 and 35% and lignin between 15 and 35%. All these determine the density of the cell wall and tissue characteristics. There is evidence that cell wall tissue density is quite constant within the tree and is not affected by growth rate. However, the amount of cell wall that is contained in a specific volume is determined by the wall thickness and the cell lumen size (Sarampää, 2003; Harris, 1969).

Another important factor to consider is the site effect on wood density. In 1979 Cown and Parker made a densitometric analysis of wood from five Douglas-fir provenances growing in Corvallis, Oregon. They found that provenances do not affect growth rates and mean wood density, but site has a major influence on both characteristics. The greater effect was in the inner rings of the tree and indicated that this species has a great adaptability to the environment through natural selection. Later, Lausberg and others (1995) studied the effect of provenance on wood properties in Douglas-fir plantations located in New Zealand. They studied twelve provenances of managed forests and found that there is a general trend over all sites and provenances for breast-height density to increase from pith to bark. There was a strong site effect on properties measured (95% confidence), but the differences within sites was not very high having a maximum of 0.15 g/cm^3 which seems to be less than the effect that has been reported for *Pinus radiata* for the same zones (0.35 g/cm^3 difference). There was also strong evidence that site has an effect on the heartwood proportion (95% confidence). With respect to altitude,

Harris (1985) mentioned that in New Zealand, high elevations would result in lower Douglas-fir wood density.

Silvicuture has also a strong effect on wood density. Heavily thinned stands respond with greatly increased latewood density and this offsets the persistent low earlywood density because of the augmented radial growth (Harris 1985).

> "Growth rates are lower on phosphate-deficient soils and wood density can be as much as 0.06 g/cm^3 higher that in trees growing on normal (non-deficient) sites in the same area" (Harris, 1965) cited by Harris (1969).

The reason is that in some sites, fertilization can be detrimental for wood density because trees tend to grow faster.

Wood density is a highly heritable characteristic in a number of species (King, 1986 cited by Loo-Dinkins and Gonzalez, 1991). However, there is some discussion generated about the correct age when density should be evaluated for breeding selection. Vargas-Hernandez and Adams (1991) investigated this particular issue in coastal Douglas-fir. They determined that earlywood and latewood, by themselves do not have higher heritability than the overall density, but they are highly correlated with overall density ($r \geq 0.74$). Overall density was positively correlated with intraring density variation ($r = 0.72$) and negatively correlated with stem volume ($r = -0.52$). Another case study, performed with

Scots pine (*Pinus sylvestris* L.), indicated that correlation between wood densities in the transition zone between juvenile to mature wood was high implying that even young trees can be assessed and compared for future wood density breeding programs (Fries and Ericsson, 2006).

2.2 NEAR INFRARED SPECTROSCOPY

NIR spectra were discovered in the early 1800's. Around 1900, W.W. Coblentz used a salt prism to build a primitive infrared spectrometer, but it wasn't until the 1950's that modern NIR instruments were developed. These were first used for food application experiments (Ciurczak and Burns, 2001).

The acceptance of NIR as an analytical technique began with the work of Karl Norris of the US Department of Agriculture in the early 1960's. Later, NIR spectroscopy flourished and expanded well into pharmaceutical, industrial, process control, food processing, remote imaging spectroscopy and other diverse applications (Barton, 2002).

The NIR region is between 850 nm and 2.5 microns on the electromagnetic spectrum, and it contains numerous overlapping absorption bands arising from overtones and combinations of X-H stretching vibrational modes (Meglen and Hames, 1999). In order to understand how it works we need to understand the

Franck-Condon principle (Barton, 2002). The Franck-Condon principle explains the intensity of vibronic transitions. Vibronic transitions are the simultaneous changes in electronic and vibrational energy levels of a molecule due to the absorption or emission of a photon of the appropriate energy (Figure 1). The principle states that during an electronic transition between molecular quantum states, a change from one vibrational energy level to another will be more likely to happen if the two vibrational wave functions overlap more significantly (Somoza, 2006).

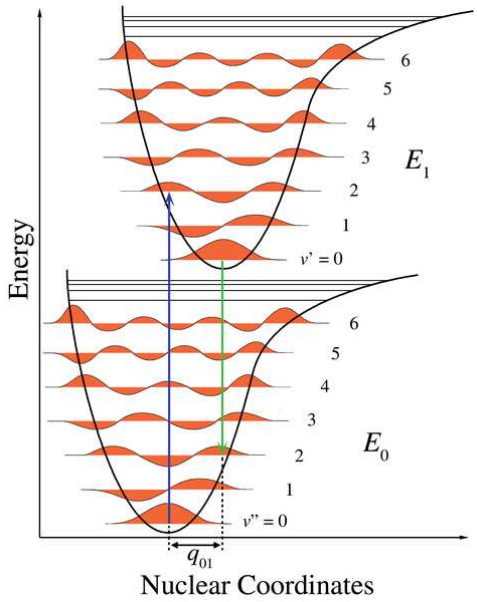

Figure 1. Franck-Condon principle energy diagram. Since electronic transitions are very fast compared with nuclear motions, vibrational levels are favored when they correspond to a minimal change in the nuclear coordinates.

When a sample is exposed to NIR energy, molecules vibrate. Then, when the NIR energy matches the natural vibration of a molecular bond within a molecule it

absorbs that energy. Each different molecule structure interacts with different wavelengths, hence samples having different chemical and physical properties will result in different NIR spectra (Jones, 2006). The data from a NIR spectrum may consist of thousand of variables measured from each sample. Each variable corresponds to the reflectance or transmittance measured from each wavelength (Haarveit and Flæte, 2006).

Various compounds in biological materials have overlapping peaks in the spectra, often making multivariate analysis compulsory (Haarveit and Flæte, 2006). This analysis, most often called Partial Least Squares (PLS), makes possible the transformation of the spectra into quantitative information. This method relates the systematic information from a matrix of X (in our study, absorption of wavelengths) to the information on a matrix of Y (in our study, wood density) with the purpose of predicting Y from X. The statistical technique simultaneously calculates multivariate projections of the predictor and independent variables so that the projection of the two data blocks are maximally correlated. In this way, a quantitative expression of the correlation between the two matrices is known (Meglen and Hames, 1999).

In order to apply PLS analysis, calibration and prediction sets of samples are needed. The calibration set is used to build the model and the prediction set to evaluate the model. Meglen and Hames (1999) performed a study were the

validation was made with a rigorous assessment criterion of full cross validation. This technique works by holding back one sample and predicting it from a model conducted from the remaining N-1 samples. Then, a different sample is held back and predicted with the remaining N-1 samples. This procedure is repeated until every sample is predicted from a model in which it was not a participant. Therefore, N models (N, being sample size) are developed. The validation plot that is generated shows prediction of the samples that were not participants in the model construction (Meglen and Hames, 1999).

NIR has been widely used to measure wood properties affecting a wide range of forest products. Many studies can be found in the literature on the prediction of physical (density, microfibril angle, tracheid length), mechanical (MOR, MOE), and chemical (glucose, lignin and extractives content) wood properties from NIR spectra for a range of softwood and hardwood species (Schimleck et al. 2002; Kelley et al. 2004b; Schimleck et al. 2004; Jones et al. 2005). Good correlations, R^2 values ranging from 0.79 to 0.96, have been reported. NIR measurements have been made on green and dry solid wood, green and dry auger shavings, and dry powdered wood. It has also been shown that mechanical properties could be predicted using a reduced spectral range (650 nm-1500 nm) with nearly as good predictive ability (Kelley et al. 2004b).

Meglen and Hames (1999) described a field test to demonstrate the ability to obtain spectra of sufficient quality to permit quantitative calibration from wood chips moving at high speeds (approximately 350 ft/min). The reason for this experiment was to demonstrate the practical use of on-line VIS-NIR spectroscopy. They made the test under environmental conditions found within a typical mill (dust, light and temperature conditions may be severe) in order to predict chemical properties of the pulp wood chips. The results indicated that visible light highly affects the measurements, which is the reason why they decided to make the predictions based on NIR spectra. They concluded that there was a high probability that fluctuations seen in the NIR predictions were due to the real fluctuations in the chemical compositions of wood.

Later, Acuna and Murphy (2006b) confirmed that oven dry wood density can be predicted from measurements of green and dry wood chainsaw chips using Near Infrared (NIR) technology. Their study was made under laboratory conditions using chips rotating on a turntable under NIR light with wavelengths ranging from 500 to 2500 nm. The results indicated that NIR measurements could be used as the basis for sorting logs into several density categories.

