Interrelationships of Specific Gravity, Stiffness, and Strength of Yellow Pine across Five Decades

Frederico Jose Nistal França,[a,]* Rubin Shmulsky,[a] Tedrick Ratcliff,[a] Benjamin Farber,[a] C. Adam Senalik,[b] Robert J. Ross,[b] and R. Daniel Seale [a]

The interrelationships among specific gravity (SG), modulus of elasticity (MOE), and strength (modulus of rupture, MOR) are largely the foundational basis for non-destructive evaluation and testing. Resource monitoring and commercial structural lumber production often rely upon such non-destructive evaluation to predict the bending and/or tension strength of individual members. These technologies require routine calibration. In addition, it is important to know the extent to which a given resource may change over time. To that end, this study investigated the relationship among SG, MOE, and MOR of small clear specimens from three samples taken across an approximate 50-year period; 1965 to 2018. Coefficients of determination among these variables are presented along with the prediction equations. These findings can be used to gain insight into the reliability and stability of these relationships over time.

Keywords: Dimensional lumber; Modulus of elasticity; Modulus of rupture; Physical property

Contact information: a: Department of Sustainable Bioproducts, Mississippi State University, P.O. Box 9820, Starkville, MS 39759 USA; b: USDA Forest Products Laboratory Madison, WI, USA;
** Corresponding author: fn90@msstate.edu*

INTRODUCTION

Over the six-plus decade period of time from 1953 to 2017, the United States Forest Service Forest Inventory Analysis (FIA) has tracked standing volume of various tree species. Among the major southern yellow pine (SYP) group (loblolly, longleaf, shortleaf, and slash (*P. taeda*, *palustris*, *echinata*, and *elliottii*, respectively)) south region reports show an increase of 134% on all lands representing 141,307 million cubic feet (4,001 million m^3). The increase is particularly significant on private lands as well at 122% representing 117,662 million cubic feet (3,332 million m^3). These private lands represent the major timberland ownership on which SYP is grown. In broad economic terms, SYP has been planted in an effort to fill the expected future demand for paper, solid, and composite-based wood products. With such a drastic increase in growing stock (*i.e.* supply) over the period, landowners (particularly private) want and need SYP utility values, and thus economic value, to remain generally consistent over time. Such stability in demand helps validate investment and assures that forestland remains in production over time.

Timberlands provide significant ecosystem services to all of society. Many of these services such as clean air and clean water are intangible and do not currently have a readily quantifiable market value. As such, the primary source of revenue opportunity or return on investment, which ultimately steers land-use decisions come through timber's economic and utility value. This value is largely associated with final harvest of timber stands, which creates raw material for the production of dimension lumber. Landowners need reliably strong lumber values for society to continually reap the benefits of ecosystem services.

Kretschmann and Hernandez (2006) noted, “The grading of timber should be viewed as part of a marketing strategy, designed to ensure that timber buyers obtain the quality of timber appropriate for their needs and timber sellers receive an optimal price for their product.” This was a favorable note for SYP landowners following Gaby (1985), wherein it was noted that the strength (MOR) and stiffness (MOE) of lumber may not be accurately reflected by visual grading. Investigating the extent to which interrelationships within the SYP resource of specific gravity (SG), modulus of elasticity (MOE), and bending strength (modulus of rupture or MOR) have changed, or not changed, over time, is an important piece of information for landowner decision making, which has decades-long implications.

The interrelationships among SG, MOE, and MOR are largely the foundational basis for non-destructive evaluation and testing. Resource monitoring and commercial structural lumber production often rely upon such non-destructive evaluation to predict the bending and/or tension strength of individual members. Various technologies such as acoustic velocity and dynamic flexure testing, utilize these relationships to predict bending strength. Better or more reliable and accurate the non-destructive methodologies have lesser amounts of variability and are thus more valuable. All forms of non-destructive evaluation require routine calibration.

In addition to machine drift, technology enhancement as well as software and hardware improvement, changes in the resource may alter the relationships between SG, MOE, and MOR over time. Such alterations may manifest in different ways across different species or species groups; SYP does not necessarily behave the same as Douglas fir, spruce-pine-fir, hem-fir, or others. The same is true for any of the commercial species or species groups. As such, it is important to know the extent to which a species groups changes over time. This study investigates the relationship among SG, MOE, and MOR of small clear specimens from three samples taken across an approximate 50-year period; 1965 to 2018.

EXPERIMENTAL

Materials

The first sample (hereafter “1966 Sample”) was taken from existing data associated with Doyle and Markwardt (1966). Similar to the 2014 Sample, the 1966 Sample data was taken from a broad sample of in-grade pine lumber. Details regarding this sampling method, and corresponding evaluation, are provided in Doyle and Markwardt (1966). From that lumber, subsequent to in-grade testing, small clear specimens were tested in bending. In total, 281 small clear specimens were tested in the 1966 Sample. Findings from this sample are seemingly attributable to the basic or inherent clear wood flexure properties of SYP global in-grade lumber at that time of sampling. It is noted that at the time of that sampling, *i.e.*, circa mid-1960s, southern pine forest management practices were perhaps not as widespread or as intensive as they were during the procurement of the 2014 and 2018 Samples.

