Modeling Mechanical Properties of 2 by 4 and 2 by 6 Southern Pine Lumber Using Longitudinal Vibration and Visual Characteristics

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Abstract

The light-frame building construction market is increasingly competitive. To maintain and grow its position in the market, the lumber industry needs to be improved and refined. The identification of the strength-reducing characteristics that affect modulus of elasticity (MOE) and modulus of rupture (MOR) are keys to improve the grading process of lumber. Herein, nondestructive techniques, visual evaluation, and mechanical testing were used to assess the structural properties of 1,044 samples of southern pine lumber. Linear regression models were constructed for 2 by 4 and 2 by 6 southern pine lumber using the static bending MOE and MOR, both as dependent variables from the destructive test. Nondestructive measurements, visual characteristics, and lumber density were used as independent variables. Linear regression models were constructed to indirectly estimate the MOE and MOR of southern pine lumber. The variables selected to predict MOE were dynamic modulus of elasticity (dMOE) and density. By adding knot diameter ratio to dMOE and density, it was possible to develop a prediction model for MOR. It was possible to improve predictability of strength (MOR) with a combination of nondestructive testing and knot evaluation.

Efficient utilization of the available wood supply is essential to meet the long-term demand for products and ensure their economic viability. Improvement of wood utilization for structural applications depends on the ability to understand and predict accurately the mechanical behavior of wood products for sustainable uses.

Southern pine is the most important timber-producing tree species group in the southern United States. Loblolly pine naturally grows primarily in the coastal plain region of this area (Cunningham et al. 2008) and is heavily planted there. Because there are great variations in the inherent properties of various species, grading is a necessary procedure to reduce the variability of each lumber class and maximize the value of the limited wood resource.

Variation in properties is common to all materials, and because wood is a natural material, it is subject to the direct influence of environmental conditions, genetic factors, and growth variations. Knowledge of the mechanical properties of structural lumber is essential for proper and efficient use of the material (Panshin and DeZeuw 1980).

Visual grading of structural lumber is the oldest and most widely used method for the prediction of mechanical properties (Kretschmann 2010). According to Mackay (1989), the purpose of grading rules is to maintain a minimum standard or measure of value among mills that manufacture the same or similar material so that final products have a uniform quality. Visual grading and machine grading are the two methods used by mills to classify lumber into different strength classes. An efficient grading system allows lumber producers to best utilize the

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valuable wood sources in a consistent manner and meet the customers' requirements. It also allows the customer to maximize their construction utility value, achieve reliable safety, and minimize building material costs.

The measurement of the characteristics present in the lumber pieces such as knot size, slope of grain, presence of pith, size of splits and checks, and length of bark and resin pockets defines the different visual grades (Iniguez et al. 2007). Visual grading is usually done by humans, and the maximum potential accuracy and yield are reduced by human judgment errors. Visual grading rules are based on lumber surface characteristics that can affect strength, stiffness, and other factors. Knots can be readily identified in southern pine on the basis of their color, size, and geometry. The position of each knot within each piece varies, thereby making the understanding of its effects on mechanical properties very subjective. The American Society for Testing and Materials (ASTM D 4761 2013a) classifies knots into 10 different types, and each class of visual grading system follows standard rules for size and position.

Characterization of knots is especially important because they are the most numerous and severe defect in southern pine lumber (Divós and Tanaka 1997). The reduction in strength and stiffness associated with knots is often magnified by the grain deviation in the wood immediately surrounding knots (Karsulovic et al. 2000). The grain deviation associated with knots is often recognized as the most significant factor in the reduction of mechanical properties.

Since the 1960s, various technologies have been developed to improve grading processes. However, the wood industry in the United States has been slow compared to Europe, for example, to adopt the newer and more efficient grading technology. The overwhelming majority of the structural lumber produced in North America is still visually graded (US Census Bureau 2012). Machine stress rated (MSR) and machine-evaluated lumber (MEL) are the two mechanical grading systems available in North America.

MSR uses a nondestructive mechanical bending machine to evaluate the modulus of elasticity (MOE) of lumber. The strength of lumber is predicted on the basis of pre-established empirical relationships between modulus of rupture (MOR) and MOE. The accuracy of the machine evaluation is based on flatwise bending stiffness, and its quality control provides a prediction of strength based on the MOE. MEL is based on a parameter, often density, nondestructively determined by mechanical grading equipment. Its quality control is based on tests of tension parallel to the grain as the way to predict strength.

In recent years automated visual grading machines have been incorporated into sawmill production lines to improve grading quality and increase the yield of the grading process. The volume of mechanically graded lumber has increased during the past few decades (Galligan and McDonald 2000, Kretschmann 2010). As more mills adopt MSR technology, consumers continually educate themselves about advantages and disadvantages of new product choices. Given the rise in MSR technology shown in Figure 1 for the South, it appears that the market appreciates MSR lumber. Given the volume of southern pine lumber produced annually, improved grading technology and practices have significant economic impacts.

