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MODELLING THE INFLUENCE OF RADIATA PINE LOG VARIABLES ON STRUCTURAL LUMBER PRODUCTION

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ABSTRACT

We run logit models to explain the variability of *Pinus radiata* structural lumber in 71 second and third unpruned logs. The response variable was the proportion of lumber with a static modulus of elasticity greater or equal than 8 GPa, *p*MSG8+, and the explanatory variables were log volume, branch index, largest branch, log internode index, wood basic density, and acoustic velocity. The average *p*MSG8+ volume was 44,30 % and 36,18 % in the second and third log respectively. Ten models were selected based on meeting statistical assumptions, their goodness of fit, and the statistical significance of their parameters. The best models (R^2 - adj. > 0,75) included acoustic velocity (AV) as explanatory variable, which explained 56,25 % of the variability of *p*MSG8+. Models without AV presented goodness of fit ranging from 0,60 to 0,75 (R^2 - adj.), and variables with the highest weight to explain the variability of *p*MSG8+ were volume, followed by wood basic density, branch index, and largest branch. It is possible to model *p*MSG8+ from log variables even when acoustic velocity is not available; however, this requires wood basic density models calibrated for the *Pinus radiata* growing zone.

Keywords: Acoustic technology, log variables, *Pinus radiata,* regression models, structural lumber.

INTRODUCTION

The quality of natural inputs, such as logs, is commonly evaluated by their performance generating products with high prices. Under a production perspective log attributes have the role of input-traits related to lumber production (Alzamora *et al.* 2013). Multipurpose forest tree species, such as *P. radiata,* feed fiber, structural and appearance wood markets that require different wood trait profiles. The value of solid wood is determined by attributes that satisfy two sets of usage requirements: appearance and structural end-uses. Appearance wood is influenced by quantity and quality traits such as volume, color, defects, knots, and resin spots (Beauregard *et al.* 2002). Structural wood is mostly determined by dynamic modulus of elasticity, wood basic density, volume, and branching (Arriaga *et al.* 2013, Tsehaye *et al.* 2000, Tsuchikawa 2007, Xu and Walker 2004). Several of these traits are under genetic control, and they could be modified by silviculture and processing technology (Schimleck *et al.* 2019).

Obtaining wood traits information from logs is not simple; logs are naturally heterogeneous, creating problems for product differentiation and for definition of quality grades and standards. Fortunately, there have been significant advances on non-destructive approaches to measure and predict wood properties such as dynamic modulus of elasticity from trees and logs (Dickson *et al.* 2003, Lasserre *et al.* 2005, Matheson *et al.* 2002, Soto *et al.* 2012, Waghorn *et al.* 2007).

According Ross (2015) and Schimleck *et al.* (2019), non-destructive tools can measure the physical and the mechanical properties of a piece of material without altering its end-use capabilities and using such information to make decisions regarding appropriate applications. Consequently, non-destructive acoustic methods can increase the efficiency of chain value in wood production. Apiolaza (2009) and Ivković *et al.* (2009) indicated that tools based on acoustics principles could be used for screening at a very early age and be related to several properties like modulus of elasticity, dimensional stability, and fibre length', among others.

Soto *et al.* (2012) used acoustic tools on standing trees for exploring influence of tree stocking on the dynamic modulus of elasticity in a mature *P. radiata* plantation growing in Biobío Region, Chile, and they reported the high variation between logs coming from a single stand. An application of acoustic methods to assess structural wood quality in logs, with the corresponding log outturn and grading, was reported by Jones and Emms (2010). These authors modeled log-level green and kiln-dried board modulus of elasticity, based on acoustic log velocity and green density.

In Chile, the prediction of structural and appearance *P. radiata* log outturn has been partially solved by using computed x-ray tomography scanners, such as the CT-Log (Schmoldt *et al.* 1993). This technology reconstructs internal log features, allowing the assessment of the optimum cutting solution in real-time. In a similar way, integrated efforts between wood researchers and forest companies have developed CALIRO-Saw (2014), a sawmill simulator based on real logs that include internal log features and generate products using lumber grading rules specified by the users. Unfortunately, all these technologies are available for a reduced group of producers due to high costs and operational issues. However, in absence of scanners and sawing simulators to support log segregation and processing decisions, we can use variables traditionally recorded in the field during primary log sorting to predict the proportion of structural lumber.