The second sample (hereafter “2014 Sample”) was production weighted. In that case, in-grade structural lumber specimens were taken from throughout the SYP lumber production range. This range is divided up into numerous (18) production regions. To that end, SYP sawmills were classified according to the regional production map (Shelley 1989) and then production statistics, by region were reviewed. Then, in 2014 and 2015, full size in grade structural lumber specimens, primarily No. 2 grade, in the 2x4 through 2x10 size classes, were procured from retailers such that a production-weighted sample was developed. Details regarding this sampling method are provided in (França *et al.* 2018). After the in-grade lumber was characterized and evaluated, small clear bending specimens were machined from the non-broken ends of the full-size flexural specimens. In total, 1,689 small clear bending specimens were tested in the 2014 Sample. This number of specimens was a subset of the total number of in-grade tests. As with the other samples, the number of small clear flexural specimens is not necessarily the same as the number of SG specimens. Findings from this sample are seemingly attributable to the basic or inherent clear wood flexure properties of SYP global in-grade lumber at that time of sampling.

The third sample (hereafter "2018 Sample") was taken from moulding and millwork producers. In particular, the membership of the Stairbuilders and Manufacturer's Association (SMA) were interested in documenting the strength and stiffness properties of several wood species. Their stair tread and riser sizes and grades are similar to, though wider than, small clear specimens as described in ASTM D143 (ASTM 2014a). Among these species of interest was the SYP group. SYP constitutes a major portion of stair tread and riser production. These manufacturers, from throughout the eastern half of the country were contacted and asked to donate materials from their production for this effort. In total, lumber donations were requested from the entire SMA membership, approximately 150 member companies.

In response, approximately 21 manufacturers, from 15 states (Figure 1) donated material during the 2017-2019-time window. It was assumed that by sampling from a large variety of remanufacturers, the variability associated with this high-quality appearance grade SYP lumber would be captured. None of this material was grade stamped. In total, 275 small clear specimens were tested in the 2018 Sample. While this sample was not production weighted, it was considered a reasonable approximation of high-quality SYP lumber from around the production region. Findings from this sample are seemingly attributable to the basic or inherent wood properties of high-quality appearance grade lumber at that time of sampling.

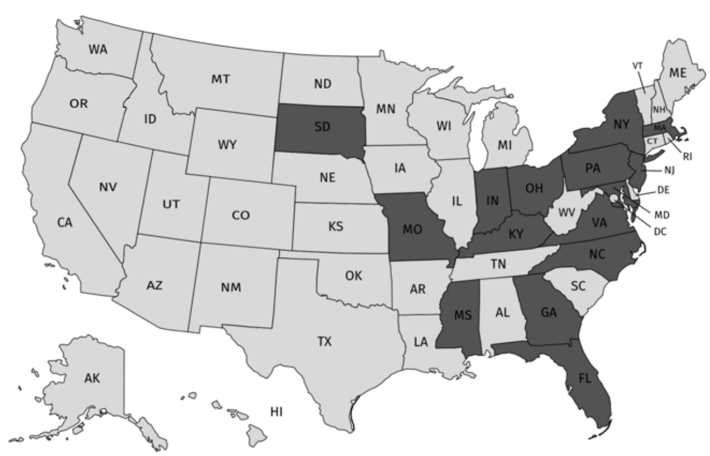

Fig. 1. Origin source of the raw material acquired from SMA, highlighted in gray

While the three samples were procured in different ways and for different ends, each provides a cross-sectional snapshot of the type of raw material that was going into and through the lumber production supply chain at the time. Because standard test methods have remained largely unchanged during this period, comparisons among and across the data from these samples are reasonable.

All specimens were environmentally conditioned at 21 °C and 65% relative humidity prior to testing. In this manner, each specimen's moisture content was at or near 12%. Specific gravity was determined according to ASTM D 143 (ASTM 2014). Oven dried mass and volume at 12% MC were measured to the nearest 0.01 g and 0.01 mm respectively. Specimens were not extracted prior to SG determination. The MC (%) was calculated based on mass difference before and after oven dried at 103 ± 2 °C following the same standard.

Static bending tests were performed on specimens of the following dimensions: 2.54 × 2.54 × 40.6 cm^3. Load was applied at the center point with a test speed of 0.127 cm per minute. In this manner, failure occurred in approximately 5-10 minutes. The span was 35.6 cm. MOE was calculated using Eq. 1. MOR was calculated using Eq. 2.

$$\mathrm{MOE} = \frac{\Delta P L^3}{4 \Delta f b h^3} \tag{1}$$

In Eq. 1, MOE is the bending modulus of elasticity (MPa); ΔP is the loading increase (N); L is the span length (m); Δf is the deflection increase (m); b is the width (m); h is the depth of the specimen (m). MOE values were not subsequently corrected or adjusted for shear deflection. The 5th percentile of the MOR data was calculated per ASTM 2915 (ASTM 2014b). Equation 2 is as follows,

$$\mathrm{MOR} = \frac{3PL}{2bh^2} \tag{2}$$

where MOR is the bending modulus of rupture (MPa); P is the maximum force (N) at the mid-span; L is the span length (m); b is the width (m); and h is the depth (m).