In the early 2010s, pine design values changed, but the visual characteristics remained constant; thus, there is a current and pressing need for the lumber industry to continue to develop and adopt cost-effective nondestructive testing (NDT) methods. The objective of this paper is twofold: (1) to investigate the effectiveness of using the longitudinal vibration method coupled with visual characteristics of lumber to evaluate the MOE of southern yellow pine 2 by 4 and 2 by 6 structural lumber, and (2) to build statistical models for predicting the bending MOE and MOR of southern pine lumber from a set of nondestructive variables from growth characteristics and longitudinal vibration parameters.

Materials and Methods

Materials

A total of 1,044 pieces of No. 2 southern pine lumber was obtained from retail stores for this study. The sampling was weighted according to the US regional production of southern pine per the in-grade program. More details about sampling methods for this study are described in França et al. (2018). The lumber was divided into two groups according to the cross-section dimensions: 542 pieces of 2 by 4 (net 38 by 89 mm) and 502 pieces of 2 by 6 (net 38 by 140 mm).

Visual characteristics

The lumber was stored in an unheated building until the visual characteristics were measured and then moved to an indoor area with a controlled environment (22°C and 61% relative humidity) before testing. A hygrometer was used to verify the conditioned indoor environment. To equalize the moisture content, all the lumber was stored indoors for about 90 days or until NDT was completed. All specimens were labeled with a unique number. A number was applied to each end, each with a different colored (green and blue) permanent marker for future reference. The distance from tension face and distance from green end were recorded for each coded knot.

The visual characteristics evaluated were ring width (RW), percentage of latewood (LW), maximum diameter of the estimated strength-reducing knot (KD), knot diameter ratio (KDR), and knot area ratio (KAR; Table 1). Measurements of RW and LW were determined on both ends of the specimen, and an average value for RW and LW was calculated for each piece.

RW was calculated by counting the number of the rings and dividing by the thickness or the width depending on the grain orientation of the piece (radial or tangential). Percentage of LW was determined using a 1 by 1 in. (2.54 by 2.54 cm) dot grid (Fig. 2). The LW is estimated by dividing the number of dots that fall on LW by the total number of dots in the grid. Both measurement techniques followed Southern Pine Inspection Bureau (SPIB) standard grading rules (SPIB 2014).

Table 1.—Visual characteristics evaluated.

Symbol	Parameter	Unit
RW	Ring width	mm
LW	Percentage of latewood	%
KD	Maximum diameter of the knot	mm
KDR	Knot diameter ratio	%
KAR	Knot area ratio	%

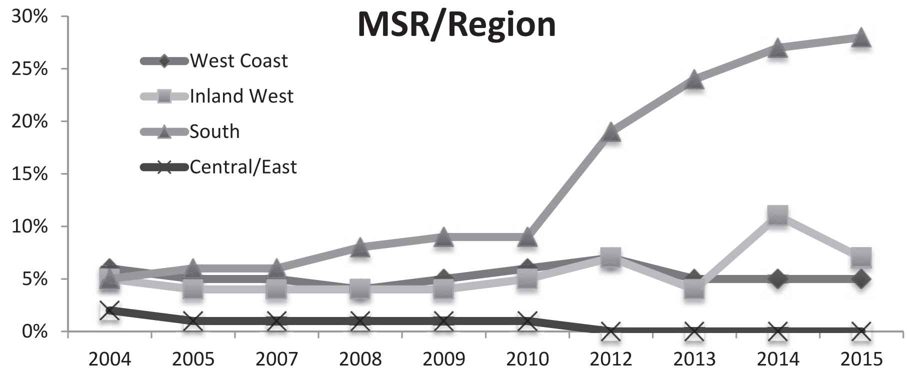

Figure 1.—Percentage of sawmills utilizing machine stress rated grading by geographic region (source: Random Lengths).

Knot measurements were collected as a way to potentially improve the accuracy of strength prediction. The weakest section of the piece inside the test span was considered to be the strength-reducing location per ASTM D 245 (ASTM 2011b).

The KD adopted in this study was the largest diameter measurement found for each knot used, and four measurements of length were collected for each knot (one on the longitudinal axis and one on the radial/tangential axis) on both sides of each piece, and recorded per ASTM D 4761 (ASTM 2013a).

KDR and KAR were selected on the basis of the literature review and used as a way to better understand the relationship between knots and mechanical properties (Grant et al. 1984, Divós and Tanaka 1997, Divós and Sismándy-Kiss 2010, Vega et al. 2011).

