Detection of wet-pockets in hemlock using, near infrared spectroscopy

F. Hart, S. Avramidis, S. Mansfield

Department of Wood Science
The University of British Columbia
Vancouver, BC, Canada

ABSTRACT

The objective of this preliminary study was to assess and develop a method of detecting the presence of wet-pockets in hemlock lamina based on near infrared (NIR) spectroscopy. Three principal component regression models with different pre-processing methods capable of predicting moisture content of hemlock within the accuracy limits of the calibration models were developed. The pre-processing of data to the first derivative resulted in the highest correlation coefficient (0.9855). This means that the use of NIR technology can provide a 99% accurate reading of the lumber's shell moisture content within the range from 0 to 27%. The resultant model is expected to give higher average moisture content predictions (they can range between 0 and 2.4%) than the oven-dry method for calculating moisture content of specimens containing wet-pockets located on the shell. Although NIR technology is able to accurately predict lumber shell moisture content, it is less accurate when predicting the average moisture content of 50-mm thick material. Regardless of that, the strong statistical evidence suggests that the technology using NIR-spectroscopy to determine shell moisture content in applications such as identifying surface wet-pockets for post-sorting kiln dried lumber or lam-stock should be developed.

INTRODUCTION

Western hemlock (*Tsuga heterophylla*) is a coastal BC species used to produce lamina for manufacturing glue-laminated timber in Japan, China, Canada, and the United States in addition to the standard cross-sectional sizes (i.e., 2x4 and 4x4). One common manufacturing issue limiting the extended use of hemlock in the industry is the occurrence of wet-wood in the heartwood. Wet-wood or wet-pocket is an area in wood with very high moisture content compared to the neighboring wood (Chafe 1996, Cooper and Jeremic 1998). Lumber with wet-pockets dries more slowly than normal heartwood (Ward 1986), and this leads to unacceptably high spread in the final moisture contents within and between kiln dried lumber.

Wet-pockets create problems during a lamination process that often become sources of weakness due to substandard adhesion. Lumber containing wet-pockets is also unsuitable in laminated timber production when radio frequency (RF) glulam presses are used. The wet-pockets absorb the RF energy and causes arcing of the RF field which in turn, results in wood burning. As such, occurrence of wet-pockets in lam-stock limits its use to cold or hot pressing technologies to cure the glue lines.

Infrared (IR) technology uses the portion of the electromagnetic spectrum with a frequency range of 700 to 10^6 nm which is further separated into near, middle, and far infrared. The near-infrared

(NIR) section is the most useful section of the spectrum for non-destructive evaluation (NDE) of materials. It ranges from 350 to 2500 nm and the reflectance of absorption bands in this range are used for qualitative analysis. The bands found below and above the range are too weak and too strong, respectively. The absorption bands occurring in the NIR region are primarily overtone and combination bands of O-H, N-H, and C-H functional groups (Shenk et al. 1992). Hydrogen species at water bands of 1450 and 1930 nm have been found in the NIR spectrum which could be used to develop predictive models for water (Adedipe and Dawson-Andoh 2008).

NIR technology has been used to predict many wood properties. For example, pulp yield, determined by cellulose and lignin content, has been successfully predicted. Studies have also shown that NIR technology can be used to predict microfibril angle (MFA), stiffness and tracheid coarseness, specific surface and wall thickness (Schimleck 2007). It has also been suggested it may be possible to predict the strength of dry wood from the NIR spectra of wet wood (Kelly et al. 2001). The use of NIR technology to predict other properties such as density distribution and grain angle (Via *et al.* 2005, Stirling 2006, Gindl 2001), as well as the moisture content in yellow poplar veneer (Adedipe and Dawson-Andoh 2008), have been researched. NIR has even been used to measure wood extractives (Taylor et al. 2008). Since NIR is a NDE method, tests are performed at rapid speed and it can be operated by unskilled personnel (Schimleck 2007). These latter two characteristics of NIR make it an attractive technique for use in the wood processing industry.

The objective of this preliminary study was to assess the NIR technology at the bench-top level as a potential non-destructive method that swiftly and accurately detects the presence of wet-pockets in 50-mm thick western hemlock lumber.