Single variable linear regression analyses ($\alpha = 0.05$) were conducted for SG as the independent variable against MOE and MOR as dependent variables and for MOE as the independent variable against MOR as the dependent variable. The linear regressions were conducted given the independent variables (either SG or MOE as represented by "*x*") and the dependent variable (either MOE or MOR as represented by "*y*"). The coefficient of determination (R^2), which measures the strength of the relationships between variables, was the main focus. The slopes of the lines, which would potentially indicate changes in these relationships over time, was a secondary focus.

The mathematical regression models between the independent variables (SG and MOE) and the static properties (MOE and MOR) were assumed to be linear and of the following form:

$$\text{Dependent variable} = \text{slope} \cdot (\text{independent variable}) + \text{intercept} + \text{error} \tag{3}$$

or

$$Y = m \cdot X + b + \mathcal{E}$$

Also, MOR was estimated based on multiple linear regression as a function of SG and MOE. In that case, ordinary least square regression procedures were used for fitting models to predict MOR using MOE and SG. The equation to predict MOR is as follow:

$$\mathrm{MOR} = \beta_0 + \beta_1 \cdot \mathrm{MOE} + \beta_2 \cdot \mathrm{SG} + \mathcal{E}_1 \tag{4}$$

RESULTS AND DISCUSSION

Table 1 presents a summary of SG for the 1966, 2014, and 2018 Samples. The following comments should be noted: (1) the 2014 Sample had a larger number of specimens, (2) The 2018 Sample exhibited the highest mean for SG, followed by the 1966 Sample, (3) the 1966 Sample exhibited higher coefficient of variation, (4) the 2014 Sample had the lowest SG value among all of the samples, and (5) the 1966 Sample had the specimen with highest (unextracted) SG. The specimen with SG of 0.88 is likely an outlier that was perhaps pitch encrusted (fatwood), compression wood, or had some other adherent characteristic(s).

Table 1. Specific Gravity Descriptive Statistics for the 2014, 2018, and 1966 Samples

Specific Gravity	N.	Mean	COV	Min	Max
1966 Sample	281	0.51	13.90	0.38	0.88
2014 Sample	1,689	0.47	12.85	0.32	0.69
2018 Sample	275	0.52	12.84	0.33	0.72

Table 2 summarizes the MOE and MOR statistics for the three Samples. The 1966 Sample 3 exhibited the highest average MOE. The 2018 Sample had the highest average MOR and had the highest variation between specimens for MOE and MOR. The 2014 Sample exhibited lowest mean for MOE and MOR and the lowest MOR 5th percentile. It should be noted that these strength values were not moisture adjusted. No significant differences were found between tested and moisture adjusted results.

Table 2. MOE and MOR Descriptive Statistics for the Three Samples

Static bending	N.	MOE (MPa)				MOR (MPa)				
		Mean	COV (%)	Min	Max	Mean	COV (%)	Min	Max	5th Percentile
1966 Sample	281	11,549	20.6	5,143	18,602	89.18	15.8	50.28	132.46	66.64
2014 Sample	1,689	9,745	23.0	2,310	23,668	87.27	17.9	35.28	161.05	62.31
2018 Sample	273	9,785	27.7	2,783	17,440	93.75	20.6	43.23	145.52	64.63

Table 3. Results of Linear Regression Analyses Relating Static Bending Modulus of Rupture (MOR) to Modulus of Elasticity (MOE) for the Three Samples

	N.	Slope (m)	Intercept (b)	Coefficient of determination (R^2)	µ	p-value
1966 Sample	281	0.0046	36.29	0.60	80.12	< 0.001
2014 Sample	1,689	0.0056	33.18	0.63	89.46	< 0.001
2018 Sample	275	0.0059	35.57	0.69	104.73	< 0.001

The coefficients *m* and *b* are used in the generalized model MOR (MPa) = m [MOE (MPa)] + b.µ is the error of estimate.

Table 3 provides summaries obtained from regression analyses between MOE and MOR for the three Samples. Figures 2 and 3 show plots of static bending MOR as predicted using MOE values. These plots show strong correlative relationships. In this case, the coefficient of determination ranged between 0.60 and 0.69. All three samples exhibited similar coefficient of variation and standard error of estimate.