KDR is a knot measurement used for the evaluation of the effect of more than one knot in the same region of the piece, also called a cluster or combination knot (a type 10 knot per ASTM D 4761 [ASTM 2013a]). It takes into account the effect of knots and their concentration by the relation of the sum of the knots' diameter and the cross-section perimeter (Fig. 3). If two or more knots exist in any 15-cm-long section, they should be considered a cluster. KDR is determined by calculating the sum of the diameter of an individual knot or a cluster of knots and then dividing that sum by the perimeter of the cross-section (Eq. 1).

$$\mathrm{KDR} = \frac{(\mathrm{a} + \mathrm{b} + \mathrm{c})}{\mathrm{perimeter}} \tag{1}$$

KAR was calculated by projecting the knot(s) onto a cross-sectional plane. The KAR for each piece was calculated by dividing the total knot area by the cross-sectional area of the specimen (Eq. 2). If two or more knots exist in any 15-cm-long section it was adopted as the sum of the individual knots.

$$\mathrm{KAR} = \frac{\text{knot area}}{\text{cross-section area}} \tag{2}$$

NDT and physical properties

Physical properties (density and moisture content) and acoustic variables (longitudinal vibration frequency, dynamic modulus of elasticity [dMOE], and logarithmic decrement [LD]) were obtained for every piece. Density and NDT variables considered in the study are listed in Table 2.

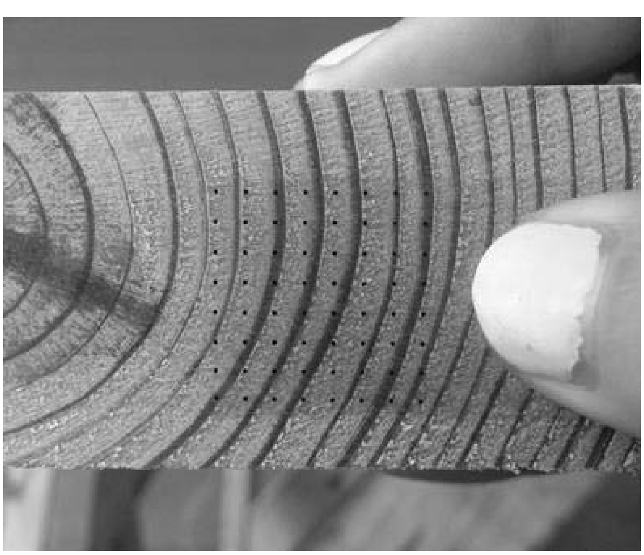

Figure 2.—Method of estimating percentage of latewood.

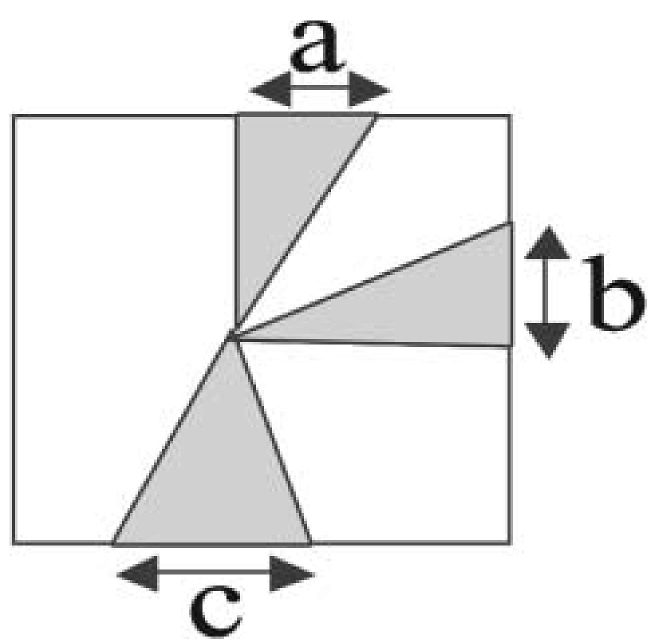

Figure 3.—Method for measuring knot diameter ratio (KDR).

Table 2.—Physical and nondestructive testing variables considered in the analysis.

Symbol	Definition	International System (SI) units
ρ	Density at 12% moisture content	kg m^{-3}
Flong	Longitudinal vibration frequency	Hz
dMOE	Dynamic modulus of elasticity	MPa
LD	Logarithmic decrement	—

For the longitudinal vibration test, two steel sawhorses were positioned at ¼ and ¾ the length to support an individual piece. A piece of foam was placed at the contact area between the sawhorse and specimen to dampen any interference of sawhorse vibration. An impact was applied with a hammer to the end of the test piece in the longitudinal direction per ASTM E 1876 (ASTM 2015c). A microphone was used to capture the vibration signal from the same end of the piece. A computer equipped with fast Fourier vibration analyzer software (Fakopp 2005) was used to receive vibration signals and calculate the longitudinal vibration frequency and LD for each piece tested.