MATERIALS AND METHODS

The work was divided into two steps, namely, the training of the NIR system by reading wood specimens of various moisture contents and wood type/configuration combinations within the hygroscopic range and the validation of the predictive model. The former is important since the apparatus needs to "learn" the characteristics of the spectra corresponding to the various moisture contents. The latter is then needed to test the model and determine its accuracy.

Wood specimens were cut from fresh green lumber (40mm x100mm x 2900mm) that was obtained from a coastal sawmill. Their dimensions were either 40mm x 40mm x 5mm or 50mm x 50mm x 5mm. There were three types of wood used, namely, juvenile, sapwood, and heartwood. For each wood type used, three grain orientations were cut: radial, tangential, and in-between (radial-tangential). There were nine combinations in total (3 types x 3 orientations) and thirty replications of each combination for a total of 270 specimens. The specimens were oven dried at 103±2^{o}C for 24 hours, scanned on the spectrometer, and then conditioned to different moisture contents in a set of conditioning chambers that control air temperature and relative humidity with very high accuracy (±0.2^{o}C and ±1%).

The target equilibrium moisture contents for each conditioning step were set to 5%, 10%, 15%, 20% and 24%, respectively. Specimen weights were monitored daily and when they remained constant for three consecutive days they were assumed to be at equilibrium. Afterwards, they were allowed to cool to ambient temperature in vacuum-sealed bags to minimize any moisture loss between the time of weight measurement and NIR scanning. NIR spectra were collected with a QualitySpec® Pro Analytical spectrometer (Bouler, CO, US) operating in a reflectance mode with a wavelength range of 350 nm to 2500 nm. Each specimen was scanned three times and an average of the scans was kept for data analysis (Fig. 1). The NIR spectra collected were converted to ASCII files using the ASD to Unscrambler ASCii Version 7.0 program. The raw data was then used to derive a principal component regression model. Two additional models were developed using both the first and second derivatives in order to improve interpretation of the spectrum and the quality of the model, as band intensity and peak location are maintained and there is apparent band resolution enhancement (Adedipe and Dawson-Andoh 2008). As soon as the scans at the various moisture contents within the hygroscopic range were completed, the specimens were fully saturated in distilled water, weighed and then re-scanned on the NIR spectrometer (Fig. 1).

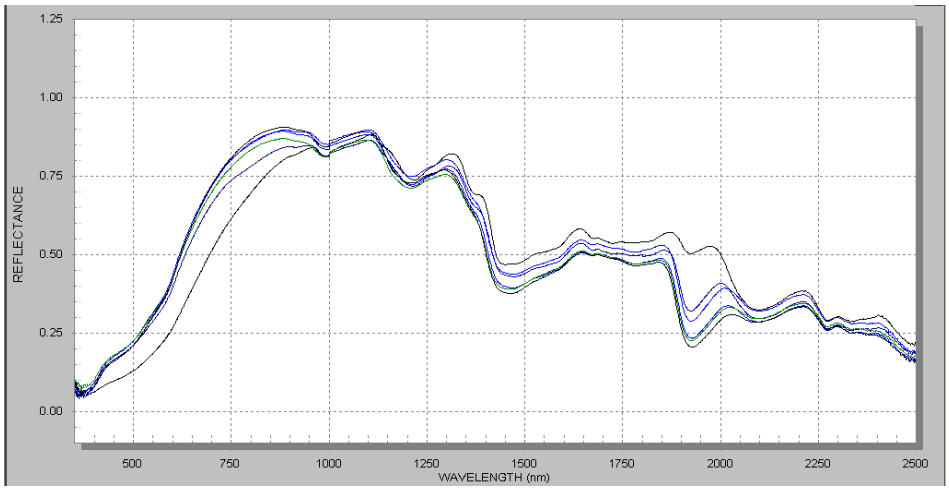

Figure 1: NIR spectra at various moisture contents

Multivariate data analysis of the raw and converted spectral data was performed using Unscrambler software version 9.1 (Camo Smart, Woodbridge, NJ, US). Data from the entire moisture content range studied (0%-28%) was employed, and the spectra data was employed to compute the principal component regression (PCR). All the NIR spectra were combined into a single data matrix (X-matrix) and the moisture content was combined into a response matrix (Y-matrix). The raw data, first derivative and second derivative calibration models, were constructed with 1523, 1565, and 1526 samples after removing 62, 20, and 59 outliers respectively, using a full cross-validation method. An additional first derivative model was created with spectra scans from the fully saturated samples included in the data set.

