USE OF LONGITUDINAL VIBRATION AND VISUAL CHARACTERISTICS TO PREDICT MECHANICAL PROPERTIES OF NO. 2 SOUTHERN PINE 2 × 8 AND 2 × 10 LUMBER

*F. J. N. França**

Assistant Research Professor
E-mail: fn90@msstate.edu

T. S. F. A. França†

Assistant Professor
E-mail: tsf97@msstate.edu

R. D. Seale

Warren S. Thompson Professor
E-mail: rds9@msstate.edu

R. Shmulsky†

Professor and Department Head
Department of Sustainable Bioproducts
Mississippi State University
Mississippi State, MS 39762-5724
E-mail: rs26@msstate.edu

(Received February 2020)

Abstract. The objective of this study was to evaluate the accuracy of single MOE and MOR and combined mechanical properties with visual characteristics to improve the prediction of 2 × 8 and 2 × 10 No. 2 southern pine lumber. This study evaluated the following variables: nondestructive tests, knots (knot diameter ratio [KDR] and knot area ratio), density, and mechanical properties (stiffness [MOE] and strength [MOR]). A total of 486 pieces were used, and linear regression models were constructed using stepwise selects to determine the best variables to estimate the MOE and MOR of southern pine lumber. The best single predictor for MOE and MOR was dynamic MOE (dMOE) followed by density. Among the two knot measurement methods used, the KDR best predicted stiffness and strength. For predicting the MOE, the variables dMOE and density were the best combination for 2 × 8 samples, and the combination for 2 × 10 samples was dMOE, density, and KDR. The results showed that the addition of knot measurements to the models is able to improve the prediction of mechanical properties.

Keywords: Knots, dimensional lumber, strength, stiffness, statistical models.

INTRODUCTION

An accurate knowledge of mechanical properties of structural lumber is necessary for the proper and efficient use of the lumber. Different from other construction materials, wood is produced by a living tree and, as a result, is highly variable because of the environment, genetics, and growth conditions (Panshin and De Zeeuw 1980).

To stay within desirable design limits, the use of lumber in structures requires knowledge of the strength and stiffness properties of the lumber by controlling defects. Visual grading of structural lumber is the oldest method, and it remains the most used method for prediction of mechanical properties of wood in the United States.

A simple and inexpensive solution to minimize the variability of the material is to sort pieces with similar mechanical properties into categories called stress grades. The base of stress grades is

* Corresponding author
† SWST member

Wood and Fiber Science, 52(3), 2020, pp. 280-291
https://doi.org/10.22382/wfs-2020-026

that mechanical properties of lumber are different from mechanical properties of clear wood because of the effect of growth characteristics (knots, slope of grain, checks and splits, shake, density, decay, heartwood and sapwood, pitch pockets, and wane) on properties. These stress grades can be characterized by one or more visual or mechanical sorting criteria, a set of properties for engineering design, or a unique grade name (Kretschmann 2010).

Southern pine species are the most important softwood for lumber production in the United States. The southeastern region is considered a very productive forested area, and the lumber production can be traced back over 150 yr. Around 60% of the wood used in the United States and 15% of the wood consumed globally is produced in this region (Wear and Greis 2002; McKeand et al 2003; Cunningham et al 2008). Southern pine is used for residential construction because it has good mechanical properties (with wide range of strength and stiffness properties to be applied in many products), dries fast, and is easily treated. Southern pine wood products make a significant contribution to the economy of the region (AWC 2012; Coyle et al 2015).

Visual assessment of structural lumber is the most widely used method for grading structural lumber in the United States and is founded on the following: 1) the knowledge of the clear wood physical and mechanical properties of a species, or combination of species, and 2) the estimation of the effects various characteristics (tree growth related—knots, the presence of juvenile or reaction wood, and density; manufacturing related—splits, checks wane, and slope of grain) have on mechanical properties (Iniguez et al 2007).

Direct application of the visual grading method, however, without adequate verification of its accuracy by the testing of full-sized, graded specimens has been under question for some years. Effects of density and, in particular, knot type and size on the strength of full-sized specimens are therefore of significance in the resolution of these arguments (Grant et al 1984).

Because of a variety of factors, visual assessments do not result in the strongest predictors of the strength properties of structural lumber. For example, the correlation between knot size and strength varies with species depending on the knot location relative to the load applied and to the way in which the effect on strength is evaluated. Nondestructive tests (NDTs) are used to assist in predicting the strength properties of structural lumber. The NDT is able to improve the prediction of the strength properties of structural lumber (Ross 2015).

Machine grading systems, including machine stress rating and machine evaluated lumber technologies, are also in use in the United States and other countries. Flatwise bending, transverse vibration, and acoustic nondestructive testing techniques are the foundation for many of the commercially available machine grading technologies (Hoyle 1968; Ross 2015). Machine grading systems rely on statistical relationships between a nondestructive parameter, such as frequency of vibration, and static mechanical properties.

Because of the advancement in technologies and changes in forest management, improvement of the lumber grading system is required and more information on NDT accuracy and its relationship with visual characteristics of wood are still needed. The economic impact is significant when prediction of mechanical properties of lumber is improved. Thus, the objectives of this study were to define and measure visual variables in No. 2 2×8 and 2×10 structural lumber, determine the NDT and visual characteristics parameters that provide the best prediction of static bending strength and the MOE, and use multivariate statistical methods to delineate correlations among principal components to identify the relationships between all variables evaluated.