2.3 THE USE OF TECHNOLOGY IN HARVESTING OPERATIONS

Forest operations in many parts of the world are becoming more mechanized and automated. The main objectives of automation are to collect, transmit and report information, thereby diminishing the mental pressure of the operator, as well as to improve the working conditions and performance of the operator. Löfgren (2006) used a forest machine simulator in Sweden to evaluate the effect of automation on performance. Their main finding was that automation was a feasible way to both increase productivity and improve the working conditions of operators. In particular, they found that automation should be directed both at knuckle boom work and log processing.

There are several other examples of studies that have proven the operational uses of instruments in order to minimize costs or improve efficiency with the extraction operation.

One of the examples is the use of GPS (Global Positioning Systems) in various pieces of harvesting equipment. Cordero and others (2006) integrated a GPS and a computer in two harvesting machines. One was cut-to-length operation consisting of a harvester and forwarder and the other was full-tree operation, consisting of a feller-buncher and a grapple skidder. Data were collected at 10 seconds intervals where position, altitude, speed and time were recorded. Both systems were clear-

cutting 12-13 years old *Eucalyptus spp.* forests. As a result, they gathered lots of valuable information which could be used to monitor and improve the efficiency of these operations. They monitored machine productivity, total harvest volume (useful for comparisons with base inventory data), harvester paths (useful for checking soil compaction and damage to culverts and ditches), felling and processing strategies on steep slopes (which affects the efficiency of fuel consumption), wood piles locations (useful for allocating transportation), etc. All this information is highly valuable to make a more efficient, economic and reduced impact operation.

Kopka and Reinhardt (2006) noted, however, that the accuracy of GPS measurements mainly depends on such things as climate, slope angle, aspect and satellite navigation systems (Russian or American) They investigated the cause of impreciseness of two different navigation systems using a Timberjack 1470D harvester in a two hectare forest stand in Northern Germany. They measured and oriented skidding tracks using the different navigation systems and then the harvester was guided only by the tracking function of the GPS software onto the skidding tracks. Under optimal signal conditions accuracy better than 10% deviation could be obtained.

Another example, as reported earlier, is the application of NIR on agricultural grain harvesters. Taylor et al. (2005) used NIR as a protein sensor on grain

harvesters and reported positive results. GPS/GIS were attached to NIR sensor in order to map crop nutrient deficiencies. An accurate site-specific determination of protein content was provided, allowing the calculation of site-specific nutrient needs and spatial patterns in crop productivity.

CHAPTER 3

MATERIALS AND METHODS

3.1 SAMPLE ORIGIN

Samples were taken from a single stand within McDonald-Dunn Forest. This forest is Oregon State University's main research, teaching, and demonstration forest. The forest lies within a transition area between the Oregon Coast Range and the Willamette Valley (Fletcher et al., 2005). The specific location of the study site is 44° 42.55'N/ 123° 19.58'W and the elevation is 280 meters. The site has a 72 year old Douglas fir stand with an average DBH of 41.6 cm (range from 15.0 – 78.5 cm). The stand had received three commercial thinnings over its life.

The DBH of each tree was measured. Trees were then felled in the summer of 2007. The total number of trees felled for the trial was 40 and 110 wood disk samples were obtained from them. Samples were cut at different heights up the tree depending on the best tree bucking alternative. The first sample was taken at the base of the tree, the second at 18, 27 or 35 ft, and the third at 18, 27 or 35 ft depending on the second log length. Samples were not collected from all potential sampling points in the 40 trees. Sample height in the tree, stem diameter and an identification number were recorded and samples were marked with crayons.

3.2 SAMPLE PREPARATION

Samples collected in the field were bagged and placed in a cold room at the end of each day. When all sample collection was finished, samples were taken out of the cold room for processing.

Wood disks were split in half, if the bark was present. One half was debarked and the other left with bark. After that, each sample was placed in a holder (Figure 2) specially designed by Oregon Cutting Systems. This holder had adjustable pins to clamp samples of any shape and allowed the samples to be safely cut with a chainsaw through the sample cross section.

Figure 2. Wood sample holder, arrows indicate adjustable holding pins.

In order to make the chip sampling protocol similar to a processor “environment”, a 0.404 inch pitch chainsaw chain was used. This decision was based on a brief survey, which indicated that approximately 60% of processor brands use chainsaw chains of these specifications on butt saws and almost 100% on topping saws (Glen Murphy, Oregon State University, Pers. Communication, January 2006).

Chain pitch is the difference between the centers of any three consecutive rivets, divided by two; an example is shown in Figures 3a and 3b (Oregon Cutting Systems Group Blount Inc., 2004). In this study, the chain pitch was 0.404 inch.

Figure 3. a) Chain pitch, b) picture of 0.404’’ pitch chain (Source: Mechanical Timber Harvesting Handbook, Oregon Cutting Systems Group Blount Inc.)

Because the idea of this project is to obtain NIR spectra from the chips that are generated while we cut the sample, a chip collector was designed. This collector was located just below the place where chips are expelled from the chainsaw. The collector accumulates the chips and channels them. The NIR sensor was located below that accumulation point. Finally, chips were collected and placed in tagged bags. These bags were stored in a cold room for further measurements, if needed. The cutting procedure and collector are shown in Figure 4.

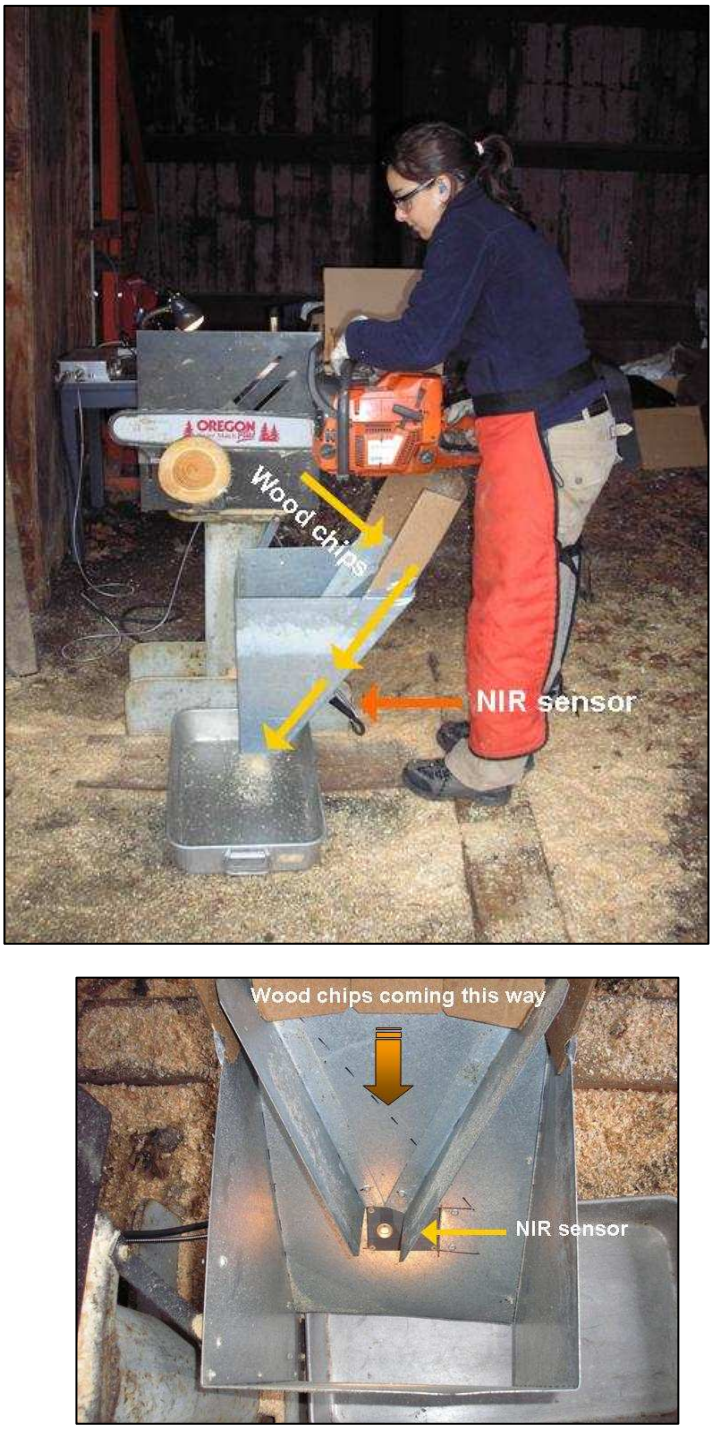

Figure 4. Top panel: wood chips path. Bottom panel: view of the collector from above.