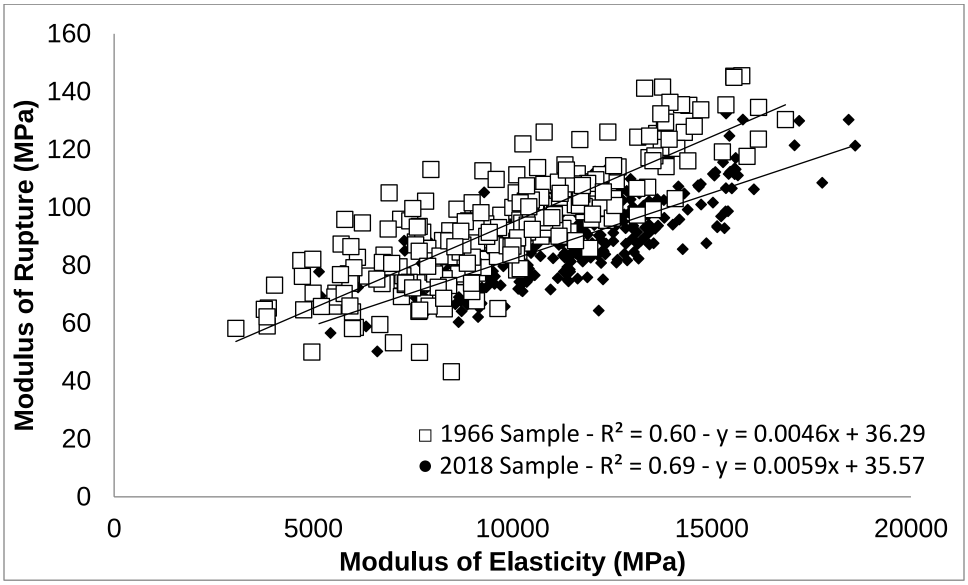

Fig. 2. Linear regression plot for the 1966 and 2018 Sample: bending modulus of elasticity (MOE) versus modulus of rupture (MOR)

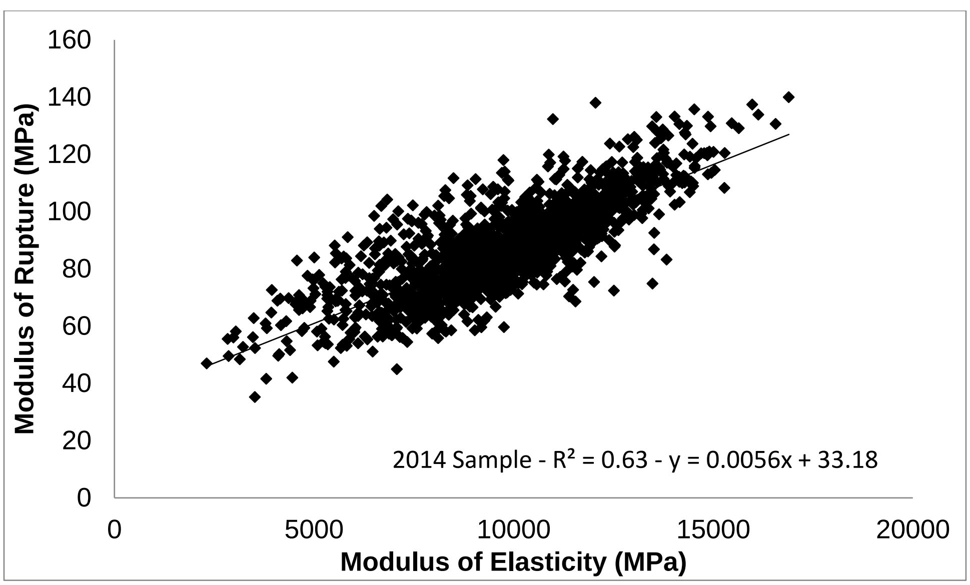

Fig. 3. Linear regression plot for the 2014 Sample: bending modulus of rupture (MOR) versus modulus of elasticity (MOE)

Table 4 provides summaries obtained from regression analyses between SG and MOR for the three Sample. Figures 4 and 5 show plots of SG versus MOR values. These plots show that moderate correlative relationships exist. In this case, the coefficient of determination ranged between 0.41 and 0.50.

Table 4. Results of Linear Regression Analyses Relating SG to Static Bending MOR for the Three Samples

	N	Slope (m)	Intercept (*b*)	Coefficient of determination (R^2)	μ	p-value
1966 Sample	281	139	17.67	0.50	10.03	< 0.001
2014 Sample	1,686	164	9.16	0.41	4.77	< 0.001
2018 Sample	275	167	2.73	0.41	13.61	< 0.001

The coefficients *m* and *b* are used in the generalized model MOR (MPa) = *m* (SG) + *b*.
μ is the error of estimate.