MATERIALS AND METHODS

For this study, 486 specimens of southern pine No. 2 lumber were obtained from retail stores across the southeastern region. The lumber was divided into two groups according to the cross-section dimensions (Table 1). Before testing, all

Table 1. Summary of sample size and dimensions of No. 2 2 × 8 and 2 × 10 southern pine lumber samples.

Nominal lumber size	*N*	Width (mm)	Depth (mm)	Length (m)
2 × 8	363	38	184	3.66
				4.27
				4.88
2 × 10	123	38	235	4.27
				4.88

specimens were stored in a controlled environment with 22°C and 61% RH. The average MC of the pieces when tested was 11.3%. Each sample was labeled with a unique number, and each end received different colors (green and blue) for future reference. In addition, the distance from the green end was recorded and the tension face from each knot coded.

Visual Characteristics

Visual characteristics evaluated in this study included ring width (RW), percentage of latewood (LW), knot diameter ratio (KDR), and knot area ratio (KAR). Measurements of RW and LW were determined on both ends of the lumber specimens, and an average value for RW and LW was calculated for each piece following the Southern Pine Inspection Bureau (SPIB) standard grading rules (SPIB 2014). More details in the methodology for RW and LW have been described in França et al (2018).

To potentially improve the strength prediction capability of the models used in this study, knots inside the test span, which was the weakest section of the lumber piece, were considered as the strength reducer characteristic and classified according to the ASTM D 245 (2015a).

Based on other studies, two different methods of knot evaluation were used: KDR) and KAR (Grant et al 1984; Divós and Tanaka 1997; Divós and Sismándy-Kiss 2010; Vega et al 2011). The KDR evaluates the effect of more than one knot in the same region of the selected piece (Fig 1). This knot type is also called a cluster or combination knot and in the ASTM D 4761 (2019b) standard and classified as "type 10 knot"—two or more knots existing in any 15-cm long section (Fig 2). This measurement takes into account the effect of knots and their concentration by the relation of the sum of knot diameter and the cross-section perimeter. Determination of the KDR is shown in Eq 1.

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

The KAR is the area a knot fills up within the piece, expressed in percentage. In this study, the KAR was calculated by dividing the total knot area by the cross-sectional area of the specimen (Eq 2). For a type 10 knot (cluster knot), the sum of the individual knot KAR was adopted.

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

NDT and Physical Properties

Density (ρ), MC, longitudinal vibration frequency, dynamic MOE (dMOE), and logarithmic decrement (LD) were obtained and recorded for every specimen The longitudinal vibration test was conducted using two steel sawhorses, positioned at ¼ and ¾ the length to support an individual piece. To reduce interferences of sawhorse

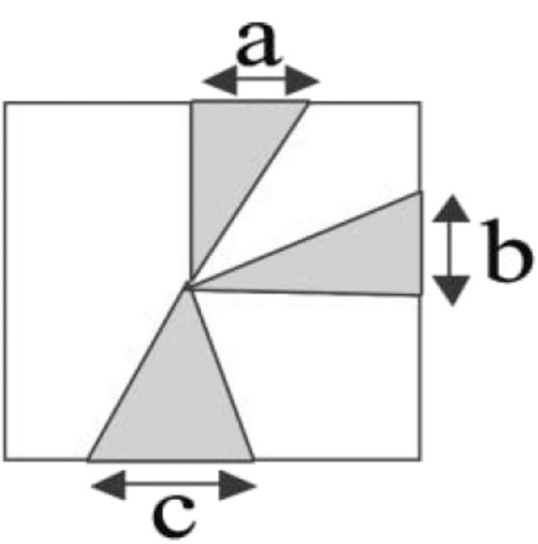

Figure 1. Knot diameter ratio measurement.

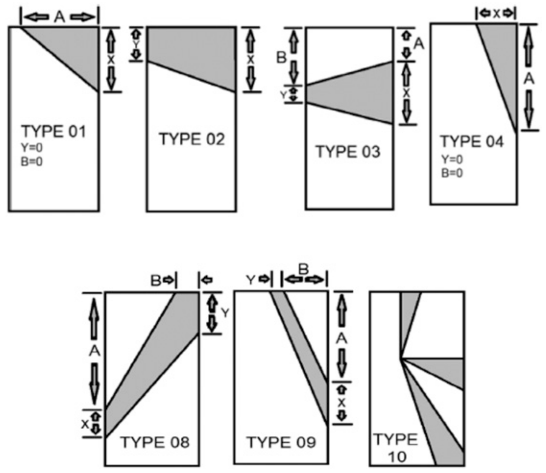

Figure 2. Description of knot measurement for different knot type.

vibration, a piece of foam was placed at the contact area between the sawhorse and specimen. 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. To calculate the longitudinal vibration frequency and LD for each piece tested, Fourier vibration analyzer software (Fakopp 2005) was used. Based on the longitudinal vibration information, length, and density of each piece, the dMOE was determined (Eq 3) as follows:

$$E_L = \rho \cdot (L \cdot f)^2, \tag{3}$$

where E_L is the dMOE (MPa), ρ is the density (kg m^{-3}), L is the length (m), and f is the first harmonic longitudinal vibration frequency (Hz). The LD was collected in the longitudinal direction on every lumber specimen. This parameter is the exponential covering curve over the sinusoidal wave curve formed by the lumber vibration (Eq 4).