3.3 NIR MEASUREMENTS

NIR measurements were synchronized with the cutting process. The instrument used was a ProSpectra^{TM} spectrometer by DSquared Development Inc. (LaGrande, Oregon). The spectrometer has a maximum range in wavelengths from 600 to 1100 nm. As noted above, Kelley *et al*. (2004b) found that reducing the spectral range from 500 to 2500 nm down to 650 to 1500 nm would not have a large effect on the NIR prediction power and would allow the use of more economical equipment. We confirmed this finding by re-analyzing data collected by Acuna and Murphy (2006b) (see later description of this analysis in Section 3.6). Using a narrower spectral range can save at least $30,000 on the equipment cost. This kind of equipment is being used on grain harvesters with an even narrower spectral range (e.g. 839 to 1045 in AccuHarvest equipment; http://www.zeltex.com/accuharvest.html, accessed 8 May 2008).

The ProSpectra was adapted by the DSquared Development Inc. to be connected to a laptop computer. Two software programs are used with this equipment; one for gathering and pre-processing data and one for analyzing spectral data.

DSquared2 software allows the gathering and displaying of data generated by the ProSpectra equipment. This software is very flexible; it has the capability of programming a method that better suits the data gathering procedure. In this case

we programmed a method that made the instrument scan the chips while the sample is cut through the entire cross section. There was a person in charge of the computer, this person had to enter the sample information (tree number, position, etc), determine when cutting of the sample is began, directed the scanning procedure to begin, stop the procedure when the cut was finished. It should be noted that the ProSpectra system has the flexibility of automatically starting and stopping measurements. However, this feature was not used since in preliminary trials it was found that a break in the stream of chainsaw chips sometimes stopped scanning prematurely.

Many scan measurements, relating to each wavelength, were gathered and averaged as the cut was made through the sample; the bigger the diameter, the more scans were obtained from the sample. The number of scans for each sample ranged from 10 to 860 and averaged 136.

3.4 WOOD DENSITY MEASUREMETS

In order to build the density estimation models, we needed the actual wood dry density of the samples. The method used to determine the dry density was the following: samples were oven dried until dry weight was stable (approx. 48 hr), then, sample volume was determined by the difference in weight between a bucket with water and the same bucket with the sample submerged, (Figure 5). Wood

density (kg/m^3) was then calculated as the ratio between dry wood weight and dry volume.

Figure 5. Dry density measurement using water displacement method.

3.5 DATA PRE-PROCESSING AND STATISTICAL ANALYSIS

Four types of models were developed for this study. All of them had the goal of predicting the wood density of the samples. The first, called the “Simple Model” was a linear regression model built to predict wood density without the use of NIR, instead, tree attributes such as DBH, sample height on the tree and sample diameter were used as predictors. The main purpose of these models was to have a

basic model to compare with the NIR performance as a predictor. The second model was developed using Multiple Linear Regression (MLR) to predict wood density of samples with the bark removed based on NIR wavelengths. The third model used Partial Least Squares (PLS) to predict wood density of samples with the bark removed based on NIR wavelengths. The fourth model used MLR to predict wood density of samples with the bark removed based on NIR wavelengths and sample height within the tree. Variants of the second and third models included the NIR measurements of samples with the bark left on.

Before building NIR models, data was preprocessed, and later analyzed, using Delight Beta software, developed by DSquared Development Inc. There were two preprocessing methods; the first was to leave the raw data as it was and the second was to take the second derivative of the absorbance values with respect to a 10 nm gap in wavelengths (10 point gap) and mean center it. The next pre-processing procedure was to trim both ends of the spectrum; this was done to eliminate noisy regions. Data was originally obtained along the 600 to 1200 nm range. The trimmed range was from 620 to 1080 nm.

The general modeling procedure was the following:

1) Construct the model based on tree attribute/NIR wavelengths to predict wood density. This means that, from within the total set of N samples with known wood

density (measured as indicated in Section 3.4), we use a sub-set of calibration samples to develop a mathematical model (Martens and Naes, 1984). Then, the coefficient of determination (R^2) and standard error of calibration (SEC) are generated and become available to evaluate the model performance. These are called the calibration models.

2) Validate the model using a validation set of samples to prove its performance. Two procedures were used for selecting samples for validation; a full cross-validation procedure (see 2.2) and split cross validation where the samples not used in the calibration set were used in the validation set. One-third of the samples were randomly selected from the total data set and used in the split cross validation procedure... Then, a new determination coefficient is generated; this one represents the correlation between the predicted density value of a sample (using the model) and the actual density of that same sample (measured). A standard error of prediction (SEP) can also be calculated. These are called the validation models.

3) Compare the calibration and validation R^2 coefficients within the several models built in order to decide whether one model performs better than the other. A calibration model can have a great R statistic when a high number of variables are used; this is due to overfitting (when a model has too many parameters and as a result a “perfect fit” false model is created). However, this can produce a poor performance once the model is validated (Acuna and Muphy, 2006b).

3.5.1 Simple model

Three “simple models” were built as a way to compare the prediction capability of the wood characteristic studied in this project with and without the use of NIR. The dependent variable was wood density. The independent variables were tree diameter at breast height, the height in the tree and the diameter of the stem where the sample was taken. The statistical procedure used was MLR using Microsoft Excel. The general equations for these three models were the following: a) density (kg/m^3) = a + b*DBH (cm), b) density (kg/m^3) = a + b*sample height (m), and c) density (kg/m^3) = a + b*sample diameter (cm), where a and b are regression coefficients.

The statistic used to measure the model performance was R^2 and standard error. For validation purposes, the data were split into two sets, one of 77 samples and the other of 33 samples. The decision about which “simple model” was going to be the final model left as a base of comparison with NIR models, was the one that had a higher R^2.

3.5.2 Multiple Linear Regression (MLR) based on NIR wavelengths

For both MLR and PLS analyses, calibration and validation models were developed.

Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. Every value of the independent variable *x* is associated with a value of the dependent variable *y*. In our study we will predict wood density (*y*) from the multiple spectrums that was obtained for each sample; those are going to be our multiple independent variables (x's). Because we have several (maybe even hundreds) of independent variables (wavelengths) that characterize each sample, we need to choose some of them to build the model. MLR allows choosing the number of independent variables we want to use in our model. So, if we want to use one (1), the software is going to search through all the wavelengths and is going to choose the one that gives the best model. If we want to use two, it is going to use the best two, and so on. In Figure 6 there is an example of the three (3) best wavelengths chosen by the Delight software to build the model.

In this study, models using from one to ten independent variables (wavelengths) were built. The general equation form for the models was the following: density (kg/m^3) = $a + b*w_1 + c*w_2 + d*w_3 + \ldots. y*w_i$ where w_i represents the "chosen" wavelength *i* for the model, and *a* to *y* represent the model coefficients.

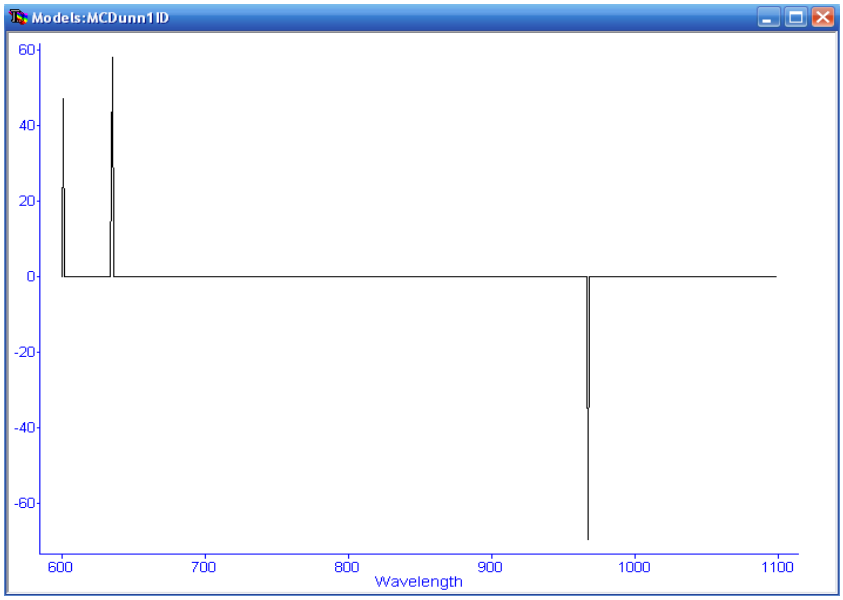

Figure 6. Example graph of wavelengths chosen to build an MLR model

Calibration and validation models were also tried for the following data sample types:

- Bark Off Samples:

    a. Prediction of Bark Off density with no validation, raw data.

    b. Prediction of Bark Off density with no validation, going from 5 to 10 variables. Second derivative transformed.

    c. Prediction of Bark Off density using full cross validation, going from 5 to 10 variables. Second derivative transformed.

- Bark On Samples:

    a. Prediction of Bark On density using full cross validation, going from 1 to 10 variables. Second derivative transformed.

    b. Prediction of Bark On density using Bark Off model going from 1 to 10 variables. Second derivative transformed.

The number of predictor variables used was related to trying to improve the model's R statistic and diminish the standard error.