Upon completion of the first step, namely, NIR training, new lam-stock lumber of 40x100mm in cross-section and 2 meters long and of unknown moisture content distribution that was deems as “wet” during commercial production by an in-line moisture meter was provided by a coastal sawmill for model verification. The moisture content of the specimens was read in the lab using a hand held capacitance moisture meter to ensure they contained sections with high moisture

content (assumed to be wet-pockets). Wood sections of 40mm x 100mm x 75mm in dimensions were thereafter cut from the lam-stock to act as a validation set. A total of 492 validation samples were used.

Each sample was scanned on the spectrometer eight times representing scans on both the top and bottom surfaces and the average of the eight spectra was used in the moisture content prediction for a total of 492 validation spectra. The scans taken from either surface were also averaged separately, and an average of the four spectra was used in moisture content prediction for a total of 984 validation spectra. The samples were immediately weighed after being scanned and then oven dried at 103±2^{o}C for 24 hours. Once their oven-dried weight was obtained, the moisture content at the point of scanning was determined. The three fully cross—validated models were then used to predict the response of the validation set. The predicted responses (a moisture content value) were compared to the calculated moisture content.

RESULTS AND DISCUSSION

Table 1 shows the relative humidity at each conditioning step and the average moisture content of all specimens obtained for that relative humidity. It also shows the standard deviation of the specimen moisture contents at each conditioning step. The total range of moisture contents obtained throughout all the conditioning steps, exempting full saturation, was 0-27.64%.

Table 1: Calibration specimens average moisture content obtained at various relative humidities

Relative Humidity [%]	Air Temperature [^{o}C]	Average MC [%]	MC St Dev. [%]
0	103	0	0
25	40	4.99	0.2561
60	40	10.27	0.3833
80	40	14.88	0.8086
91	40	19.12	1.2384
98	35	24.39	1.6055

Table 2 is a summary of the three regression models developed. The model developed with the first derivative pre-processed data has a very high R-value for calibration (0.9855) and the highest for prediction (0.5403). It also has the lowest root mean square error of calibration (RMSEC) and standard error of calibration (SEC). In addition, the first derivative model has the lowest standard error of prediction (SEP). However, the first derivative model's mean square error of prediction it also has the highest R-value of 0.5402. Although this is not a strong correlation between the predicted and calculated Y-values, it is by far the strongest R-value of the three models. The first derivative model's RMSEP and bias are larger than the second derivative's. The first derivative's

Table 2: Principal component regression models

Preprocessing method	PC[1]	R-value calibration	RMSEC[2]	SEC[3]	R-value prediction	RMSEP[4]	SEP[5]	BIAS
Raw Data	4	0.9487	2.5841	2.5850	0.2954	7.0973	1.3511	6.9678
1st Derivative	3	0.9855	1.3606	1.3610	0.5402	2.4175	1.0717	2.1674
2nd Derivative	4	0.9013	3.4201	3.4212	0.1676	1.5066	1.3185	0.7312
1st Derivative with saturated specimens	3	0.9877	6.5366	6.5384	0.4630	2.8657	2.4189	-1.5404

[1]*Optimum number of principal components,* [2]*Root mean square error of calibration,* [3]*Standard error of calibration,* [4]*Root mean square error of prediction,* [5]*Standard error of prediction.*

(RMSEP) and bias are higher than the second derivative pre-processed data model. The model developed with second derivative preprocessed data had the lowest R-value for both calibration and prediction. It also has the highest RMSEC and SEC. The second derivative model did however have the lowest RMSEP and bias. The model developed with raw data was in between the other models for the R-values (both calibration and prediction), RMSEC, SEC, and SEP. It had very large RMSEP and bias. Although, the first derivative model with the fully saturated specimens included has a calibration R-value of 0.9877, the RMSEC/RMSEP and SEC/SEP were higher, and the prediction R-value was lower, than the first derivative model that did not include the saturated specimens.