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

where LD is the logarithmic decrement, β is the parameter of the exponential covering curve, and T is the period of time.

Static Bending Test

After NDT measurements, the static MOE and MOR values were obtained for all specimens via four-point static tests in edgewise bending using a span-to-depth ratio of 17:1 per ASTM D 198 (2015d), where the ratio span was 3.13 m for 2 × 8 and 3.99 m for 2 × 10. The rate of loading followed ASTM D 4761 (2019b).

Statistical Analysis

Statistical analyses and associated graphs were completed according to ASTM D 2915 (2017e) using SAS version 9.4 (SAS Institute 2013). The variables MOE and MOR were used as multiple linear functions of NDT properties and visual characteristics. To predict the MOE and MOR using NDT variables and visual characteristics, ordinary least square regression procedures were used for fitting models. The following equations were used to predict the MOE (Eq 5) and MOR (Eq 6):

Table 2. Basic properties of the 2 × 8 pieces.

Variable	Mean	Minimum	Maximum	C.V (%)[a]
Ring width (mm)	5.59	1.34	14.19	57.44
Latewood (%)	43.18	21.09	76.56	22.23
Knot diameter ratio (%)	28.31	0	98.57	86.42
Knot diameter area (%)	29.22	0	97.84	87.77
Density (MC = 12%) ($kg \cdot m^{-3}$)	540	427	726	9.50
Longitudinal frequency (Hz)	530	333	710	15.38
Dynamic MOE (GPa)	10.61	4.78	17.93	24.61
Logarithmic decrement	0.037	0.009	0.333	50.30
MOE (GPa)	10.58	5.14	16.70	21.17
MOR (MPa)	39.60	9.55	74.04	32.55

[a] Coefficient of variation.

Table 3. Basic properties of the 2 × 10 pieces.

Variable	Average	Minimum	Maximum	C.V (%)[a]
Ring width (Mm)	6.64	1.36	19.05	32.29
Latewood (%)	44.38	25.78	78.91	27.46
Knot diameter ratio (%)	15.50	0	99.71	79.41
Knot diameter area (%)	18.54	0	98.99	81.36
Density (MC = 12%) ($kg \cdot m^{-3}$)	552	441	740	56.99
Longitudinal frequency (Hz)	483	632	305	12.83
Dynamic MOE (GPa)	10.55	4.06	20.22	26.73
Logarithmic decrement	0.036	0.008	0.88	29.50
MOE (GPa)	10.45	4.35	18.48	23.00
MOR (MPa)	42.77	8.11	90.79	36.35

[a] Coefficient of variation.

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

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

The variables were selected using statistical criteria (eg entry or removal criterion), and the selected variables were used in each linear regression. The significance level to enter and a significance level to stay were set to 0.15 and 0.05, respectively. After stepwise selections, all variables that remained in the regression models were found to be significant at the 0.05 level.

Coefficients of determination (r^2), the root mean square error, the mean absolute error and error index of the predictions, and bias were used to evaluated the models. In addition, the normality of distribution of residuals (observed-predicted) and multicollinearity for each regression model were checked by using the Shapiro–Wilk test (Shapiro and Wilk 1965).

Table 4. Coefficients of determination between stiffness and strength with other properties.

	Coefficients of determination (r^2)			
	MOE		MOR	
Variable	2 × 8	2 × 10	2 × 8	2 × 10
Ring width	0.10	0.17	0.03	0.06
Latewood	0.20	0.23	0.07	0.08
Knot diameter ratio	0.03	0.07	0.08	0.22
Knot area ratio	0.03	0.04	0.05	0.16
Density	0.41	0.42	0.13	0.21
Longitudinal frequency	0.30	0.31	0.02	0.07
Dynamic MOE	0.81	0.75	0.15	0.20
Logarithmic decrement	0.02	0.10	0.01	0.07

RESULTS AND DISCUSSION

Basic Properties

In this study, knot types 5, 6, and 7 listed in ASTM D 4761 (ASTM 2019b) were not found in 2 × 8 and 2 × 10 specimens. Tables 2 and 3 show the result summary for each growth characteristic, and physical and mechanical properties for specimens tested. As expected, higher RW, LW, and ρ values were found for 2 × 10 samples (6.64 mm, 44.38%, 552 $kg \cdot m^{-3}$, respectively) than 2 × 8 (5.59 mm, 43.18%, 540 $kg \cdot m^{-3}$, respectively). Similar MOE values were found for both 2 × 8 (10.45 GPa) and 2 × 8 samples (10.58GPa), whereas MOR value for 2 × 10 (42.77 MPa) was higher than that for 2 × 8 samples (39.60 MPa).

The RW values found in this research are higher than the values reported by França et al (2018) on No. 2 southern pine 2 × 4 and 2 × 6 lumber (6 mm). In addition, the results show that the mean MOE value found in this study exceeded the new published design value (9.7 GPa) and met the previous SPIB design values (11.0 GPa; AFPA 2005; ALSC 2013).