3.5.3 Partial Least Squares (PLS) based on NIR wavelengths

PLS is a technique that generalizes and combines features from principal component analysis and MLR (Abdi, 2003). MLR finds a combination of the predictors that best fit the response, then principal component analysis finds combinations of the predictors with large variance, reducing correlations. The technique does not use response values. PLS finds combinations of the predictors that have a large covariance with the response values. PLS therefore combines information about the variances of both the predictors (wavelengths) and the responses (wood density), while also considering the correlations among them.

The NIR data were mean centered prior to carrying out the PLS analysis. Mean centering data is almost always applied when calculating any multivariate

calibration model. The process involves calculating the average spectrum of all the spectra on the data set and then subtracting the result from each spectrum. In addition, the mean value for the constituent (measured wood density) is calculated and subtracted from the constituent value of every sample. This process makes the differences between the samples substantially enhanced in terms of both constituent value and spectral response. This usually leads to calibration models that give more accurate predictions.

For this type of analysis, models using from one to ten latent variables (wavelengths) were built. The general equation form for the models was the following: density (kg/m^3) = $a + b*w_1 + c*w_2 + d*w_3 + \ldots y*w_i$ where w_i represents the "chosen" wavelength *i* for the model, and *a* to *y* represent the model coefficients.

Once the models were obtained, the same statistics as for the MLR procedure were calculated.

As described in previous sections, there were two types of samples, samples with bark on and samples with bark off. They were analyzed in the following way:

- Bark Off Samples:

    a. Prediction of Bark Off density with no validation, raw data.

b. Prediction of Bark Off density with no validation from 1 to 10 latent variables. Second derivative transformed.

c. Prediction of Bark Off density using full cross validation from 1 to 10 latent variables. Second derivative transformed.

- Bark On Samples:

a. Prediction of Bark On density using full cross validation from 1 to 10 latent variables. Second derivative transformed.

b. Prediction of Bark On density using Bark Off model from 5 to 10 latent variables. Second derivative transformed.

The number of latent variables used was related to trying to improve the model's R statistic and diminish the standard error.

Every disk was treated as an independent sample, even though there were 110 disks that came from a group of 40 trees.

3.5.4 Multiple Linear Regression (MLR) based on NIR wavelengths and sample height within the tree.

The procedure for this model is the same as described in Section 3.5.2 with the only difference being that sample height is included in the model as another

predictor. The reason for building this model is to add the sample height predictive power to the NIR model and verify if it is going to make it stronger.

This model was only developed with Bark Off samples, preprocessed with 10 point second derivative. In order to validate the model, the data was divided so that two thirds of the samples were used to build the model and the remaining third was used for model validation. In both types of models (calibration and validation) we t using 10 and 5 variables (wavelengths) plus height on stem at which wood sample was collected. The five and ten wavelengths selected were chosen based on the analyses completed in Section 3.5.2.

The general equation form for the models was the following: density (kg/m^3) = a + b*sample height + c*w_1 + d*w_2 +….y*w_i where w_i represents the "chosen" wavelength i for the model (in this case i was 5 and 10), and a to y represent the model coefficients.

3.6 ANALYSIS OF EFFECTS OF REDUCED WAVELENGTH RANGE

Acuna (2006) evaluated the utility of NIR and multivariate analysis based on wavelengths ranging from 500 to 2200 nm. His original calibration and validation models were constructed for density predictions based on samples of green wood chips and the full range of wavelengths. Using the original data sets different

ranges of the spectra were analyzed: 650-1050 nm, 1500-2200 nm and 1050-2200 nm. This analysis was done to verify the effects of reducing the spectrum (band width) on calibration and validation models as reported by Kelley 2004b.

CHAPTER 4

RESULTS

4.1 WOOD DENSITY

Wood density determined by water displacement method is summarized in Table 1. Because the information is presented by different heights on the tree, it can be clearly seen that density decreases with tree height, while the standard deviations increase. The standard deviation pattern is mostly affected by the lower number of samples in the upper parts of the trees.

Table 1. Descriptive statistics of wood dry density (kg/m^3) by sample height.

	Average	**SD**	**Min**	**Max**	**N**
Base (0 ft)	570	40.4	496	640	40
First log (18-35 ft)	513	43.8	430	606	37
Second log (36-70 ft)	486	49.0	362	605	29
Third log (54-105 ft)	422	109.0	268	511	4
Total	523	61.3	268	640	110

4.2 SIMPLE HEIGHT MODEL

Of the three simple models tested, (DBH, sample stem diameter and sample height) sample height provided the best R^2 value.

As shown in Figure 7, the simple DBH model has an R^2 that explains very little of the variation in wood density. Diameter at the sampling point provided a slightly better R^2 value (0.15). When the calibration model was built using sample height to predict wood density, the R^2 value was 0.46. In general, this is a normal value for this type of model and species.

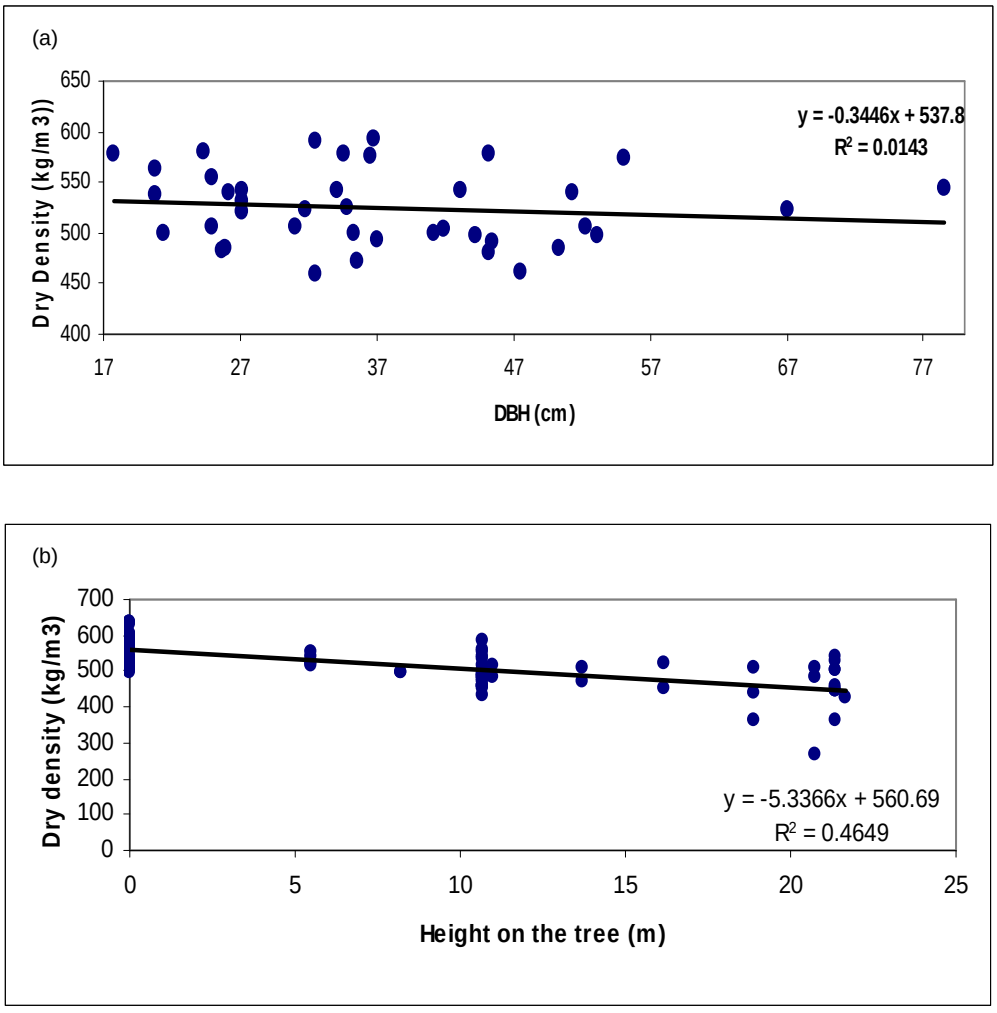

Figure 7. Calibration models to predict wood density from a) DBH and, b) Height in the tree.

When the simple height model was validated against one third of the data that were left out to build the calibration model, the R^2 value dropped to 0.29 (Figure 8).