The objective of this study was to develop models that explain the variability of structural lumber with static modulus of elasticity greater or equal to 8 GPa using log variables: volume (VOL), acoustic velocity (AV), wood basic density (BD), branch index (BI), largest branch (LB), corewood (CW) and internode index (INT). The models that use AV were compared with those that use BD and other variables regularly measured at the field.

MATERIALS AND METHODS

Log and lumber attributes

Log and lumber data were provided by the New Zealand Wood Quality Initiative, as a sample of 71 *Pinus radiata* (D. Don) unpruned 5 m long logs (35 second and 36 third logs) coming from managed and mature trees with ages between 26 and 28 years old. Table 1 presents a summary of log attributes. Log volume (VOL) was estimated by using the Smalian formula (Bruce 1982), which considers the small and large log end-diameters and the log length (5 m). Branch index (BI) is the mean diameter of the four largest branches of the log, one per quadrant (North, East, West, and South). Largest branch (LB) is the diameter of the largest branch of the log. Branches have a negative influence on structural lumber production, where high branch angle and size reduce the quality of structural products (Grant *et al.* 1984, Xu and Walker 2004).

Internode index (INT) is the sum of the lengths of internodes greater or equal than 0,6 m divided by the log length (Grace and Carson 1993). 0,6 m is the critical value for short clear wood products in the local industry, particularly for the finger-joint processing (Fernández *et al.* 2017). Corewood (CW), is the inner part of the stem (considering the first 10 growth rings, juvenile wood), which presents low wood quality for most end-uses, including low wood basic density, short cells, high microfibril angle, high spiral grain, and high longitudinal shrinkage (Xu and Walker 2004). CW was measured as the percentage of the cross-section at the large end diameter of the log.

Basic density (BD) is the amount of dry matter (at 12 % moisture level) per unit of green volume, a trait highly related to strength, stiffness and hardness in outerwood.

Modulus of elasticity measures a wood's stiffness, and dynamic modulus of elasticity, or Young's modulus of elasticity (MOE_d) which according Beall (2001) it is estimated by a dynamic phenomenon that consists in passing of stress waves within wooden materials that can be released in wood and analyzed and affiliated with mechanical properties

Table 1: Mean values and standard deviations (SD) of second and third log attributes.

Variable		Second log		Third log	
		Mean	SD	Mean	SD
Volume (VOL)	m^3	0,895	0,321	0,729	0,276
Acoustic velocity (AV)	km/s	2,947	0,267	2,931	0,242
Dynamic modulus of elasticity (MOE_d)	GPa	7,921	1,460	7,930	1,278
Basic density (BD)	kg/m^3	382,3	28,8	377,9	28,7
Branch index (BI)	cm	4,946	1,612	5,922	1,902
Largest branch (LB)	mm	60,286	20,967	73,333	26,592
Corewood (CW)	%	44,836	9,489	51,044	9,813
Internode index (INT)	%	14,857	17,362	12,383	15,710

The acoustic measurements (AV) in logs to estimate MOE_d were collected with the Director HM200 tool (Fibre-gen, New Zealand). Logs attributes assessed in the study have been reported as influencing traits to produce structural lumber from *P. radiata* (Ivković *et al.* 2006, Jones and Emms 2010, Waghorn *et al*. 2007), and to characterize the most efficient log attributes profile to produce structural lumber grades (Alzamora *et al.* 2013).

Sawmill product evaluation

Once the logs were assessed in the field, they were processed at the mill, and assessed for static modulus of elasticity (MOE_s) by using a testing machine. Processing aimed to maximize the recovery of lumber with a static modulus of elasticity greater or equal than 8 GPa. The volume of lumber grade recovery for each log type is in Table 2, where MSG stands for machine stress graded, and the number is the MOE_s in GPa.

Table 2: Descriptive statistics of lumber grades volume (m^3) per log.