The overall results for the KDR and KAR for both dimensional sizes tested are 21.9% and 38.04%, respectively. Higher values of the KDR and KAR were found for 2 × 8 samples (28.31% and 29.22%, respectively) than for 2 × 10 samples

Table 5. Regression model, coefficient of determination (r^2), standard error of the estimate, and improvement of the linear regression with the MOE for 2 × 8.

MOE	r^2	SE (MPa)	Improvement (%)
Knot diameter ratio (KDR)	0.03	2213.2	—
Density	0.41	1728.7	21.9
Dynamic MOE (dMOE)	0.81	986.3	42.9
dMOE + density	0.82	958.2	2.8
dMOE + density + KDR	0.82	959.4	−0.1

All regressions were significant ($P < 0.05$).

(15.5% and 18.54%, respectively). A study conducted by Grant et al (1984) on the effects of knots and density on bending properties of structural *Pinus radiata* timber found KAR values varying between 1 and 81%, whereas values found by França et al (2019b) for 2 × 4 and 2 × 6 lumber No. 2 southern pine lumber varied between 0 and 99%, with averages equal to 26% for the KDR and 29% for the KAR.

Coefficient of Determination

Table 4 shows the coefficients of determination between stiffness (MOE) and other properties for 2 × 8 and 2 × 10 southern pine lumber. All coefficients of correlation were significant at $P < 0.05$.

A moderate predictive ability for the MOE was exhibited by RW and LW variables, and a low predictive ability when tested for the MOR. Results for the correlation between RW and the MOE, and between LW and MOE were slightly lower for 2 × 8 ($r^2 = 0.10$ and $r^2 = 0.20$, respectively) than for 2 × 10 ($r^2 = 0.17$ and $r^2 = 0.23$, respectively). Johansson et al (1992) found a similar correlation between RW and the MOR of 0.21 for stress-graded spruce timber obtained from Sweden and German. The effect of RW on mechanical properties of pine lumber was studied by Hanhijärvi et al (2005), and the results were higher than those of the present study ($r^2 = 0.40$ for MOE; $r^2 = 0.34$ for MOR), and França et al (2019b) also found slightly higher r^2 between RW and MOE for 2 × 4 and 2 × 6 No. 2 southern pine lumber ($r^2 = 0.36$ and $r^2 = 0.24$, respectively). RW and LW are important measurements for growth characteristics. Density was a more consistent variable for this study on predicting the MOE and MOR.

Statistically significant correlations between knot measurements (KDR and KAR) were found for the MOE and MOR. All correlations found for the MOE and MOR on 2 × 10 samples were higher than the correlation found for a 2 × 8 lumber. This difference is due to the longer length of lumber pieces in 2 × 8 and the larger bending test span in the 2 × 10 lumber test. In static bending, there is a larger change for the failure to occur if a knot or other growth characteristic is located between the load heads.

The r^2 between the KDR and KAR and MOE for 2 × 8 samples were slightly lower ($r^2 = 0.03$ for both knot measurements) than MOR ($r^2 = 0.08$ for KDR, and $r^2 = 0.05$ for KAR). The same trend was found for 2 × 10 lumber, where the r^2 between KDR, and KAR and MOE lumber was lower ($r^2 = 0.07$ and $r^2 = 0.04$, respectively) than MOR ($r^2 = 0.22$ for KDR, and $r^2 = 0.16$ for KAR). The low correlation was expected for the MOE, and it is explained because knots are local defects and have a greater effect on the MOR, while MOE is a global property. Both knot measurement methods used in this study are suitable. However,

Table 6. Regression model, coefficient of determination (r^2), standard error of the estimate, and improvement of the linear regression with the MOE for 2 × 10.

MOE	r^2	Standard error (MPa)	Improvement (%)
Knot diameter ratio (KDR)	0.07	1924.8	—
Density	0.42	1841.3	4.3
Dynamic MOE (dMOE)	0.75	1208.2	34.4
dMOE + density	0.76	1182.9	2.2
dMOE + density + KDR	0.79	1128.6	4.6

All regressions were significant ($P < 0.05$).

Table 7. Regression model, coefficient of determination (r^2), standard error of the estimate, and improvement of the linear regression with the MOR for 2 × 8.

Bending strength (MOR)	r^2	Standard error (MPa)	Improvement (%)
Knot diameter ratio (KDR)	0.08	12.40	—
Density	0.13	12.06	2.7
Dynamic dMOE	0.15	11.88	1.5
dMOE + density	0.17	11.74	1.2
KDR + density	0.18	11.70	0.3
dMOE + KDR	0.20	11.58	1.0
dMOE + density + KDR	0.22	11.45	1.1
dMOE + density + KDR + latewood	0.22	11.47	−0.2

All regressions were significant ($P < 0.05$).

the KDR exhibited better performance in both sizes when predicting the MOR.