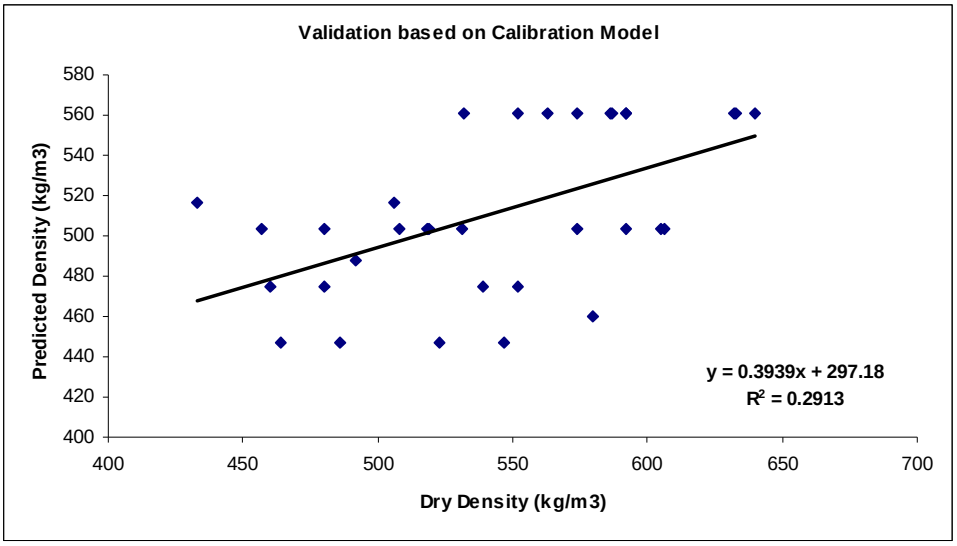

Figure 8. Validation of model height/dry density

This simple height model constituted our baseline for comparison with the NIR based models. On these following models we evaluated whether NIR contributed to higher or lower predictive power in comparison with this simple model.

4.3 EFFECT OF REDUCED WAVELENGTH RANGE (BASED ON DATA COLLECTED BY ACUNA (2006))

As stated above, the instrument used for the current study only collected data over an abbreviated spectral range compared to previous attempts for prediction of

wood density from NIR data. Therefore, we used the available data set from Acuna (2006) to learn how this smaller range could potentially affect predictions.

The results of the models prepared to verify the effect of the spectral range reduction are shown on Table 2.

Table 2. Coefficient of determination for different band width ranges on green chips wood samples.

Band Width (nm)	R^2 Calibration	R^2 Validation
650-1050	0.80	0.61
1500-2200	0.83	0.63
1050-2200	0.80	0.62
500-2200 (control)	0.89	0.74

There were very little differences between the R^2 derived from the three band widths. When compared with control (500-2500 nm), however, the R^2 results for the calibration and validation models are lower. These results are consistent with, Kelley's (2004b) finding that a reduced range of band width results in a drop in R^2 of about 10%.

4.4 NIR PREDICTION MODELS

4.4.1 MLR based on NIR wavelengths

a) Bark off samples

As shown in Figure 9 there is a significant improvement in the calibration model R^2 values, compared with raw data, when a second derivative transformation is applied to the spectral curves. In Figure 9a the R^2 statistic is extremely low (0.01). The transformation increases the R^2 to 0.56 (Figure 9b). Using 10 wavelengths as predictors resulted in the best model in statistical terms with respect to the other five models tested (five to nine wavelengths). This result seems acceptable compared with the calibration simple height model (R^2 = 0.46). The other five models are not presented here, but in the appendix there are graphs that show the statistical parameters of the other models.

However, when the best calibration model is cross-validated using the Delight software, the R^2 value drops dramatically to 0.006; this model has no predictive power (see Figure 9c).

Validation of the best MLR calibration model using split data gives a slightly higher R^2 value than found for the full cross validation, but it is still too weak to be evaluated as a good model (Figure 15 in appendix).

There may be outliers in the data (Figure 9). Removing these would give a very small improvement in the R^2 values. However, careful examination of individual points did not provide strong evidence as to why the “outliers” should be removed.

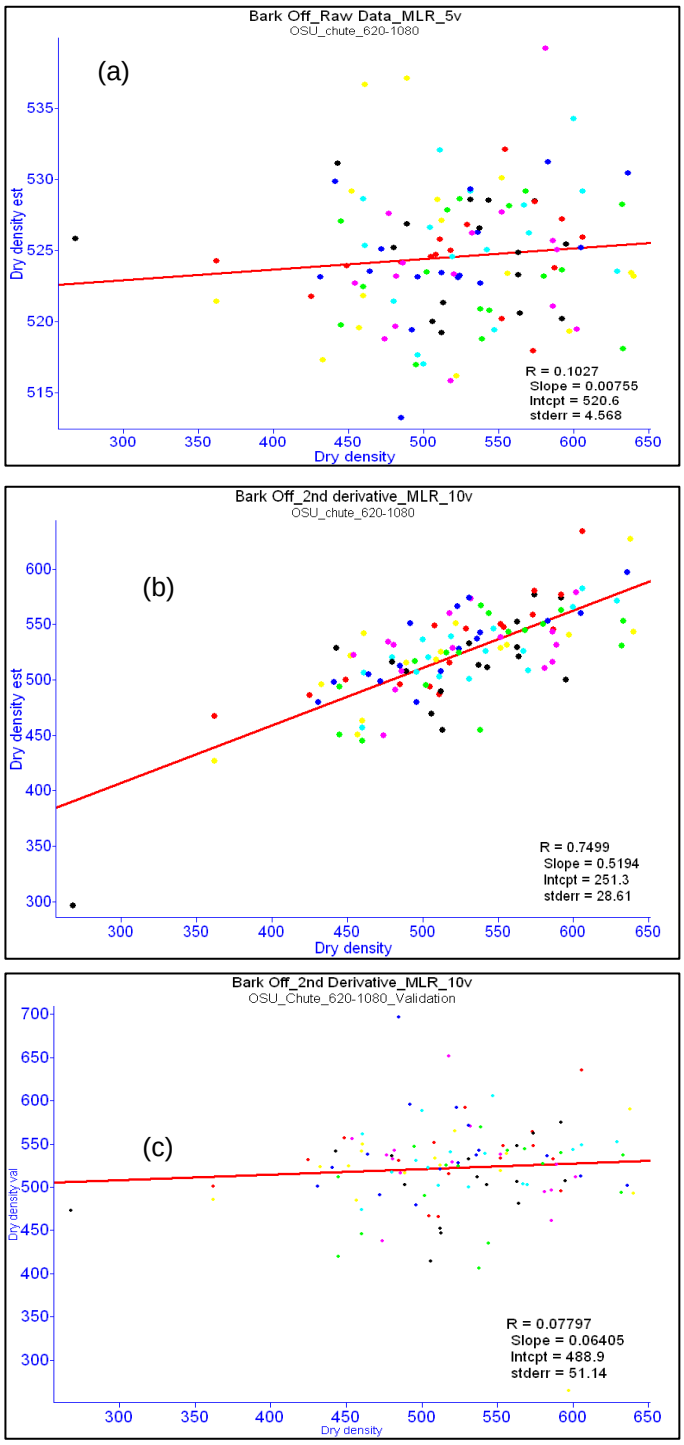

Figure 9. a) Prediction of Bark Off density with no validation, raw data. b) Prediction of Bark Off density with no validation, second derivative transformed. c) Prediction of Bark Off density using full cross validation, second derivative transformed.

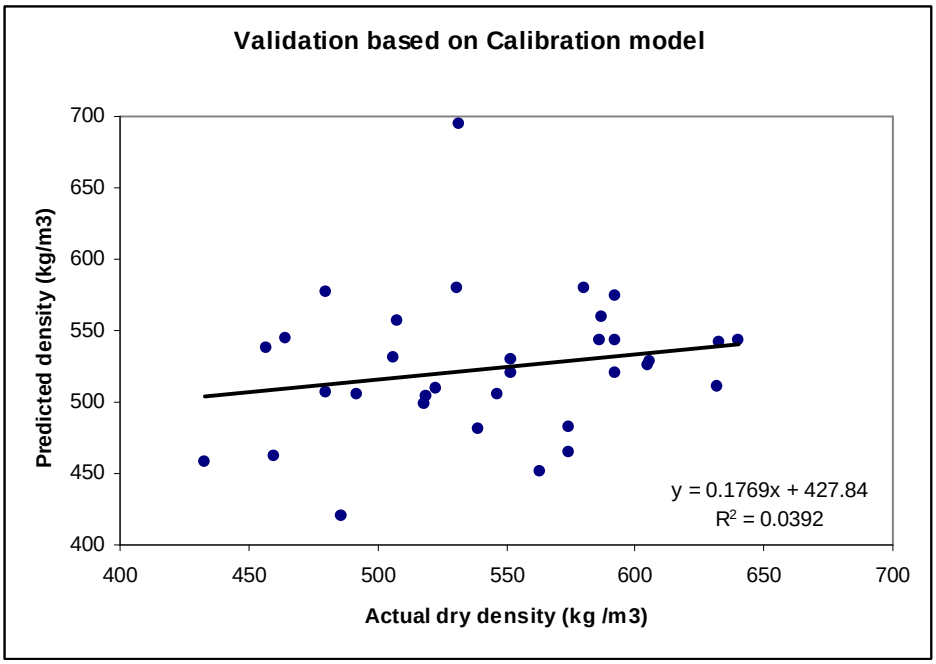

Figure 10. Prediction of Bark Off density using split data validation, second derivative transformed.

b) Bark on samples

Because of the increase in R^2 values resulting from the second derivative transformation in bark off spectral data, we went directly to the transformed version of the model for the bark on samples. From all the trials, the calibration model with a single wavelength was the best statistically (Figure 15).