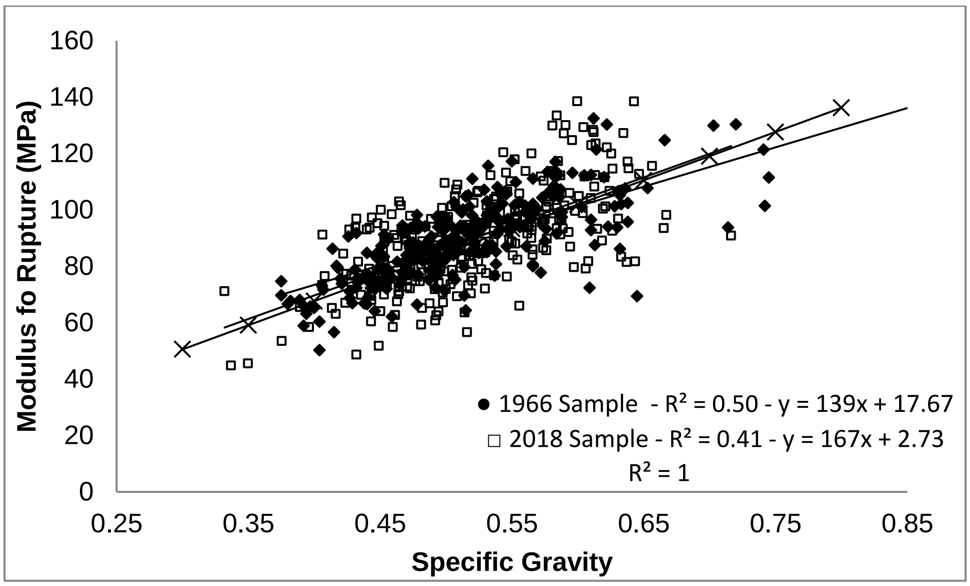

Fig. 4. Linear regression plot for the 1966 and 2018 Samples: SG *vs.* MOR.

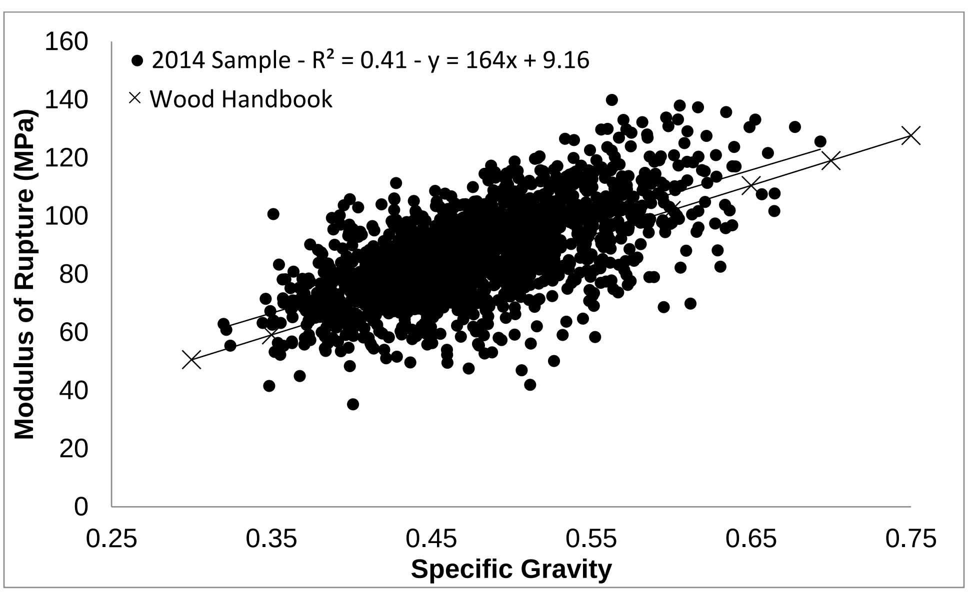

Fig. 5. Linear regression plot for the 2014 Sample: SG *vs.* MOR.

The 1966 Sample exhibited higher correlation for SG *vs.* MOR (r2 = 0.50) when compared to the other 2 samples. The 2014 Sample exhibited a lower error cause by the larger number of specimens when compared to the other 2 samples.

Table 5 provides summaries obtained from regression analyses between SG and MOE for the three Samples. Figures 6 and 7 show plots of SG *vs.* MOE values. These plots show that relatively low correlative relationships existed between these two variables. In this case, the coefficient of determination ranged between 0.15 and 0.19. The 2014 and 1966 Samples exhibited similar coefficients of determination (R^2 = 0.19) but the 2014 Sample had a lower standard error of estimate due to larger number of specimens. No SG by MOE relationship changes appeared obvious among the three Samples.