	<MSG8	≥ MSG8	Reject
Second log	m^3	m^3	m^3
Mean value	0,221	0,163	0,056
Maximum value	0,630	0,594	0,614
Minimum value	0,020	0,000	0,000
Standard deviation	0,167	0,164	0,112
Third log			
Mean value	0,190	0,106	0,040
Maximum value	0,515	0,514	0,361
Minimum value	0,000	0,000	0,000
Standard deviation	0,129	0,117	0,076

Model components

An analysis of correlations was addressed to notice relationships between log attributes. The correlation matrix results are shown in Table 3. It was noticed higher correlation between BD and AV and *p*MSG8+, and between BI with LB, AV, VOL and *p*MSG8+ . The results about variables and correlations were used to define variables being used in the modeling regressions.

Table 3: Correlations matrix between log attributes.

	BD	BI	INT	CW	LB	AV	VOL	*p*MSG8+
BD	1,00	-0,12	0,06	-0,20	-0,14	0,66	-0,21	0,68
BI	-0,12	1,00	0,04	-0,30	0,95	-0,54	0,50	-0,52
INT	0,06	0,04	1,00	0,06	0,12	0,01	-0,16	0,16
CW	-0,20	-0,30	0,06	1,00	-0,27	0,25	-0,64	-0,21
LB	-0,14	0,95	0,12	-0,27	1,00	-0,52	0,45	-0,50
AV	0,66	-0,54	0,01	0,25	-0,52	1,00	-0,63	0,75
VOL	-0,21	0,50	-0,16	-0,64	0,45	-0,63	1,00	-0,33
*p*MSG8+	0,68	-0,52	0,16	-0,21	-0,50	0,75	-0,33	1,00

Modeling regression functions requires information on the response and predictor variables, as well as assumptions about distributions. In this study, the response variable is the lumber proportion with a static modulus of elasticity greater or equal than 8 GPa, which will be named as *p*MSG8+ (%). The predictors are LOG (a categorical variable to indicate second or third log), VOL, BI, LB, BD, AV, INT and CW. Equation 1 presents the functional form of the model.

$$pMSG8+= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \qquad [1]$$

*p*MSG8+ corresponds to the proportion of structural lumber derived from the *i^th^* log and x_i is the vector of *j* attributes in the *i^th^* log, and ε is model error. Equation 2 illustrates the calculation of *p*MSG8+:

$$p\text{MSG8+}=\frac{MSG_8+MSG_{10}+MSG_{12}}{\text{Reject}+MSG_{86}+MSG_8+MSG_{10}+MSG_{12}} \qquad [2]$$

In summary, Equation 2 represents the proportion of commercial volume with MOE_s greater or equal to 8 GPa.

We run models to obtain the best goodness of fit, and meeting the normality, independence, and homogeneous variance of residuals assumptions, as well as accounting for multicollinearity of the predictors. Normality of the residuals was tested using the Shapiro-Wilk test and homoscedasticity with de Breusch-Pagan test. We used a logit transformation of the response to avoid predictions of the proportion outside of the range of 0 to 1. Equation 3 illustrates the calculation of *p*MSG8+ in a logit model:

$$\ln\left(\frac{pMSG8+}{1-(pMSG8+)}\right) = z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon \qquad [3]$$

The new response variable is $z = l - - - n\left(\frac{(pMSG8+)+0.03}{1-(pMSG8+)+0.03}\right)$, as Gujarati and Porter (2010) suggest for transforming a response variable defined as a proportion. Thus, the multiple linear regressions were fitted using the z variable; however, for recovering the original response variable (*p*MSG8+), we used the transformation variable $z_e = \frac{1}{1+e^{-z}}$.

RESULTS AND DISCUSSION

The average proportion of lumber with a static modulus of elasticity higher than 8 or equal GPa was 37,04 % in the second log, and 31,55 % in the third log. These results could be explained by the slightly superior MOE_d in third logs (see Table 1). This result does not follow the trend reported by Xu and Walker (2004), who indicate that the highest MOE_d would be concentrated in the second log, between 4 m to 8 m, and then decrease. The correlations between log attributes, and structural lumber production resulted according to comparable studies (e.g. Ivković *et al.* 2006). Thus, there was a negative and significant correlation between AV and VOL (-0,63, $p < 0,05$). The correlation between AV and BD was also significant (0,66, $p < 0,05$). The average predictor variables are similar to other reported studies (e.g. Apiolaza 2009). For instance, the maximum values of AV and LB for second and third logs were 3,59 km/s and 3,45 km/s, and 110 mm and 125 mm, respectively which are similar to those obtained by comparable studies (e.g., Xu and Walker 2004).