The correlation between density with the MOE and MOR was higher for 2 × 8 (0.42 and 0.21, respectively) than that for 2 × 10 (0.41 and 0.13, respectively). This variable showed good predictive potential for stiffness. Similar results were found by Hanhijärvi et al (2005) when studying the relationship between the MOE and density in the structural size of *Picea abies* and *Pinus sylvestris* timber. The authors also classified density as a moderate predictor of strength (MOR) if used independently. Although studies indicated density as a better predictor for strength than the KDR and KAR, the coefficients of determination values were still moderate.

Among the variables analyzed, dMOE was the best single predictor of lumber stiffness for both sizes in this study ($r^2 = 0.81$ for 2 × 8 and $r^2 = 0.75$ for 2 × 10), and low correlations were found for strength, where correlation for 2 × 10 ($r^2 = 0.21$) was slightly higher than 2 × 8 ($r^2 = 0.13$). Yang et al (2015) and França et al (2018) investigated the ability of different NDT tools on predicting the MOE on No. 2 southern pine lumber and found a correlation of determination higher than the one found in this research.

The best strength predictor was the KDR in 2 × 10 ($r^2 = 0.22$). The lower correlation values in 2 × 8 ($r^2 = 0.16$) for knot evaluation was not as effective as on 2 × 10 because of the knot position of samples during bending tests. This result indicates the importance of knot evaluation and potential this variable has to increase the prediction of lumber strength. Similar results were found by Divós and Sismándy-Kiss (2010) using density and the KDR as independent variables ($r^2 = 0.50$). Nocetti et al (2010) studied pine structural timber and found a slightly higher relationship between the MOR and knot measurement ($r^2 = 0.42$) than with density ($r^2 = 0.45$).

Models for MOE and MOR Prediction

After evaluating the coefficient of determination, variables with higher correlations were chosen for

Table 8. Regression model, coefficient of determination (r^2), standard error of the estimate, and improvement of the linear regression with the MOR for 2 × 10.

Bending strength (MOR)	r^2	Standard error (MPa)	Improvement (%)
Dynamic dMOE	0.20	13.93	—
Density	0.21	13.89	0.4
Knot diameter ratio (KDR)	0.22	13.81	0.5
dMOE + density	0.25	13.58	1.7
KDR + density	0.37	12.47	8.2
dMOE + KDR	0.37	12.42	0.4
dMOE + density + KDR	0.40	12.17	2.0
dMOE + density + KDR + latewood	0.40	12.21	−0.3

All regressions were significant ($P < 0.05$).

Table 9. Summary of linear regression models and coefficients of determination (r^2) for the 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 dMOE	0.42
Yang et al (2017)	Southern pine dimensional lumber	dMOE	0.28
Wright (2015)	Southern pine lumber	dMOE + knot area ratio (KAR)	0.69
Iniguez et al (2007)\	*Pinus radiata* *Pinus sylvestris*	dMOE + knot diameter ratio (KDR)	0.68
Vega et al (2011)	Spanish chestnut	dMOE + maximum diameter + length	0.34
Divós and Sismándy-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* *Pinus sylvestris*	dMOE + density + KAR	0.65-0.77
Diebold et al (2000)	Spruce	dMOE + X-ray (knots + density measurement)	0.66
	Pine		0.72
	Larch		0.53
	Douglas-fir		0.61
França et al (2019b)	Southern pine lumber	dMOE + KDR + density	0.47

the models to improve the prediction of the MOE and MOR. The results for the regression model, coefficient of determination (r^2), and improvement of the linear regression for the MOE on 2 × 8 and 2 × 10 pieces for the MOE are shown in Tables 5 and 6 The variables selected for the MOE included the KDR, density, and dMOE. For the MOR, all variables used for the MOE were kept and LW was added. Because RW and the KAR showed low correlations, these variables were left out from the models for both sizes tested. All correlations were statistically significant ($P < 0.05$).

The dMOE showed higher improvement on both sizes for the MOE, and 2 × 8 showed a higher improvement than 2 × 10 (42.9% vs 34.4%, respectively). Density had the second best improvement, and the improvement for 2 × 8 was much higher than that for 2 × 10 (21.9% vs 4.3%, respectively). Combining dMOE with density, the model gives a similar improvement on prediction of the MOE for both sizes (2 × 8 = 2.8% and 2 × 10 = 2.2%, respectively). The addition of the KDR in the model provided improvements for 2 × 10 and no improvement for prediction of the MOE on 2 × 8 (4.6% vs −0.1%, respectively).

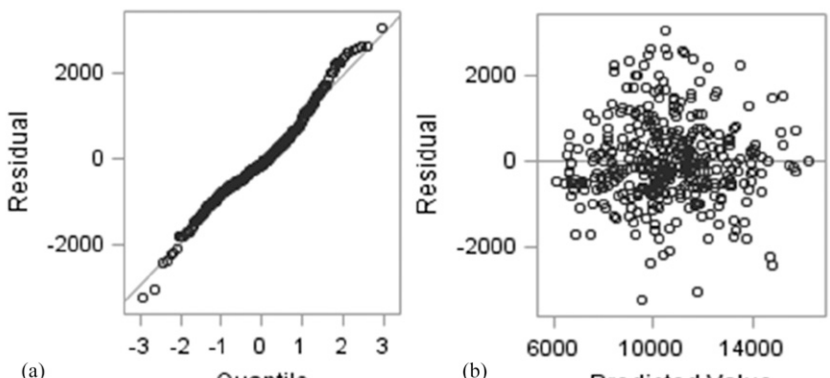

Figure 3. Analysis of residual of the linear regression model for the dependent variable MOE: (a) normality of the residuals and (b) heteroscedasticity of the residuals for 2 × 8 pieces.