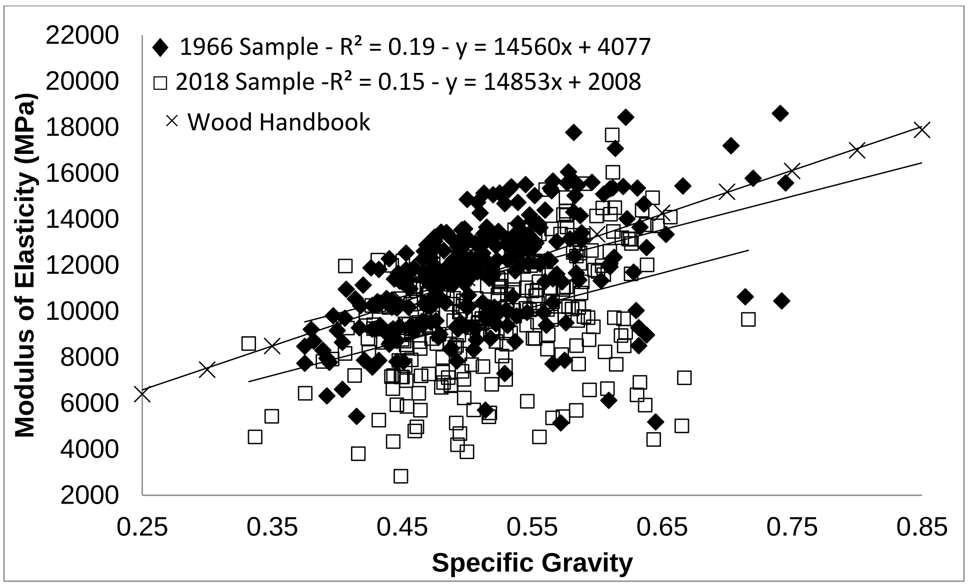

Fig. 6. Linear regression plot for the 1966 and 2018 Samples: Bending modulus of elasticity (MOE) *vs.* specific gravity (SG)

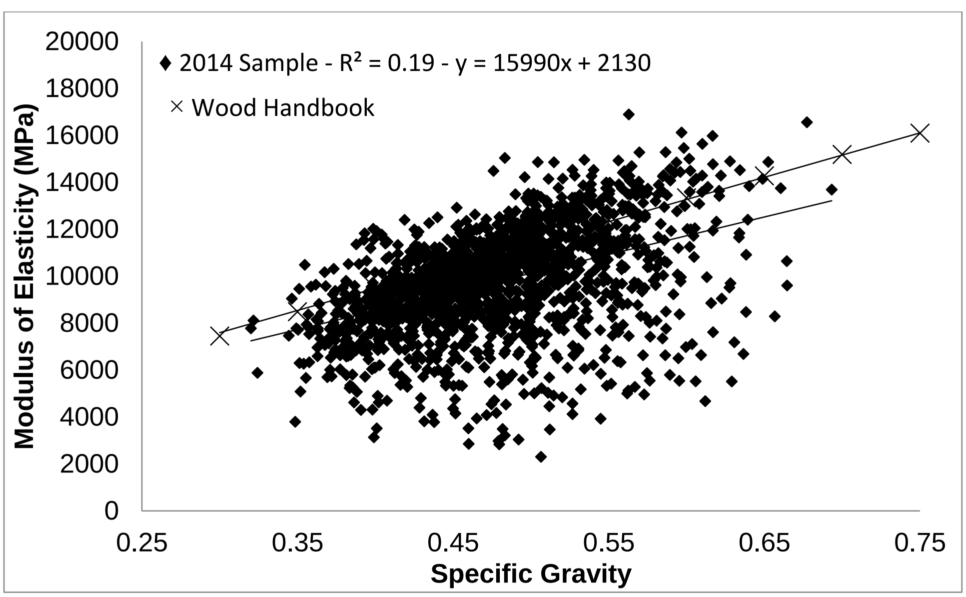

Fig. 7. Linear regression plot for the 2014 Sample: Bending modulus of elasticity (MOE) *vs.* specific gravity (SG)

Table 5. Results of Linear Regression Analyses Relating Static Bending Modulus of Elasticity (MOE) to Specific Gravity (SG) for the Three Samples

	N	Slope (*m*)	Intercept (*b*)	Coefficient of determination (R^2)	μ	p-value
1966 Sample	281	14,560	4,077	0.19	8.45	< 0.001
2014 Sample	1,686	2,149	15,951	0.19	7.45	< 0.001
2018 Sample	275	14,853	2,008	0.15	13.12	< 0.001

The coefficients *m* and *b* are used in the generalized model MOE (MPa) = *m* (SG) + *b*.
μ is the error of estimate.

Table 6 shows the regression model equation coefficients of determination (R^2), and error of estimate (μ) for the three Samples. The prediction of MOR improved when MOE and SG were combined to predict the strength (MOR). The 1966 Sample exhibited higher R^2 when compared to the 2014 and 2018 Samples.

Table 6. Linear Regression Models with Coefficient of Determination (R^2) and Error of Estimate (μ) for Dependent Variables Modulus of Elasticity (MOE) and Specific Gravity (SG)

	β_0	β_1	β_2	R^2	μ	p-value
1966 Sample	3.813	0.003	6.39	0.76	47.14	<0.001
2014 Sample	-0.082	0.004	92.88	0.73	63.69	<0.001
2018 Sample	1.440	0.004	8.62	0.73	76.42	<0.001

The coefficients β_0, β_1, and β_2 are used in the generalized model: MOR (MPa) = $\beta_0 + \beta_1 \cdot$MOE (MPa) + $\beta_2 \cdot$SG + $\mathcal{E}_1$. μ is the error of estimate.