Concerning structural lumber products (≥ MSG8), at least one structural board was generated in 86 % of the second logs, and 83 % of the third logs.

Table 4: Multiple regression models to estimate structural lumber production (*p*MSG8+).

Models	Parameter Estimate	Standard Error	R^2 – adj.
1) $z = \beta_0 + \beta_1 LOG + \beta_2 BI + \beta_3 INT + \beta_4 AV + \beta_5 CW$			0.8203
Intercept	-8,5237***	1,4051	
LOG	0,5896***	0,1896	
BI	-0,2988***	0,0600	
INT	0,0222***	0,0050	
AV	4,5157***	0,3895	
CW	-0,0905***	0,0095	
2) $z = \beta_0 + \beta_1 BI + \beta_2 INT + \beta_3 AV + \beta_4 CW$			0,7967
Intercept	-9,6115***	1,4475	
BI	-0,2228***	0,0583	
INT	0,0200***	0,0053	
AV	4,6509***	0,4117	
CW	-0,0779***	0,0091	
3) $z = \beta_0 + \beta_1 LOG + \beta_2 BI + \beta_3 AV + \beta_4 CW$			0,7703
Intercept	-8,7978***	1,5872	

LOG	0,4749**	0,2124	
BI	-0,2678***	0,0674	
AV	4,5929***	0,4400	
CW	-0,0855***	0,0107	
4) $z = \beta_0 + \beta_1 BI + \beta_2 AV + \beta_3 CW$			0,7565
Intercept	-9,6689***	1,5839	
BI	-0,2079***	0,0637	
AV	4,6977***	0,4504	
CW	-0,0756***	0,0098	
5) $z = \beta_0 + \beta_1 LOG + \beta_2 BI + \beta_3 INT + \beta_4 VOL + \beta_5 CW + \beta_6 BD$			0,7548
Intercept	-4,7378**	2,1022	
LOG	0,5114**	0,2362	
BI	-0,4632***	0,0713	
INT	0,0166***	0,0061	
VOL	-1,0624**	0,5294	
CW	-0,0746***	0,0139	
BD	0,0279***	0,0038	
6) $z = \beta_0 + \beta_1 BD + \beta_2 VOL + \beta_3 B + \beta_4 CW$			0,6999
Intercept	-4,0444*	2,3228	
BD	0,0266***	0,0042	
VOL	-1,9444***	0,5271	
LB	-0,0235***	0,0048	
CW	-0,0736***	0,0152	
7) $z = \beta_0 + \beta_1 BI + \beta_2 BD$			0,6341
Intercept	-12,3624***	1,6467	
BI	-0,3683***	0,0647	
BD	0,0362***	0,0041	
8) $z = \beta_0 + \beta_1 BI + \beta_2 BD + \beta_3 VOL$			0,6287
Intercept	-12,3800***	1,7167	
BI	-0,3698***	0,0745	
BD	0,0362***	0,0042	
VOL	0,0178	0,4466	
9) $z = \beta_0 + \beta_1 LB + \beta_2 BD$			0,6043
Intercept	-12,6571***	1,7110	
LB	-0,0248***	0,0050	
BD	0,0360***	0,0043	
10) $z = \beta_0 + \beta_1 LB + \beta_2 BD + \beta_3 VOL$			0,6000
Intercept	-12,4125***	1,7859	
LB	-0,0235***	0,0055	
BD	0,0357***	0,0044	
VOL	-0,2295	0,4497	
* Significant at 0,1 level; ** significant at 0,05 level; *** significant at 0,01 level			

The high significance of the correlations between structural lumber volume (≥MSG8) and log variables supported building models to explain *p*MSG8+. Table 4 presents the resulting models explaining the variability of the proportion of structural lumber volume in terms of log variables.