dMOE of each specimen was determined from the first longitudinal vibration resonance frequency, length, and density of each piece using Equation 3, where E_L = dynamic MOE (MPa), ρ = density (kg m^{-3}), L = length (m), and f = first harmonic longitudinal vibration frequency (Hz).

$$E_L = \rho(Lf)^2 \tag{3}$$

The LD was collected in the longitudinal direction. LD is the parameter of the exponential covering curve over the sinusoidal wave curve formed by the lumber vibration, given by Equation 4 where LD = logarithmic decrement, β = the parameter of the exponential covering curve, and T = period of time. The LD of every piece was recorded in the database.

$$\mathrm{LD} = \beta T \tag{4}$$

Static bending test

Each piece was then destructively evaluated in edgewise bending by four-point static tests per ASTM D 198 (ASTM 2014d) to obtain the static MOE and MOR values. The bending span-to-depth ratio (17:1) was selected for every cross-section tested to match prior in-grade testing (Green et al. 1989). Thus, the possible influence of overhang (extra length) on the ultimate bending stress value was negligible and not considered in the results from static bending tests.

Cross-section measurements were collected in two locations on each side of each piece. The thickness and width of each piece were calculated as the average of the two measurements. Length was measured once on each piece. Weight was recorded using a conventional calibrated scale.

Statistical analysis

MOE and MOR were expressed as multiple linear functions of nondestructive properties and visual characteristics. Therefore, ordinary least square regression procedures were used for fitting models to predict MOE and MOR using the nondestructive variables and visual characteristics. The system of two equations for prediction of MOE (Eq. 5) and MOR (Eq. 6) is as follows:

$$\mathrm{MOE} = f(\mathrm{dMOE}, \mathrm{LD}, \mathrm{RW}, \mathrm{LW}, \mathrm{KT}, \mathrm{KAR}, \mathrm{KDR}, \rho) + \varepsilon_1 \tag{5}$$

$$\mathrm{MOR} = f(\mathrm{dMOE}, \mathrm{LD}, \mathrm{RW}, \mathrm{LW}, \mathrm{KT}, \mathrm{KAR}, \mathrm{KDR}, \rho) + \varepsilon_2 \tag{6}$$

where ε_1 and ε_2 are error terms for Equations 5 and 6, respectively.

For each linear regression, a set of variables was identified. Predictor variables were selected by statistical criteria (e.g., entry or removal criterion). In this study, the significance level to enter and significance level to stay were set to 0.15 and 0.05, respectively. Therefore, all variables that remained in the regression models after stepwise selections were found significant at the 0.05 level.

The models were evaluated on the basis of the multiple coefficients of determination (r^2), the root mean square error, the mean absolute error and error index of the predictions, and bias. For each regression model, the normality of distribution of residuals (observed-predicted) and multicollinearity were checked by using the Shapiro-Wilk test (Shapiro and Wilk 1965). SAS (SAS Institute Inc. 2013) was used for all statistical computations.

Results and Discussion

Strength-reducer identification

The knot or other characteristics within the testing span that was considered a strength-reducing characteristic was identified. If this was a knot, the diameter and position measurements were collected. The knot types identified and measured in this study are shown in Figure 4. Knot types 5, 6, and 7 listed in ASTM D 4761 (ASTM 2013a) were not found in the lumber specimens. Using these measurements and applying regular triangle and rectangle trigonometric equations, it was possible to estimate the KDR and KAR for each knot type on each piece.

Growth characteristics, NDT results, and physical and mechanical properties

The average moisture content of the pieces when tested was 11.4 percent. The mean, minimum, maximum, and coefficient of variation for each growth characteristic, physical property, and mechanical property for the 2 by 4 specimens are shown in Table 3. The mean RW was 5.98 mm. The minimum RW was 1.56 mm and the maximum was 14.82 mm. The percentage of LW ranged between 18 and 79 percent, with a mean of 44 percent. The mean values for density, MOE, and MOR were 548 kg m^{-3}, 11.1 GPa, and 57.4 MPa, respectively. The mean values for KD, KDR, and KAR were 28.1 mm, 26.4 percent, and 28.2 percent, respectively.