The first derivative model appears to be the best model in terms of the calibration results. It has a strong calibration R-value of 0.9855 and had the lowest errors. When looking at prediction results, SEP is lower than the second derivative's, however the second derivative's prediction R-value is 0.1671. Also, the calibration results for the second derivative model were the worst of the three models. Therefore, it appears the first derivative model is the best. Fig. 2 is a plot of the predicted vs. measured values for the first derivative preprocessed data set. The trend of the plotted data somewhat resembles a sigmoid, or S, shape.

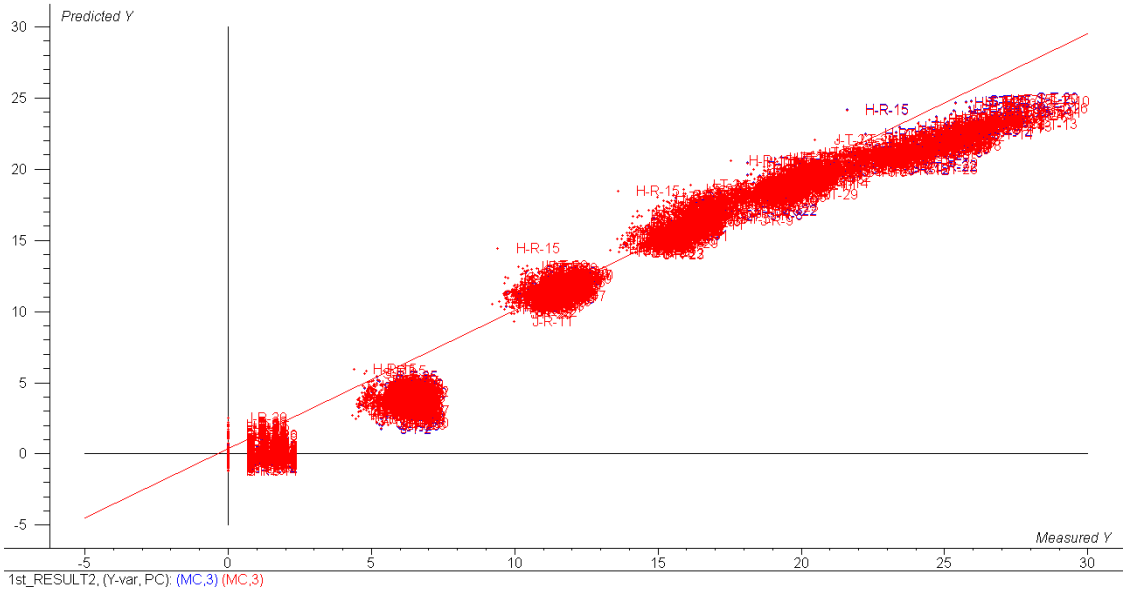

Figure 2: Calibration - measured (x-axis) vs. predicted (y-axis) average moisture content with regression trend line

The model is 99% accurate in predicting the shell moisture content within the moisture content range studied (0-27%). However, the first derivative model predicted Y-values were consistently higher than the measured (oven-dry moisture content) Y-values (Fig. 3). Of the 492 spectra used in the validation, 485 predictions were overestimates, and 7 predictions were underestimates of their corresponding measured moisture contents. The results for the prediction may be explained by the characteristics of the validation specimens. The specimens were 40 mm thick and the depth of the NIR spectrometer scan is approximately 4 mm. The difference in thickness and spectrometer scan means the spectrometer can only give a description of the moisture content at the shell of the specimens. Furthermore, the calculated moisture content used in the validation was an average of the whole piece. This is an oversight in the experimental design. The research should have measured the shell moisture content and should not have attempted to extrapolate to the entire block, including core moisture. If there was variation between the shell and core of the specimens, or a large moisture gradient, the result would be higher prediction errors of the model.