As shown in Figure 11a the validation R^2 value was 0.12, which is higher than was found for the bark off validation model (R^2~0.0). We have no explanation for this. When the model built with bark off was validated with bark on data the R^2 value dropped dramatically (R^2 = 0.03).

The presence or absence of bark will, therefore, be a source of variability in density predictions since the mechanized processor may or may not take the bark off each log as it is being delimbed and cut.

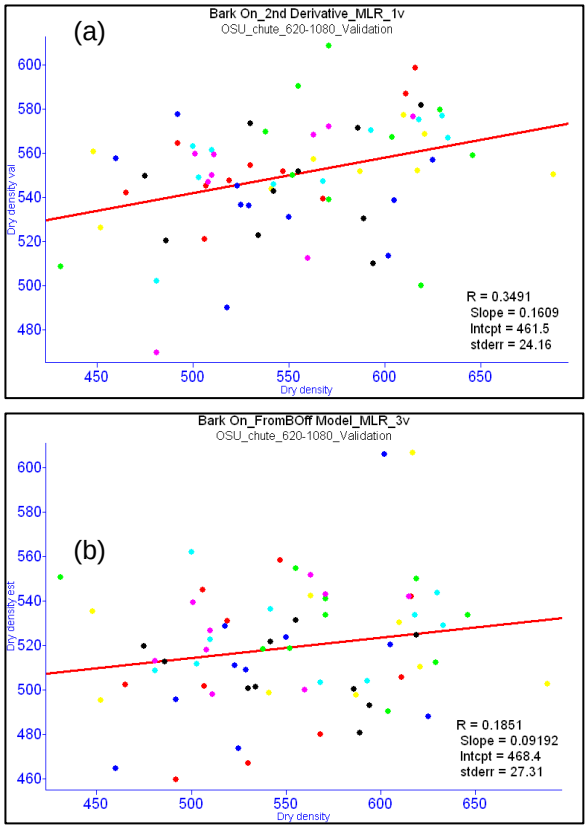

Figure 11. a) Prediction of Bark On density using full cross validation, second derivative transformed. b) Prediction of Bark On density using Bark Off model, second derivative transformed.

4.4.2 PLS based on NIR wavelengths

a) Bark off samples

When PLS is applied to raw data, it gives a better, although still poor model, compared with MLR. The best model was found using five latent variables (five wavelengths) which yields an R^2 of 0.20 (Figure 12a).

When a second derivative transformation is applied, the PLS model explains 97% (R^2 = 0.97) of the variation, which is excellent considering the previous results. The best model, from the ten tested (from 1 to 10 latent variables), was found using ten latent variables and is shown in Figure 12b.

When cross validation was applied to the best PLS model (2^{nd} derivative), the validation model predictive power dropped significantly to an R^2 of 0.02 (Figure 12c). This reduction in predictive power is similar to the results for the MLR models.

b) Bark on samples

PLS analysis of 2^{nd} derivative transformed data did not improve the validation model compared with the best MLR derived model (Figure 13a). The same behavior was observed in the model built with bark off samples and validated with bark on. The best model found used six latent variables (six wavelengths) and is shown in Figure 13b.

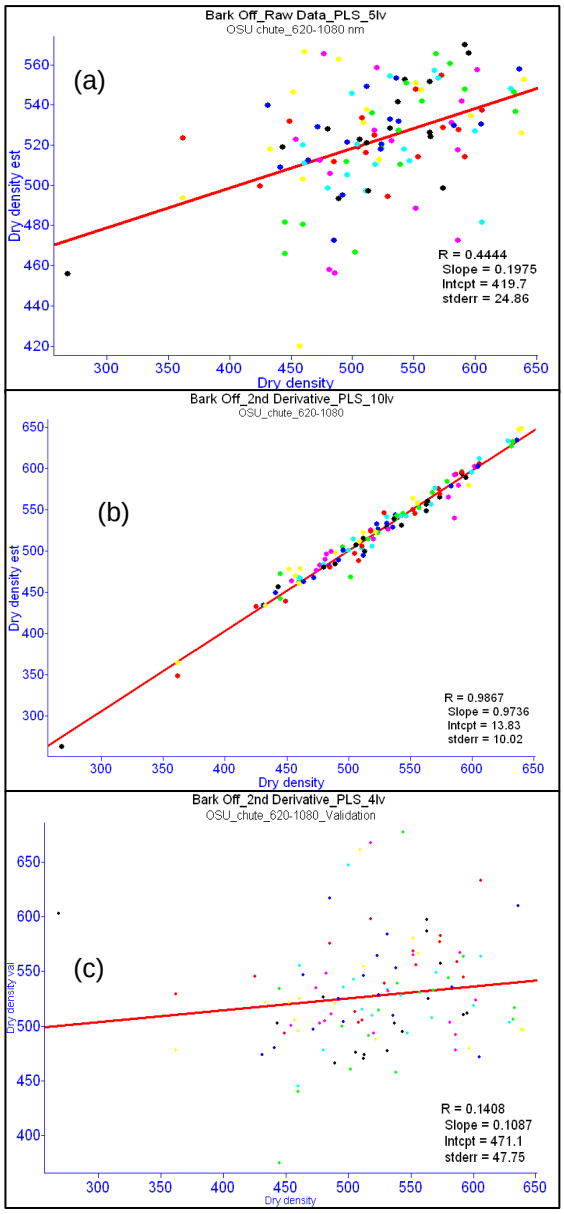

Figure 12. a) Prediction of Bark Off density with no validation, raw data. b) Prediction of Bark Off density with no validation, second derivative transformed. c) Prediction of Bark Off density using full cross validation, second derivative transformed.

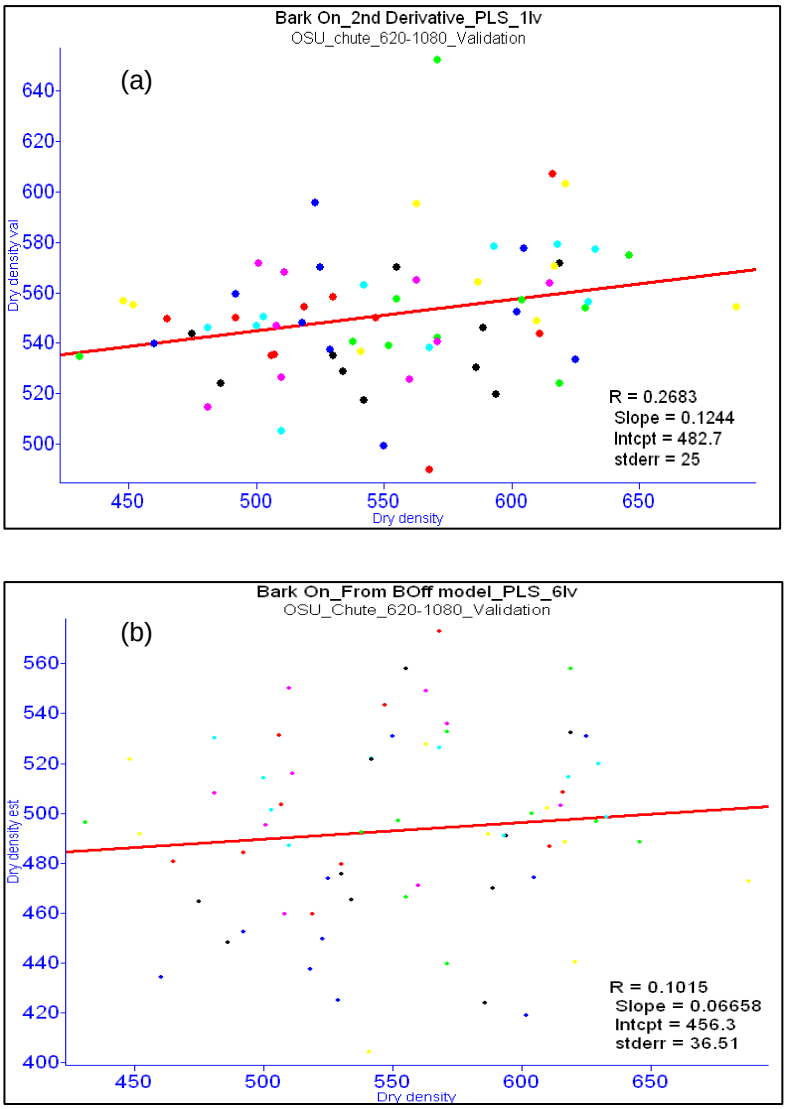

Figure 13. a) Prediction of Bark On density using full cross validation, second derivative transformed. b) Prediction of Bark On density using Bark Off model, second derivative transformed.