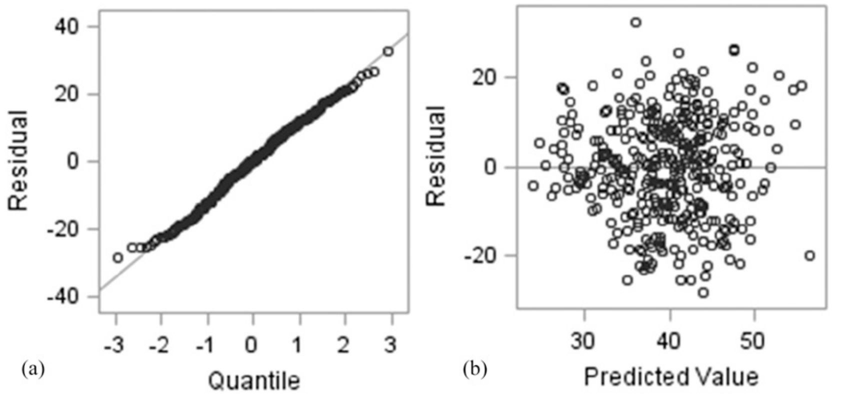

Figure 4. Analysis of residuals of the linear regression model for the dependent variable MOR: (a) normality of the residuals and (b) heteroscedasticity of the residuals for 2 × 8 pieces.

Tables 7 and 8 show the results for the regression model, coefficient of determination (r^2), and improvement of strength added the linear regression for the MOR on 2 × 8 and 2 × 10 southern pine lumber samples. Good improvements are obtained when dMOE, density, and knot properties are added to the models. On 2 × 8 specimens, density gave the highest improvement on prediction of the MOR (2.7%) followed by dMOE (1.5%). When dMOE and density are combined, the prediction of the MOR increases 1.2%. The combination of dMOE + KDR and dMOE + density + KDR gave similar improvement to the models (1.0% and 1.1%). For 2 × 10 samples, the highest improvement on prediction of the MOR was with the combination of KDR + density (8.2%) followed by dMOE + density + KDR (2.0%). For both sizes, adding LW in the models showed no improvement on prediction of the MOR because of its collinearity with density.

The results in this study are similar to the results from the literature. Piter et al (2004) studied single and combined parameters of *Eucalyptus grandis* timber, and the highest correlation with strength were obtained through the combination of the MOE, density, and knot measurements. Bacher (2008) also achieved high prediction of strength, stiffness, and density when visual characteristic measurements were combined to the models. Other studies also confirm the benefit and importance of combining different grading

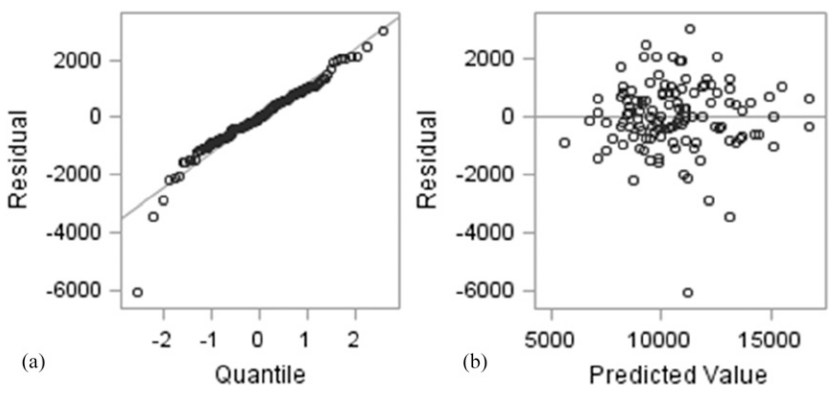

Figure 5. Analysis of residual of the linear regression model for the dependent variable MOE: (a) normality of the residuals and (b) heteroscedasticity of the residuals for 2 × 10 pieces.

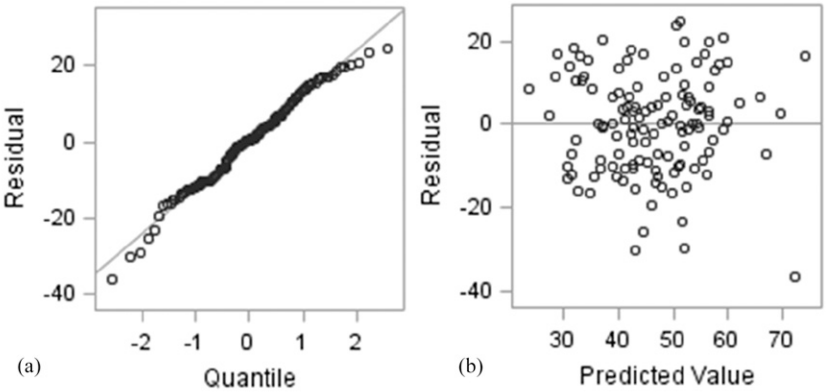

Figure 6. Analysis of residuals of the linear regression model for the dependent variable MOR: (a) normality of the residuals and (b) heteroscedasticity of the residuals for 2 × 10 pieces.

parameters on prediction of the MOR (Diebold et al 2000; Denzler et al 2005; Hanhijärvi and Ranta-Maunus 2008; Hanhijärvi A, Ranta-Maunus 2008; França et al 2019b).