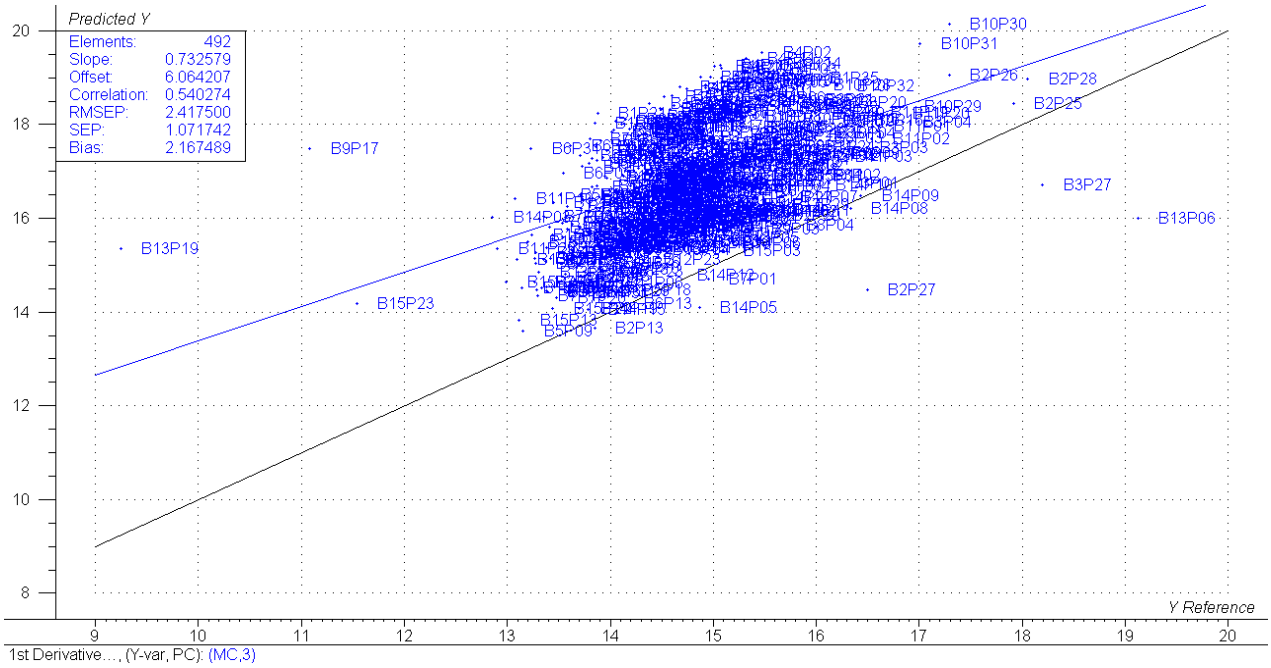

Figure 3: Prediction - measured vs. predicted average moisture content for whole specimen average with regression (blue) and target (black) trend lines

The first derivative model was also used to predict the moisture content values for specimens with separately averaged sides to see if the differences between either side of each specimen (Fig. 4). Of the 984 spectra used in the validation, 877 predictions were overestimates, and 107 predictions were underestimates of their corresponding measured moisture contents. There is a difference in the ratio of underestimated and overestimated predictions between the whole specimen average and the specimens with sides separately averaged. The difference in results may be due to the moisture content profile within individual specimens. There were three scenarios identified: (a) both sides are overestimated (over-over); (b) one side is overestimated and the other is underestimated (over-under); and (c) both sides are underestimated (under-under). The most common scenario was the over-over, while over-under was second most common, and there were only two case of the under-under scenario.

The over-over scenario may be explained by wet-pockets only being present in the shell giving a profile of high moisture content at the shell and lower moisture content in the core. If the majority of the specimen has lower moisture content than the shell, the oven-dry (reference) moisture content will be lower than the shell (predicted) moisture content. The over-under scenario may be explained