Collinearity between explanatory variables of the models was tested by variance inflation factors (VIF), which identifies the correlation between independent variables and the strength of that correlation (Gujarati and Porter 2010). A VIF value of 1 indicated that there is no correlation between this independent variable and any others. Results indicated VIF values of all models and variables were less than 3, which indicated weak multicollinearity, and it was not necessary to do corrective measures (Gelman and Hill 2007). Thus, both coefficients and *p*-values of models presented in Table 4 are statistically consistent to explain the variability of *p*MSG8+ coming from *P. radiata* unpruned logs.

For the studied set of logs, AV explained 56,25 % of the variability of structural lumber volume (≥ MSG8), ($p < 0,01$), which supports the importance of this information, as well as the results of comparable studies (Waghorn *et al.* 2007). Wood density (BD) explained 46,24 % of structural lumber volume (> 8 GPa) variation, which confirmed why this variable is considered a central wood property for multiple end uses (Kimberley *et al.* 2015).

Models 1, 2, 3, 4 and 5 in Table 4 showed the best performance in terms of goodness of fit (R^2 - adj > 0,75). Model 1 presented an R^2 – adj. of 0,82, and all coefficients were significantly different from zero ($p < 0,01$). AV had a high weight to explain the variability of *p*MSG8+, which supports results by Jones and Emms (2010). Considering Model 1 for the second log and using the average values of the explanatory variables BI, INT, AV, and CW, the estimated value of *p*MSG8+ was 39 %. When increasing AV by 1 %, this proportion increased more than proportionally by 3 % because the velocity goes as a squared variable in the formula to estimate the MOE_d.

As we expected, branching represented by branch index (BI), the largest branch (LB), as well as corewood (CW), had a negative contribution to the *p*MSG8+ estimations. Branching has a negative influence on the production of structural grades, where high branch angle and diameter reduce the quality of structural products (Beauregard *et al.* 2002, Xu and Walker 2004). Increasing BI by 1 % generated a decrease less than proportional of 0,35 % in *p*MSG8+ (Model 1, second log), and this decrease ranged from 0,25 % to 0,58 % across all models that considered the variable BI. In models that included LB as an explanatory variable, the *p*MSG8+ reduction ranged from 0,34 % to 0,38 % when increasing LB by 1 %. Alzamora *et al.* (2013) reported a similar trend when valuing the effect of branches in the value recovery of logs for structural end uses; an extra millimeter in branch diameter decreased the log value by US$ 0,27. In New Zealand, the largest branch (LB) is the branching variable used to classify and price logs due to its high correlation with structural grades recovery.

CONCLUSIONS

As we expected, branching represented by branch index (BI), the largest branch (LB), as well as corewood (CW), had a negative contribution to the *p*MSG8+ estimates. Branching negatively influences the structural grades production, where high branch angle and branch diameter reduce the quality of structural products. AV, BI, LB, BD, and CW had a significant contribution to explain the recovery of structural lumber grades (≥ MSG8), and the magnitude and sign of their coefficients along the ten models were comparable with those reported by the literature.

The proportion of structural lumber (*p*MSG8+) was strongly related to acoustic measurements and negatively associated with branching variables. Acoustic velocity (AV) was the explanatory variable with the highest weight, explaining 31,55 % of *p*MSG8+ variability in the set of second and third logs. The log internode index (INT) also had a positive contribution to explain the variability of *p*MSG8+

because the higher the internode is, the lower is the negative influence of branches and knots on structural wood quality.

The largest branch (LB) and the branch index (BI) made an equivalent contribution across the models. This result is propitious for using LB as operative criteria to characterize logs because collecting LB information is less time consuming that determining the branch index (BI).

Modeling the variability on *p*MSG8+ was possible based on a set of variables collected in primary logs classification processes such as BI, LB, CW, INT, and other more expensive variables acoustic velocity (AV) and wood basic density (BD). Models using AV presented higher goodness of fit than those using BD. However, models including BD would be more appealing because they could use mean wood basic density information derived from wood density models used by forest companies. This study's results are also pertinent for Chile since structural lumber exported to Europe must be mechanically certified by UNE-EN 519 (1995) in grades C16 and C24, corresponding with a static modulus of elasticity of 7,9 GPa and 10,2 GPa, respectively.

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