Table 9 shows results of regression models and coefficients of determination (r^2) for strength prediction using the NDT only and combination of the NDT with knot measurements from other studies. The r^2 values presented from previous studies vary from 0.18 to 0.72, and this variation is explained to be due to the differences within materials and methods used in each investigation. All studies indicated dMOE as the best single predictor of the MOR, and models with visual parameters combined with dMOE yielded the highest correlation on prediction of the MOR.

Figures 3-6 show the analysis of the residuals with evidence of normality and homoscedasticity for the MOE and MOR models, as well as the absence of autocorrelation according to the Durbin–Watson statistics. In Figs 3(a), 4(a), 5(a) and 6(a), a straight line indicates normality, and the well-distributed points in Figs 3(b), 4(b), 5(b) and 6(b) show evidence of homoscedasticity.

CONCLUSIONS

The efficacy of using single and combination of nine parameters as bending stiffness and strength predictors of 2 × 8 and 2 × 10 No. 2 southern pine lumber was investigated in this study. The results show the importance of ongoing research on investigating the capability of improving prediction of the MOE and MOR when two or more variables are added to the models.

Higher mean values of RW and LW were found for 2 × 10 lumber, and no variation was found 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.

The best single predictor of the MOE and MOR was dMOE followed by density. When comparing the two knots methods tested in this study, the KDR was the best single predictor of stiffness and strength. The variables dMOE and density were the best combination for prediction of the MOE in 2 × 8 samples, whereas the combination of dMOE, density, and the KDR yielded the better correlation in 2 × 10 samples.

ACKNOWLEDGMENTS

The authors acknowledge the support of the US Department of Agriculture (USDA) Research, Education, and Economics; Agriculture Research Service; Administrative and Financial Management; Financial Management and Accounting Division; and Grants and Agreements Management Branch under Agreement No. 58-0202-4-001. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the view of the USDA. The authors acknowledge the support from the USDA Forest Service Forest Products Laboratory in Madison, WI, as a major contributor of technical assistance, advice, and guidance to this research. This article was approved as journal article SB 970 of the Forest & Wildlife Research Center, Mississippi State University.

REFERENCES

American Forest and Paper Association (AFPA) (2005) National design specification (NDS) for wood construction with commentary and supplement: Design values for wood construction 2005 edition. American Forest & Paper Association, Washington, DC.

American Lumber Standards Committee (ALSC) (2013) American lumber standard committee board of review: Board of review minutes. American Lumber Standards Committee, Germantown, MD.

ASTM (2015a) D 245: Standard practice for establishing structural grades and related allowable properties for visually graded lumber. Annual Book of ASTM Standards, West Conshohocken, PA.

ASTM (2019b) D 4761: Standard test methods for mechanical properties of lumber and wood-base structural material. Annual Book of ASTM Standards, West Conshohoken, PA.

ASTM (2015c) E 1876: Standard test method for dynamic Young's modulus, shear modulus, and Poisson's ratio by impulse excitation of vibration. Annual Book of ASTM Standards, West Conshohoken, PA.

ASTM (2015d) D 198: Standard test methods of statics of lumber in structural sizes. Annual Book of ASTM Standards, West Conshohoken, PA.

ASTM (2017e) D 2915: Standard practice for sampling and data-analysis for structural wood and woodbased products. Annual Book of ASTM Standards, West Conshohoken, PA.

American Wood Council (AWC) (2012) National design specification® (NDS®) for wood construction. AWC, Leesburg, VA.

Bacher M (2008) Comparison of different machine strength grading principles. Pages 183-193 *in* JV Kuilen and WF Gard, eds. COST E53 Conference, October 29-30, Delft, The Netherlands.

Coyle DR, Klepzig KD, Koch FH, Morris LA, Nowak JT, Oak SW, Otrosina WJ, Smith WD, Gandhi KJ (2015) A review of southern pine decline in North America. For Ecol Manag 349:134-148.

Cunningham K, Barry K, Walkingstick T (2008) Managing loblolly pine stands from A to Z. Publication FSA5023. University of Arkansas Cooperative Extension Service, Little Rock, AR.

Denzler J, Diebold R, Glos P (2005) Machine strength grading—Commercially used grading machines—Current developments. Pages 9-16 *in* FW Broker and F Eberswalde, eds. Proc. 14th International Symposium on Nondestructive Testing of Wood, May 2-4, 2005, Hannover, Germany.

Diebold R, Schleifer A, Glos P (2000) Machine grading of structural sawn timber from various softwood and hardwood species. Pages 139-146 *in* F Divos, ed. Proc. 12th International Symposium on Nondestructive Testing of Wood, September 13-15, 2000, Sopron, Hungary.