4.4.3 MLR using NIR and sample height within the tree

When height is included in the model, it has a positive effect on the model's R^2 in the calibration model. It goes from 0.56 (Figure 9b) with NIR alone to 0.81 when

height on the tree is included (Figure 14a). But when the model is validated, the R^2 drops again to 0.16 (Figure 14b).

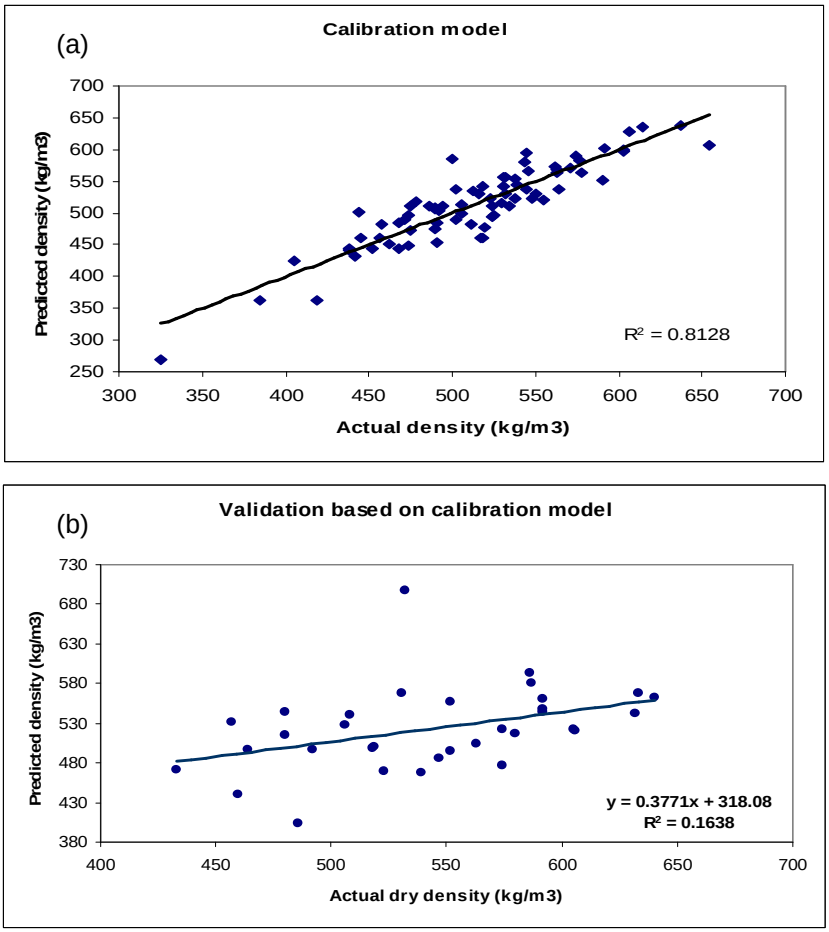

Figure 14. MLR using NIR and height on the tree a) calibration model, b) validation model

4.5 MODEL PARAMETER SUMMARY

On the following table (Table 3), the R^2 statistics for the simple height model, the best of the NIR models and the model that includes both height and NIR wavelengths are summarized. Here it is easy to notice that for calibration models,

NIR had a significant improvement on the predictive ability of the model. However, when the calibration models were validated, the simple height model (without NIR) was the one with the best predictive ability.

Table 3. Coefficient of determination (R^2) for all the bark off models

	Calibration	**Full cross validation**	**Split validation**
Simple height model	0.46	------	0.29
MLR based on NIR wavelengths	0.56	0.006	0.04
PLS based on NIR wavelengths	0.97	0.020	-----
MLR based on NIR wavelengths and Height	0.81	-----	0.16

CHAPTER 5

DISCUSSION AND CONCLUSIONS

The first step of this research was to build the “simple model” as a baseline to predict wood density. The analyses were done initially building three different models using as independent variables: diameter at breast height (tree size), sample diameter, and sample height on the tree .The strongest model that we found was the one using sample height as an independent variable. The other two models had very weak correlations (diameter versus density, and DBH versus density). These low correlations are consistent with other studies in Douglas-fir (Barbara Lachenbruch, pers. Comm., Acuna and Murphy, 2006b).

Because height itself was not very strong in terms of wood density prediction, we considered the use of NIR as a way to characterize wood density. This idea was based on the satisfactory results obtained by other researchers such as L. Schimleck (2002), S. Kelley (2004a, 2004b), P. Jones (2006) and M. Acuna (2006).

When NIR was used to predict wood density as a calibration model without any mathematical transformation the results were not very good. We also found that when a second derivative was applied, the model improved significantly. In the study performed by Acuna and Murphy (2006b) although this mathematical

transformation was not applied to their models, they had good results for calibration and validation models.

Particularly with the use of MLR, our models gave good results compared with the simple model but they did not have good performance when they were validated. PLS is the most widely used analysis method when NIR is used to build models. Many authors had used this method and had satisfactory results. This led us to try this method to as the basis for model construction. The calibration models were, in general, excellent in terms of R^2, but were poor when the calibration models were validated. This may have been due to overfitting of data in the calibration models. However, reducing the number of latent variables to a few did not lead to great improvements in the validation statistics.

Based on these results we developed a model in which both height in the tree and up to ten NIR wavelengths were used as explanatory variables. The calibration model resulted in a highly significant increase in the R^2, better than NIR, and height by themselves. When the model was validated, the R^2 dropped substantially to a level where it was slightly better than the other models but not good enough to reach at least 50% of the explanation of the variability.

In general, none of the models that included NIR data performed better than height alone (density (kg/m^3) = a + b*sample height) when the models were validated.

Since these results contradict the findings of other studies some possible explanations are required.

As we discussed in the background section, the tree has great variability in wood properties in both longitudinal and radial directions. For our study, variability in the radial direction, within rings and from pith to bark, is crucial. Compared with our measurement procedures, other researchers gathered their spectral data on wood samples with lower variability. As an example, we have the studies performed by Schimleck *et al* (2002) and Jones (2006). They used NIR to predict wood stiffness from individual rings in increment cores and had good results. Another example is the study performed by Acuna and Murphy (2006b) where they used small blocks of wood (~ 5cm X 5cm) taken from the same part of the wood disk on each of the samples. This also reduced the variability of the properties of the wood sample. In other words, it is possible that our models performed poorly because of the large variability across disks relative to our sample size. A larger sample size could have lead to improved ability to estimate density based on NIR.

Another important issue when working with NIR is the sample water content. This issue was addressed by Acuna and Murphy (2006b) and they reported a drop in the green chip model's ability to predict density compared with dry chips. In our case we have the variability in both water content between heartwood-sapwood

(sapwood is generally saturated with water), as well as density, across the whole diameter of the disk.

A third cause could be the use of a narrower band of wavelengths. There is evidence in the literature (Kelley et al. (2004b); Acuna and Murphy (2006b)) that the reduction of the bandwidth will result in a drop of the predictive ability of NIR based models.

With regards to the bark effect on NIR models we found that in all of the models tried, the presence of bark slightly improved the ability to predict wood density when compared with bark off models. There was a difference between bark on and bark off models that might be a limitation in the potential use of NIR technology; if the instrument is attached to a harvester/processor, we can not be sure that the bark is going to be present on each log that is being cut.

There are a number of limitations related to this study. These follow:

- we worked with one species, Douglas-fir.
- the sample was representative of only one site in the Coast Range of Oregon.
- we tried one method of exposing the sample to the NIR sensor (there are several other methods such as spinners or stationary samples).

- we selected 5 or 10 best wavelengths for MLR when sample height on the tree was included. If we could have included the height as an independent variable in the Delight software, the software may have chosen different wavelengths due to the effect of the height variable.

With respect to our original objectives we conclude that:

(1) it was not possible to make strong prediction models of a sample's specific gravity from external characteristics alone; the best validation model had an R^2 value of 0.29.

(2) calibration model correlations could be improved by including data from NIR absorbance spectra collected from green chainsaw chips, however these models performed poorly when applied to validation data sets.

(3) the presence of bark in the saw chips adversely affected prediction power of the models.

We also conclude that since other researchers have reported good to strong relationships between NIR measurements and wood density we can not attribute the low performance of our models to the NIR technology alone. We believe that the sampling protocol, that is, the method of presenting the chips to the sensing system, used in this study and the great variability from pith to bark may have caused the poor performance. This technology requires continuing research.