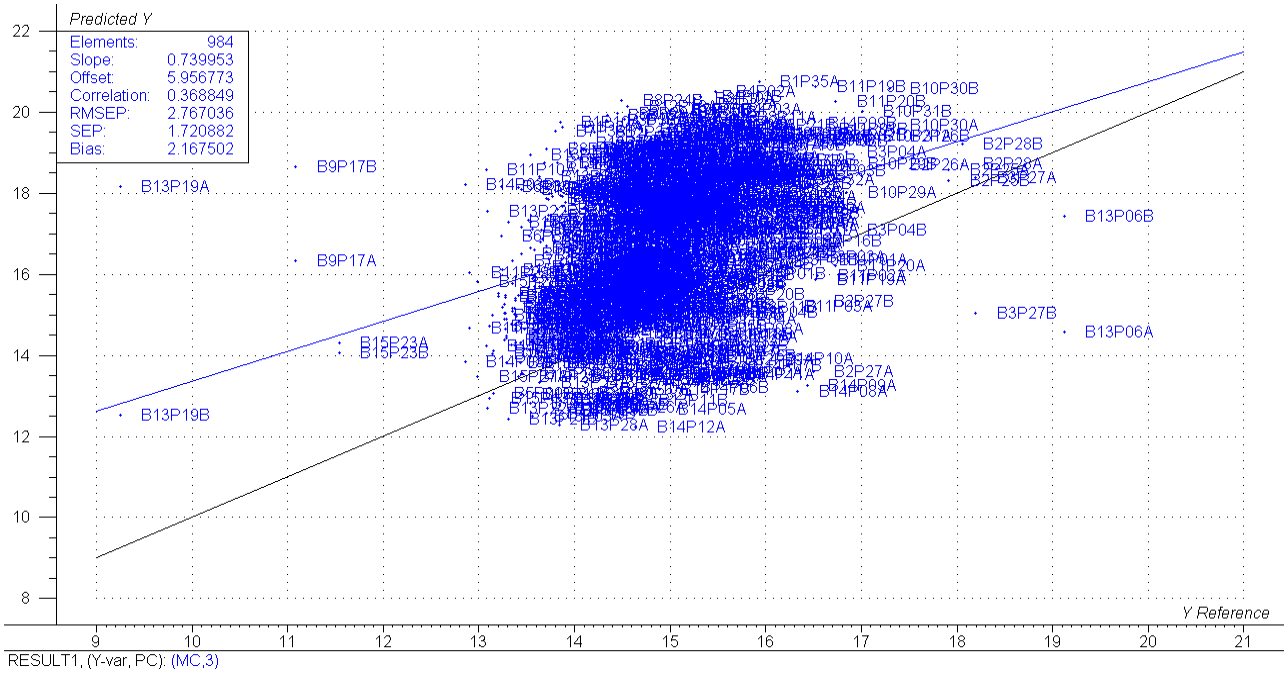

Figure 4: Prediction – predicted(y-axis) vs. measured (x-axis) average moisture content for either side of specimen averaged with regression (blue) and target (black) trend lines

by one side of the specimen having wet-pockets and the other having none. The side with wet-pockets will have high moisture content and the side without wet-pockets will have lower moisture content. The oven-dry (reference) moisture content, an average of the whole piece, will be slightly lower or slightly higher than either side. The under-under scenario could be the result of the core having a higher moisture content than the shell. The underestimation could be due to: the drying schedule used; the shell losing moisture content before the NIR scans were taken; and/or wet-pockets in the core.

CONCLUSION

Principal component regression models capable of predicting moisture content of hemlock within the accuracy levels of the calibration models were successfully developed based on the raw NIR readings of precisely conditioned hemlock specimens within the hygroscopic range (moisture content between 0 and 27%). The pre-processing of data to the first derivative resulted in the highest correlation coefficient (a measure of how strong the relationship is between the moisture content and the spectra), of 0.9855 for the calibration stage. The model is expected to have an average prediction error (deviation from the reference value) up to 2.4%. For example, when the shell contains areas of high moisture content, or wet-pockets, the prediction of the model is expected to be 0-2.4% higher than the oven-dry method calculated moisture content.

The model developed with NIR spectroscopy was capable of accurately predicting the shell moisture content of the specimens used in this study. The strong statistical evidence in the calibration stage proves that this technology is capable to detect wet pockets on the surface of rough lumber with high accuracy. It must always be kept in mind that this technology is surface related; therefore it cannot detect wet-pockets, or the moisture content, in the core of lumber at this time. Possible technological developments in the future might allow this.

In summary, this preliminary study has shown that NIR spectroscopy combined with principal component regression modeling is a promising new technology for determining the shell moisture content of lumber thus allowing for swift and accurate determination of the existence of wet-pockets on the surface. It is a rapid, easily operated and non-destructive method for surface moisture content evaluation. The use of NIR technology can provide a 99% accurate reading of the lumber's shell moisture content from 0 to 27%.

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