Divós F, Sismándy-Kiss F (2010) Strength grading of structural lumber by portable lumber grading—Effect of knots. Pages 538-544 *in* D Ridley-Ellis and J Moore, eds. The Future of Quality Control for Wood and Wood Products, May 4-7, 2010, Edinburgh, Scotland.

Divós F, Tanaka T (1997) Lumber strength estimation by multiple regression. Holzforschung 51(5):467-471.

Fakopp (2005) Fast Fourier vibration analyzer user's guide. Fakopp Enterprise Bt, Fakopp Enterprise Publication, Agfalva, Hungary.

França TSFA, França FJN, Seale RD, Shmulsky R (2018) Bending strength and stiffness of no. 2 grade southern pine lumber. Wood Fiber Sci 50(2):1-15.

França FJN, Seale RD, Shmulsky R, França TSFA (2019a) Modeling mechanical properties of 2 by 4 and 2 by 6 southern pine lumber using longitudinal vibration and visual characteristics. Forest Prod J 68(3):286-294.

França FJN, Seale RD, Shmulsky R, França TSFA (2019b) Assessing southern pine 2×4 and 2×6 lumber quality: Longitudinal and transverse vibration. Wood Fiber Sci 51(1):2-15.

Grant DJ, Anton A, Lind P (1984) Bending strength, stiffness, and stress-grade of structural *Pinus radiata*: Effect of knots and timber density. N Z J For Sci 14(3):331-348.

Hanhijärvi A, Ranta-Maunus A (2008) Development of strength grading of timber using combined measurement techniques. Report of the Combigrade-project r phase 2. VTT Publication 686, Espoo, Finland.

Hanhijärvi A, Ranta-Maunus A, Turk G (2005) Potential of strength grading of timber with combined measurement techniques. Report of the Combigrade-project phase 1. VTT Publications 568, Espoo, Finland.

Hoyle RJ (1968) Background to machine stress rating. Forest Prod J 18(4):87-97.

Iniguez G, Esteban M, Barrett JD, Arriaga F (2007) Visual grading of large structural coniferous sawn timber according to Spanish standard UNE 56544. Forest Prod J 57(10):45-50.

Johansson CJ, Brundin J, Gruber R (1992) Stress grading of Swedish and German timber. Swedish National Testing and Research Institute, Building technology, SP Report 1992:23, Borås, Sweden.

Kretschmann DE (2010) Stress grades and design properties for lumber, round timber, and ties. Pages 7-1-7-16 *in* RJ Ross, ed. Wood Handbook Gen Tech Rep FPL-GTR-190. USDA For Serv Forest Products Laboratory, Madison, WI.

McKeand S, Mullin T, Byram T, White T (2003) Deployment of genetically improved loblolly and slash pine in the south. J Forestry 100(3):32-37.

Nocetti M, Bacher M, Brunetti M, Crivellaro A, Van de Kuilen JG (2010) Machine grading of Italian structural timber: Preliminary results on different wood species. Pages 285–291 *in* A Ceccotti, ed. Proc 11th World Conference on Timber Engineering, June 20-24, 2000, Riva del Garda, Italy.

Panshin AJ, De Zeeuw C (1980) Textbook of wood technology, 4th edition. McGraw-Hill, New York, NY.

Piter JC, Zerbino RL, Blaß HJ (2004) Machine strength grading of *Argentinean eucalyptus grandis*. Main grading parameters and analysis of strength profiles according to European standards. Holz als Roh- Werkst 62(1):9-15.

Ross RJ (2015) Nondestructive evaluation of wood, 2nd edition. Gen Tech Rep FPL-GTR-238. USDA For Serv Forest Products Laboratory, Madison, WI. 176 pp.

SAS (2013) SAS Institute Inc. Version 9.4, Cary, NC.

Shapiro SS, Wilk MB (1965) An analysis of variance test for normality (complete samples). Biometrika 52:591-611.

Shmulsky R, Selae RD, Snow RD (2006) Analysis of acoustic velocity as a predictor of stiffness and strength in 5-in-diameter pine dowels. Forest Prod J 56(9): 52-55.

Southern Pine Inspection Bureau (SPIB) (2014) Standard grading rules for southern pine lumber. SPIB, Pensacola, FL. 147 pp.

Vega A, Guaita M, Dieste A, Majada J, Fernández I, Baño V (2011) Evaluation of the influence of visual parameters on wave transmission velocity in sawn chestnut timber. Pages 311-318 *in* F Divós, ed. 17th International Nondestructive Testing and Evaluation of Wood Symposium, Sopron, Hungary.

Wear DN, Greis JG (2002) Southern forest resource assessment: Summary of findings. J Forestry 100(7):6-14.

Wright SL (2015) Mapping the effects of knots on loblolly pine lumber. MS thesis, University of Georgia, Athens, GA. 48 pp.

Yang BZ, Seale RD, Shmulsky R, Dahlen J, Wang X (2015) Comparison of nondestructive testing methods for evaluating no. 2 southern pine lumber: Part A, modulus of elasticity. Wood Fiber Sci 47(4):375-384.

Yang BZ, Seale RD, Shmulsky R, Dahlen J, Wang X (2017) Comparison of nondestructive testing methods for evaluating no. 2 southern pine lumber: Part B, modulus of rupture. Wood Fiber Sci 49(2):134-145.