For the 2014 and 2018 Samples there was no difference between using MOE as single predictor and MOE combined with SG. The R^2 between SG and MOR found in these studies were about 0.41. For the 1966 Sample, it was 0.50. This finding appears to show that the variation in MOR caused by SG is almost completely explained by the variation in MOR caused by MOE. However, the correlation between MOE and SG was very low for all three samples, indicating that those variables were largely independent. For that reason, the use of the two independent variables (MOE and SG) is acceptable regarding MOR prediction. When both predictors were used, no improvement was seen overusing just one for the 2018 Sample. That finding contrasts with the 1966 Sample where using both predictors increased the R^2 from 0.60 for MOE alone to 0.76 for MOE and SG combined. 2014 Sample raised the R^2 from 0.63 for MOE alone to 0.73 for MOE and SG combined.

Residual by regressors for MOR for the three Samples are show in Figure 8, 9 and 10 respectively. Analyzing the predictors residual range, it was possible to identify that the 1966 Sample exhibited a different residual range compared to the 2014 and 2018 Samples. The majority of specimens in 2014 Sample and 2018 Samples ranged from -20 to 20. The 1966 Sample exhibited a lower prediction residual (from -10 to 10) what improved the R^2 of the combined regression model.

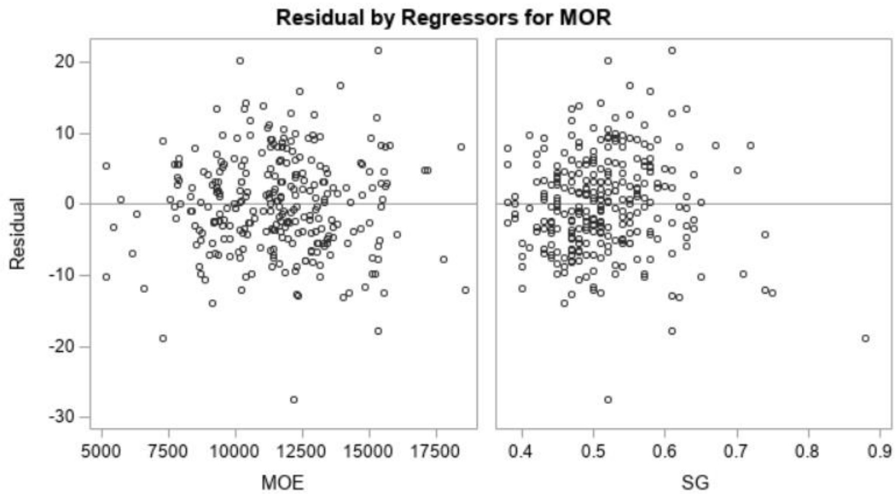

Fig. 8. Residual by regressors for MOR for the 1966 Sample

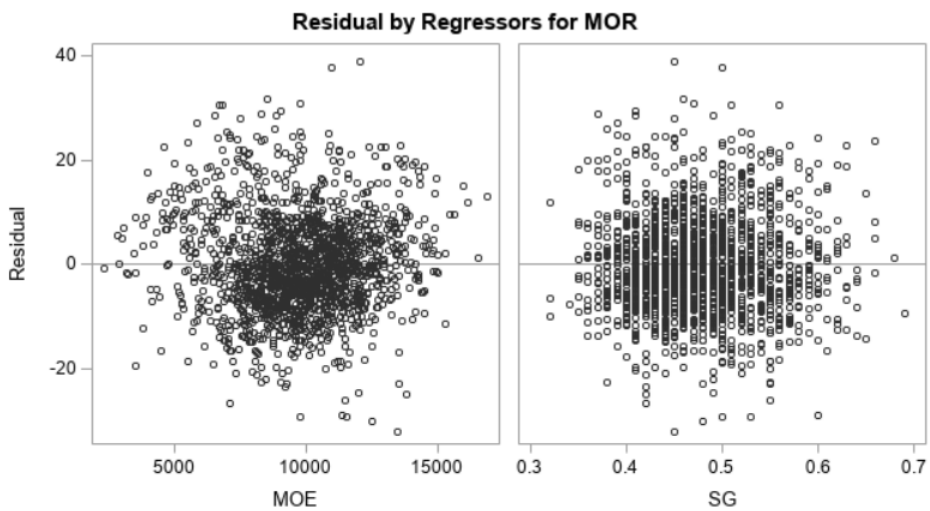

Fig. 9. Residual by regressors for MOR for the 2014 Sample

Fig. 10. Residual by regressors for MOR for the 2018 Sample

CONCLUSIONS

1. For all samples, SG versus MOE correlations were relatively low and generally ranged from approximately 0.15 to 0.20. This relationship is known to be relatively weak. However, each of these (SG and MOE) is known to be a relatively good predictor of MOR. These relatively low correlations between SG and MOR were not unexpected for two reasons in particular. The first reason is that some of the pine specimens appeared to contain significant amounts of extractives. Shmulsky and Jones (2019) note that "In some species, including pine, it has been shown that the presence of extractives contributes significantly to observed specific gravity variation." High extractive loading increases specimen weight but not MOE. The second reason is that some of the specimens contained compression wood, which is known to often increase weight while reducing MOE.
2. Brown *et al.* (1952) noted that for specimens, including southern yellow pine, containing appreciable amounts of compression wood have proved to be stronger in static bending MOR than control specimens devoid of such tissue but, the MOE values were only two-thirds as much. Had only compression wood-free specimens been used and had each specimen been extracted, these correlative relationships likely would have been higher.
3. The contemporary Samples (2014 & 2018) showed slightly higher correlations between MOE and MOR (0.63 and 0.69, respectively) as compared to the earlier data from the 1966 Sample (0.60). However, these differences were very small and likely negligible. The slopes of the lines between MOE and MOR were generally very similar. This finding suggests that MOE is both a reasonably good and reasonably stable predictor of MOR over time.