The mean, minimum, maximum, and coefficient of variation for each growth characteristic, physical property, and mechanical property for 2 by 6 specimens are shown in Table 4. The mean RW was 6.04 mm. The minimum RW was 1.73 mm and the maximum was 15.2 mm. The percentage of LW ranged between 18 and 82 percent, with a mean of 46 percent. The mean values for RW and LW were higher for 2 by 6 specimens. The mean value of density for

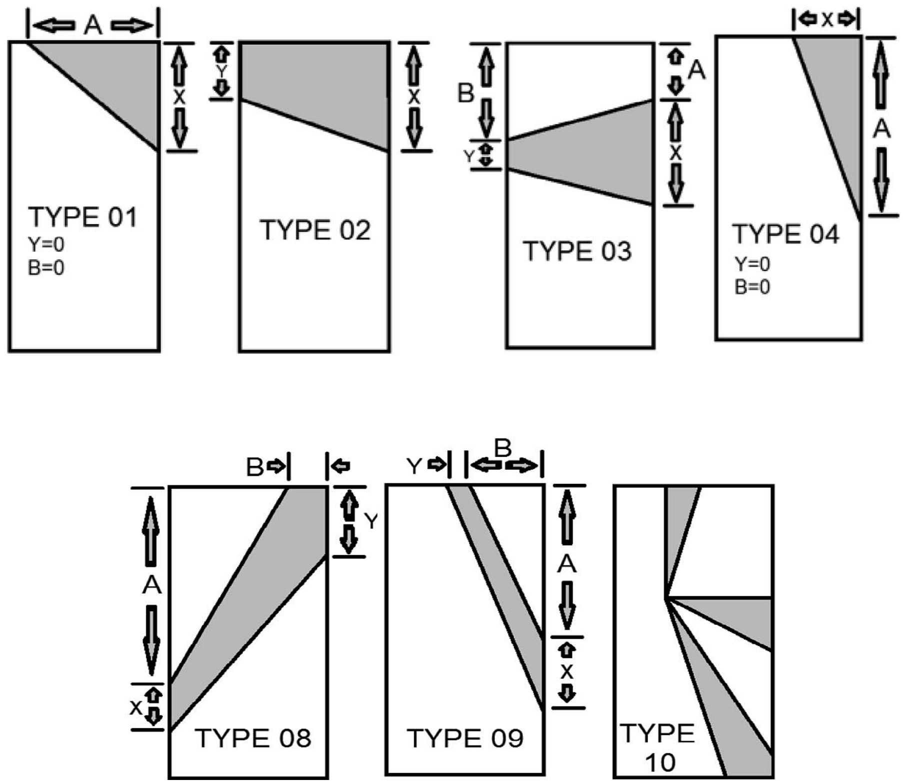

Figure 4.—Knot type descriptions and measurements collected.

Table 3.—Basic properties of the 2 × 4 specimens.

Variables	Unit	Mean	Min.	Max.	Coefficient of variation (%)
Ring width	mm	5.98	1.56	14.82	39.3
Latewood	%	43.95	18.75	78.91	27.6
Maximum knot diameter	mm	28.1	0	127.0	69.8
Knot diameter ratio	%	26.40	0	96.88	80.2
Knot diameter area	%	28.20	0	94.05	80.9
Density (moisture content = 12%)	kg m^{-3}	548	406	774	11.1
Longitudinal frequency	Hz	642	310	1043	26.6
Dynamic modulus of elasticity	GPa	11.73	3.95	21.42	25.5
Logarithmic decrement	—	33	10	79	27.9
Modulus of elasticity	GPa	11.07	3.78	19.14	24.9
Modulus of rupture	MPa	57.39	10.89	121.35	36.2

Table 4.—Basic properties of the 2 × 6 specimens.

Variables	Unit	Average	Min	Max	Coefficient of variation (%)
Ring width	mm	6.04	1.73	15.24	38.7
Latewood	%	45.86	18.75	82.03	24.4
Maximum knot diameter	mm	38.0	0	122.2	65.0
Knot diameter ratio	%	28.59	0	99.55	81.2
Knot diameter area	%	28.79	0	93.56	81.9
Density (moisture content = 12%)	kg m^{-3}	548	428	764	10.8
Longitudinal frequency	Hz	704	503	823	11.5
Dynamic modulus of elasticity	GPa	11.51	3.82	20.77	25.1
Logarithmic decrement	—	35	6	100	30.0
Modulus of elasticity	GPa	10.71	3.65	18.27	22.2
Modulus of rupture	MPa	48.41	7.70	99.25	36.4

2 by 6 was similar to the density of 2 by 4 lumber (548 kg m^{-3}). The mean values for MOE and MOR were 10.7 GPa and 48.4 MPa, respectively. The mean values for KD, KDR, and KAR were 38.0 mm, 28.59 percent, and 28.8 percent, respectively.

The mean MOE value found in this research exceeded the new published design value (9.7 GPa) and also met the previous SPIB design values (11.0 GPa; AFPA 2005, ALSC 2013). Johansson et al. (1992) found an average of 2.1 mm for RW on spruce from Europe, which is lower than the results found for both sizes studied in this research. Grant et al. (1984) studied the effects of knots and density on the bending strength of structural *Pinus radiata* timber, and found KAR values varying between 1 and 81 percent.