Finally, we note that with the technology available to us at present, even given the methodological problems encountered in the current study, it is clear that NIR does not sample green chips quickly enough or thoroughly enough for the real time application. Each of our wood disks was related to the mean curve from as many as 10 to 860 scans. A larger number of scans is simply not feasible with this technology. Therefore, we suggest that research be aimed at getting more representative NIR spectra, through such approaches as multiple simultaneous NIR sensors, different chip homogenizing techniques, or other technologies. When this issue is overcome, the method may hold promise for improving our ability to predict wood density in real time in the forest as we harvest.

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APPENDIX

Graphs showing variation in R and Standard Error for calibration and validation models

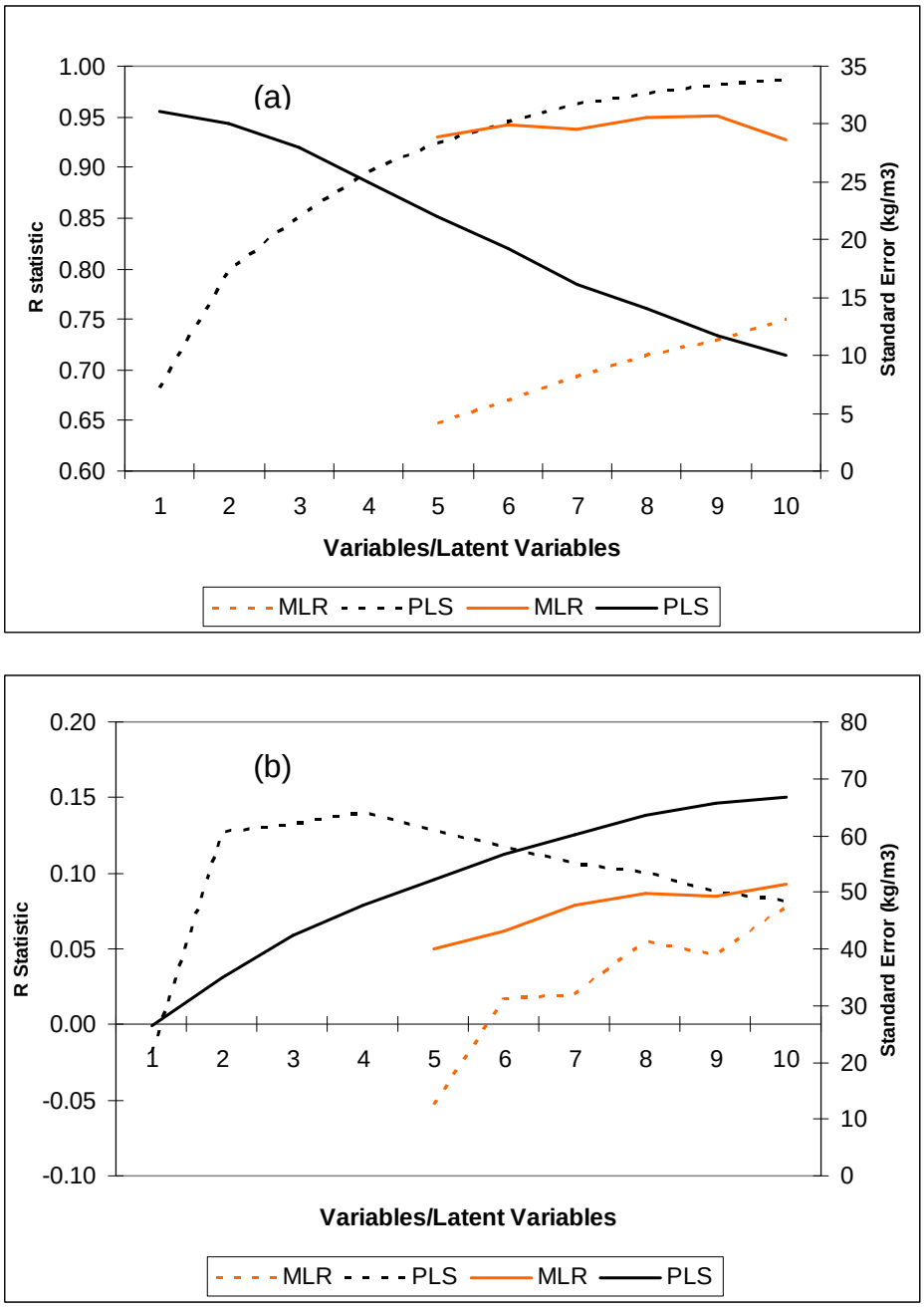

Figure 15. Statistics (R and Standard Error) for the different variables tried in a) Calibration, b) Validation for the bark off models. MLR: Multiple Linear Regression and PLS: Partial Least Squares.

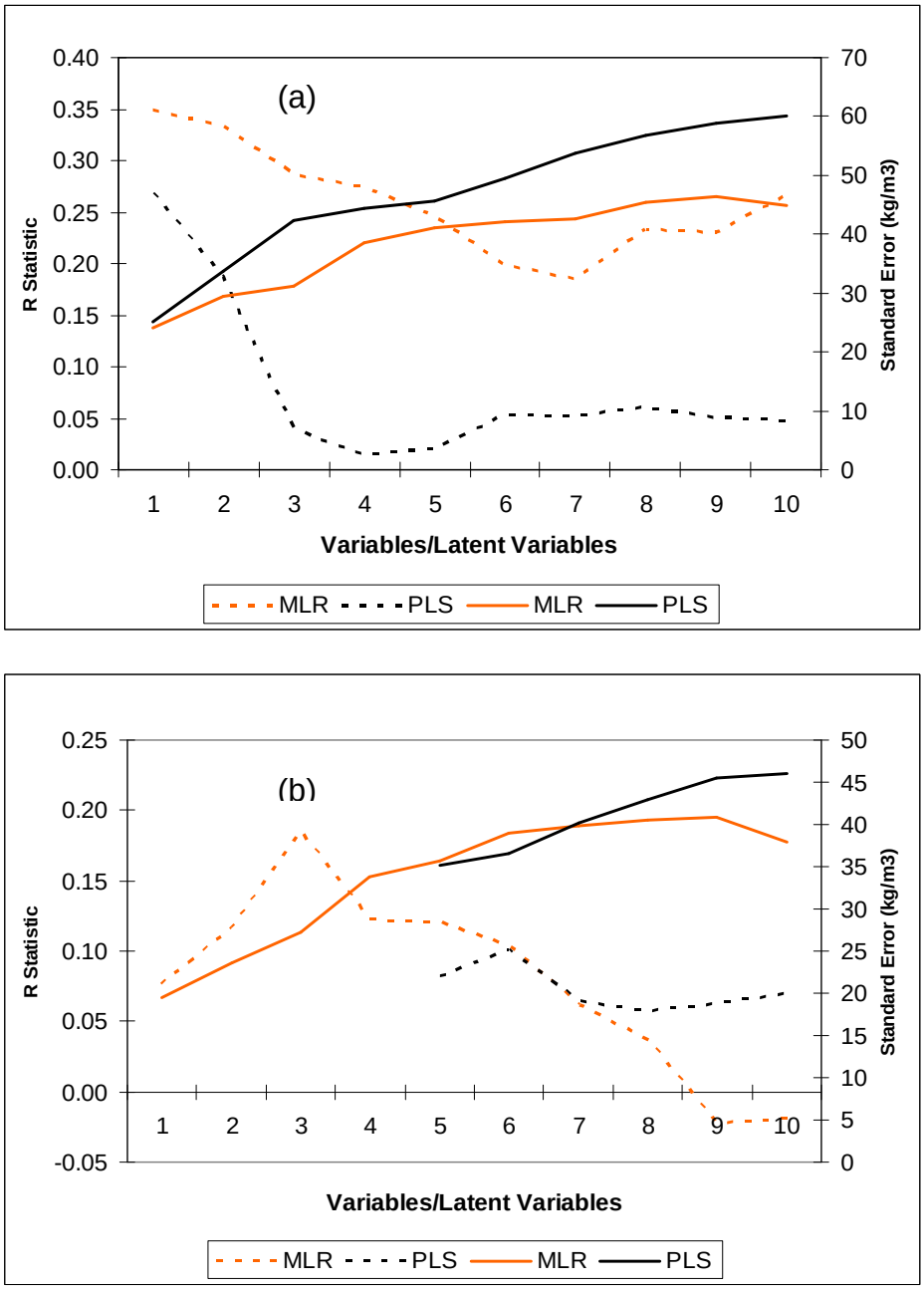

Figure 16. Statistics for the different variables tried in a) Validation models based on bark on calibration models b) Validation models for bark on data based on bark off calibration models. MLR: Multiple Linear Regression and PLS: Partial Least Squares.