4. The contemporary Samples (2014 & 2018) showed slightly lower correlations between SG and MOR (0.41 for both samples) as compared to the earlier data from the 1966 Sample (0.50). However, these differences were also small. The slopes of the lines between SG and MOR were generally very similar. This finding suggests that SG is both a reasonably good and reasonably stable predictor of MOR over time. This finding also suggests that SG is not as strong of a predictor as MOE with respect to MOR.
5. The relationship between MOE and SG was relatively weak, and thus not likely highly collinear, so these two variables were combined in an effort to predict MOR. For the 1966 Sample, the addition of SG to MOE, to predict MOR, increased the R^2 value from 0.60 to 0.76. That relationship was not the same for the 2014 and 2018 Samples. In those two contemporary Samples, the MOE to MOR R^2 values were on the order of 0.63, and the addition of SG as a predictor increased the R^2 to 0.73 (2014 Sample) and $R^{2\,=}$ 0.64 for 2018 Sample.
6. MOE, MOR = Constant (SG)^*x*, where the constants for MOE and MOR are 2.97 and 24,760, respectively. Reported values for *x* are 1.34 and 1.01 for MOE and MOR. While these models are not species-dependent, using them to estimate clearwood properties is a common practice. Figures 3 to 6 show estimated values as calculated using these models in comparison to the data for this study. The data, and the corresponding relationships observed, are in close agreement with those calculated for the broad range of softwood species as reported in the Wood Handbook.

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REFERENCES CITED

ASTM (2014a) D 143–14. "Standard methods for testing small clear specimens of timber." American Society for Testing and Materials, West Conshohocken, PA.

ASTM (2014b) D 2915-14. "Sampling and data-analysis for structural wood and wood-based products." American Society for Testing and Materials International, West Conshohocken, PA

Brown, H. P., Panshin, A. J., and Forsaith, C. C. (1952) *Textbook of Wood Technology*, Volume 2. McGraw Hill Book Company. New York, NY. 509 pp.

Doyle, D. V., and Markwardt, L. J. (1966). *Properties of Southern Pine in relation to Strength Grading of Dimension Lumber*. USFS RP FPL-64. 62 pp.

Forest Products Laboratory. (2010). *Wood Handbook—Wood as an Engineering Material*, General Technical Report FPL-GTR-190. Madison, WI: U.S. Department of Agriculture, Forest Service, Forest Products Laboratory. 508 pp.

França, T. S. F. A., França, F. J. N., Seale, R. D., and Shmulsky, R. (2018). "Bending strength and stiffness of No. 2 grade southern pine lumber," *Wood Fiber Sci.* 50(2), 205-219.

Gaby, L. I. (1985). *Southern Pines: Loblolly Pine* (*Pinus taeda* L.), *Longleaf Pine* (*Pinus palustris* Mill.), *Shortleaf Pine* (*Pinus echinata* Mill.), *Slash Pine* (*Pinus elliottii* Engelem.), USDA Forest Service, Madison, WI. FS 256. 11 pp.

Kretschmann, E. D., and Hernandez, R. (2006). "Grading timber and glued structural members," in: *Primary Wood Processing: Principles and Practice*, 2nd Ed., Springer, Dordrecht, Netherlands, pp. 229-390.

Shelley, B. E. (1989). "Sampling procedures used in the in-grade lumber testing program," in: *In-grade Testing of Structural Lumber*. Proc 47363. Forest Products Society. Madison, WI. pp. 15-26.

Shmulsky, R., and Jones, P. D. (2019) *Forest Products and Wood Science, an Introduction,* 7th Ed., Wiley-Blackwell, London, England.

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