Coefficient of determination

Table 5 shows the coefficients of determination between stiffness and other properties for 2 by 4 and 2 by 6 southern pine lumber. All coefficients of correlation were significant ($P < 0.05$). dMOE and its related longitudinal frequency exhibited the highest correlations with MOE in both sizes. MOE was also correlated with density.

RW and LW exhibited moderate predictive ability for MOE and low predictive ability for MOR. The correlation between RW and MOE was slightly higher for 2 by 4 ($r^2 = 0.36$) than for 2 by 6 ($r^2 = 0.24$). The same happened with LW, where correlations between LW and MOE were slightly higher for 2 by 4 ($r^2 = 0.33$) than for 2 by 6 ($r^2 = 0.30$). The r^2 of the correlation between RW and MOR for 2 by 4 was 0.15, and for 2 by 6 was slightly higher (0.16). Hanhijärvi et al. (2005) studied the effect of RW on mechanical properties of pine lumber and found a r^2 of 0.40 for MOE and 0.34 for MOR. Johansson et al. (1992) found a correlation between RW and MOR of 0.21. Similar results were found in this study, where RW and LW exhibited multicollinearity with density. Wide and more frequent LW rings add weight and resistance to the material.

Correlations between knot measurements (KD, KDR, and KAR) and MOE were statistically significant yet low as expected, since knots are local defects having a greater effect on MOR. For 2 by 4 sample, the r^2 between KD, KDR, and KAR and MOE were 0.05, 0.13, and 0.08, respectively. For MOR, the r^2 between KD, KDR, and KAR were 0.10, 0.21, and 0.18, respectively. The r^2 between KD, KDR, and KAR and MOE for 2 by 6 lumber were 0.09, 0.13, and 0.10, respectively. For MOR, the r^2 for KD, KDR, and KAR was 0.21, 0.20, and 0.16, respectively. All correlations found for MOE and MOR on a 2 by 6 sample were slightly higher than the correlation found for a 2 by 4 sample. The knot measurements used in this study are suitable, but overall KDR exhibited better performance in both sizes when predicting MOR.

Density showed good predictive potential for stiffness, where the correlation for MOE and MOR of 2 by 4 (0.46 and 0.40, respectively) were higher than for 2 by 6 (0.36 and 0.36, respectively). These results are congruous with those of Hanhijärvi et al. (2005), who found a strong relationship between MOE and density in structural size of *Picea abies* and *Pinus sylvestris* timber. The authors also concluded that density was a moderate predictor of strength if used independently.

Overall, density was better related to strength when compared with all three knot measurements, but the values of the coefficients of determination were still moderate.

Table 5.—Coefficients of determination between stiffness and strength with other properties.

Variable	Coefficients of determination (r^2): Modulus of elasticity 2×4	2×6	Modulus of rupture 2×4	2×6
Ring width	0.360	0.235	0.147	0.169
Latewood	0.334	0.304	0.220	0.252
Knot diameter	0.052	0.092	0.095	0.209
Knot diameter ratio	0.127	0.127	0.210	0.197
Knot area ratio	0.081	0.102	0.184	0.162
Density	0.461	0.496	0.347	0.355
Longitudinal frequency	0.674	0.627	0.224	0.241
Dynamic modulus of elasticity	0.856	0.832	0.376	0.393
Logarithmic decrement	0.138	0.091	0.048	0.042

Table 6.—Regression model, coefficient of determination (r^2), standard error of the estimate, and improvement of the linear regression with modulus of elasticity (MOE) for 2×4 and 2×6 combined.

MOE	r^2	Standard error (MPa)	Improvement (%)
Knot diameter ratio (KDR)	0.127	2415.57	—
Density	0.472	1878.23	22.24
Dynamic MOE (dMOE)	0.843	1026.10	45.37
dMOE + density	0.846	1011.56	1.42
dMOE + density + KDR	0.847	1010.95	0.01

Table 7.—Regression model, coefficient of determination (r^2), standard error of the estimate, and improvement of the linear regression with modulus of rupture (MOR) for 2×4 and 2×6 combined.[a]

Bending strength (MOR)	r^2	Standard error (MPa)	Improvement (%)
Knot density ratio (KDR)	0.200	17.76	—
Density	0.334	16.20	8.78
Dynamic modulus of elasticity (dMOE)	0.372	15.73	2.90
dMOE + density	0.418	15.15	3.69
KDR + density	0.422	15.10	0.01
dMOE + KDR	0.429	15.00	0.01
dMOE + density + KDR	0.470	14.45	3.6
dMOE + density + KDR + latewood	0.471	14.15	0.01

[a] All correlations were significant ($P < 0.05$).

Divós and Sismándi-Kiss (2010) found similar strength prediction ability using density and KDR as independent variables ($r^2 = 0.50$). Nocetti et al. (2010) found a higher relationship between MOR and knot measurement compared with density studying pine structural timber (0.42 vs. 0.45).

The regression analysis between bending strength and independent variables shows that dMOE was the best single predictor of lumber stiffness and strength for both sizes included in this study, indicating a higher efficiency of vibration techniques over visual grading in regard to lumber

Table 8.—Summary of linear regression models and coefficients of determination (r^2) for modulus of rupture (MOR) from other authors using nondestructive testing (NDT) parameters only, and NDT combined with knots measurements.

Reference	Species	Model for MOR	Coefficient of determination (r^2)
Shmulsky et al. (2006)	Southern pine dowel	Dynamic modulus of elasticity (dMOE)	0.42
Yang et al. (2017)	Southern pine dimensional lumber	dMOE	0.28
Wright (2017)	Southern pine lumber	dMOE + knot area ratio (KAR)	0.69
Iniguez (2007)	*Pinus radiata*	dMOE + knot diameter ratio (KDR)	0.68
	Pinus sylvestris		
Vega et al. (2012)	Spanish chestnut	dMOE + maximum diameter + length	0.34
Divós and Sismándi-Kiss (2010)	Spruce, larch and pine	dMOE + logarithmic decrement + KDR + density	0.68
Nocetti et al. (2010)	Structural chestnut	dMOE + knot parameter	0.18
Hanhijärvi et al. (2005)	*Picea abies*	dMOE + density + KAR	0.65–0.77
	Pinus sylvestris		
Diebold et al. (2000)	Spruce	dMOE + X-ray (knots + density measurement)	0.66
	Pine		0.72
	Larch		0.53
	Douglas-fir		0.61

Table 9.—Linear regression models with the largest coefficient of determination (r^2) and smallest error of the estimate (μ) for dependent variables modulus of elasticity (MOE) and modulus of rupture (MOR).

	β_0	β_1	β_2	β_3	μ	r^2	Durbin-Watson
MOE = $\beta_0 + \beta_1$·dynamic MOE (dMOE) + μ	1,528.40	805.68			1,026.10	0.843	2.000
MOR = $\beta_0 + \beta_1$·dMOE + β_2·KDR + β_3·density + μ	−17.50	2.16	−0.22	0.09	14.45	0.471	1.819

strength prediction. Yang et al. (2015) studied the use of different NDT tools to predict MOE using different NDT methods on No. 2 southern pine lumber, and found a correlation of determination higher than the one found in this research ($r^2 = 0.92$). Similar results were found in previous studies (Piter et al. 2004, Ravenshorst et al. 2004, Hanhijärvi and Ranta-Maunus 2008, Divós and Sismándi-Kiss 2010). As Divós and Sismándi-Kiss (2010) found in their study of spruce, larch, and pine structural lumber, the LD showed no correlation on stiffness and strength.

Models for MOE and MOR prediction

Tables 6 and 7 show the regression model, coefficient of determination (r^2), and improvement of the linear regression for MOE and MOR on 2 by 4 and 2 by 6 samples. KDR was the only visual measurement used since it gave a slightly higher coefficient of correlation of MOE (0.13) and MOR (0.20) for both sizes tested. The variables chosen to estimate the improvement on prediction of MOE were KDR, density, and dMOE. For MOR we used the same variables listed for MOE, in addition to LW. RW was not added because this variable gave an improvement lower than 0.01 percent. All correlations were statistically significant ($P < 0.05$).

Several studies showed the benefit of combining different grading parameters (Diebold et al. 2000, Denzler et al. 2005, Hanhijärvi and Ranta-Maunus 2008). For MOE, the dMOE showed the higher improvement (45.4%), followed by density (22.2%). Combining dMOE with density, the model gives a 1.42 percent improvement on prediction of MOE. When KDR is added, the model improves 0.01 percent. Density gave the highest improvement on prediction of MOR (8.78%). The prediction of MOR increases 3.69 percent when dMOE and density are combined. The combination of dMOE, density, and KDR gave a 3.6 percent improvement on the prediction of MOR.

The prediction of lumber strength greatly improved when the three properties (dMOE, density, and knots) were combined to predict the strength. The results in this study are in agreement with results from other authors (Piter et al. 2004, Giudiceandrea 2005, Bacher 2008, Hanhijärv and Ranta-Maunus 2008). The use of a fourth independent variable (LW) did not improve predictability because of its collinearity with density.

Table 8 summaries regression models and coefficients of determination (r^2) for strength prediction using NDT methods only, and NDT combined with knots measurements from other authors. For all studies listed, dMOE was the best single predictor of MOR. For chestnut lumber, all studies listed show that the second-best predictor of MOR was the combination of visual parameters and dMOE. The r^2 value varies between the different researchers (0.18 – 0.72), which may be explained by differences in the materials and methods of each investigation. The result shows that the capability of prediction can be improved when two or more variables are added to the model. The regression equations with the best models to predict MOE and MOR are shown on Table 9. Models with independent variables whose addition did not improve the model are not shown.

Analysis of the residuals shows evidence of normality and homoscedasticity for MOE and MOR models, as well as the absence of autocorrelation according to the Durbin-Watson statistics (Figures 5 and 6). A straight line in Figures 4a and 5a indicates normality. In Figures 4b and 5b well-distributed points show evidence of homoscedasticity.

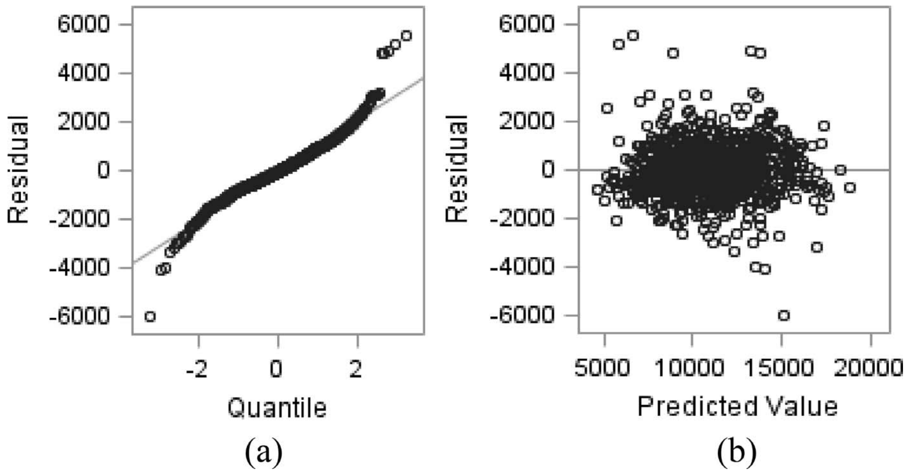

Figure 5.—Analysis of residuals of the linear regression model for the dependent variable modulus of elasticity: (a) normality of the residuals and (b) heteroscedasticity of the residuals.

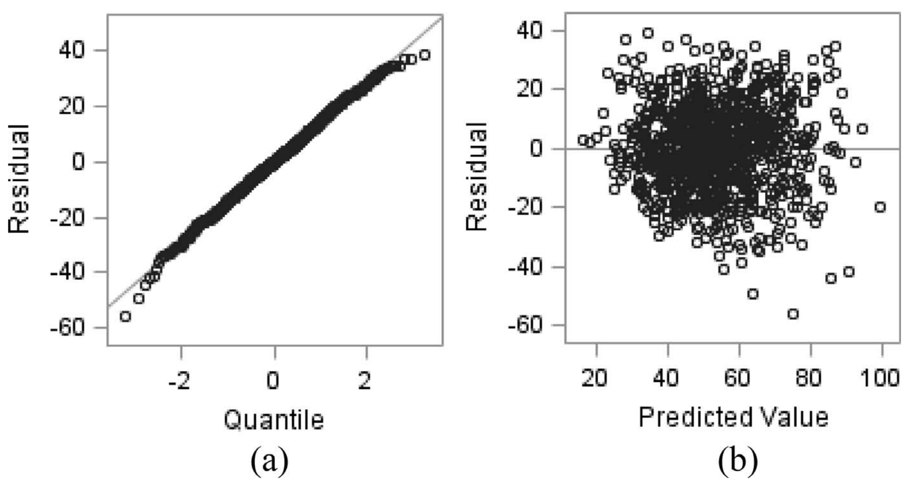

Figure 6.—Analysis of residuals of the linear regression model for the dependent variable modulus of rupture: (a) normality of the residuals and (b) heteroscedasticity of the residuals.

Conclusions

This study investigated the reliability of nine different parameters as bending stiffness and strength predictors. MOE and MOR were determined by static bending tests and longitudinal vibration, density, and three-knots measurements. The results of this study show that:

1. the 2 by 4 lumber had higher mean values of RW and LW than 2 by 6 lumber. There was no variation in density among sizes. The mean MOE values for both sizes tested were higher than the new design value, and met the previous design value for No. 2 southern pine lumber.
2. dMOE was the best single predictor of MOE and MOR, followed by density.
3. from all knot measurements tested, KDR was the best single predictor of MOE and MOR.
4. on the basis of r^2 analysis, the best combination to predict MOE was dMOE and density, with an improvement of 1.42 percent. The combination that gave a higher improvement on prediction of MOR was dMOE, density, and KDR, with an improvement of 3.6 percent.
5. compared with visual grading, the combination of visual parameters and NDT methods can allow structural lumber to be upgraded to higher strength classes more reliably. This combination can improve the quality of the lumber produced in southern US region. During the grading process, this information can be used to downgrade the weaker pieces.

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