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RESEARCH ARTICLE

Using a production approach to estimate economic weights for structural attributes of *Pinus radiata* wood

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Abstract

We modeled the technical relationships between volume of *Pinus radiata* D. Don structural lumber (with stiffness >8 GPa) and log attributes using a stochastic frontier approach. The production models were Cobb–Douglas and Translog, while the log attributes were small end diameter (SED), wood stiffness (STF), and largest branch (LBR); however, the effect of the latter trait was not significant ($p>0.05$). Economic values of log traits were represented by their values of marginal product (VMP). The coefficients for the Cobb–Douglas frontier were statistically significant and the model met most of the production theoretical properties. VMP derived from the Cobb–Douglas were 2.23 NZ$/cm for SED and 16.88 NZ$/GPa for STF. The Translog frontier coefficients were also significant ($p<0.05$) and VMP derived from this model were 1.67 NZ$/cm for SED and 9.15 NZ$/GPa for STF. Thus, for the analyzed production stage, changes to SED and STF were relevant for improving log value recovery above MSG8+. Technical efficiency derived from the frontiers allowed to identify and characterize the best logs to produce structural grades with stiffness of 8 GPa or higher.

Keywords: *Wood traits,* Pinus radiata*, structural lumber, breeding objectives, technical efficiency.*

Introduction

The suitability of wood for a particular end use depends on the physical and chemical traits, which are determinants of wood quality (Mitchell 1961). In the case of lumber, demand for logs depends on the wood properties suitable for particular grades, as well as on the demand of particular lumber grades in lumber markets.

In New Zealand, forestry is the third largest export industry, contributing 8.9% to the total export sector and 2.9% of gross domestic product (GDP). This industry supplies 1.1% of the world's and 8.8% of Asia Pacific's forest products trade, from 0.05% of the world's forest resource (N.Z.F.O.A. 2010). New Zealand has 1.7 million hectares of forest plantations, and 90% of the area corresponds to Radiata pine (*Pinus radiata* D. Don).

One of the major products obtained from Radiata pine is structural lumber, which is graded and marketed by wood stiffness (STF) (Gaunt 1998; Xu & Walker 2004; Waghorn et al. 2007; Jones & Emms 2010). The improvement of this attribute is expected to have a big impact on forest revenue; thus, a 25–50% increase in corewood (defined as the first 10 rings) stiffness, would result in 50% of corewood being up-graded from industrial quality to uses like framing, which could benefit New Zealand growers by $250 million per year (Dickson & Walker 1997; Xu & Walker 2004; Walker 2010). Radiata pine wood production has achieved sustained improvements in production efficiency through the development of breeding programs, which have defined breeding objectives for multiple-trait selection in various breeds, emphasizing a combination of growth, form and wood properties including basic density and stiffness. In this context, wood attributes could be considered as inputs for lumber production, and tree breeding as a mechanism to obtain the required levels of these traits (Cotterill & Jackson 1985; Shelbourne 1997; Watt et al. 2000; Apiolaza & Garrick 2001; Jayawickrama 2001; Kumar 2004; Ivković et al. 2006).

Tree breeding requires the economic values of wood attributes to define economic breeding objectives, which are in turn used to build selection

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indices (Hazel 1943). Common approaches to estimate those values are bioeconomic models and partial regressions. Bioeconomic models consider the value of an attribute as the change in profitability of a forest production system, due to a change in the wood trait (Borralho et al. 1993; Apiolaza & Garrick 2001; Ivković et al. 2006; Berlin et al. 2012). Partial regressions link the attributes of logs and trees with the value of end-products obtained at the mill; after that, the economic values are obtained from the partial derivatives of the regression with respect to the attributes (Cotterill & Jackson 1985; Ernst & Fahey 1986; Aubry et al. 1998). Other methods to derive economic values of attributes are linear programming (Ladd & Gibson 1978; Sivarajasingam et al. 1984) and hedonic models (Bloomberg et al. 2002; Alzamora & Apiolaza 2010).

Economic values for wood traits can be obtained by using production functions of final products as lumber. A production function represents the maximum output attainable from each input level given the current state of technology (Varian 1992). The production approach has been used to determine indirect use values of natural resources and environmental services, where the environmental variable enters the production function along with other factors to produce a marketed good (e.g. Acharya 2000; Freeman 2003; Núñez et al. 2006). The economic value is then estimated as the marginal physical product of the environmental variable valued at the market price of the good, which corresponds to the value of the marginal product (VMP; Freeman & Harrington 2001).

In production research, producers are assumed to optimize their decisions, and production functions are fitted with a deterministic component and random noise. However, most production processes present inefficiencies that can be represented by assuming a distribution of technical inefficiency in addition to the random noise (Coelli et al. 2005). The stochastic frontier (SF) approach allows generating a parametric production frontier as well as technical efficiency (TE) measures, and has been broadly used since it was proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). SF converts the input–output observations to a production frontier, accounting for inefficiency and random noise. In forestry, SF applications have focused mainly on obtaining the TE of harvesting systems (e.g. Carter & Cubbage 1994, 1995). This is the first study in a tree breeding context.

This study uses a SF approach to value Radiata pine log attributes obtained from a structural timber sawing study. Cobb–Douglas and Translog frontier functions are used to model lumber production in terms of log small end diameter (SED), log STF, and largest branch (LBR). These attributes are suitable input-traits since they have been suggested as breeding objective traits to produce structural products from Radiata pine (e.g. Shelbourne 1997; Ivković et al. 2006). The economic value of an attribute corresponds to the VMP, which is the marginal product of the attribute multiplied by the price of the final product (lumber). The efficiency results are used to identify the relative participation of logs traits that distinguish the most productive logs to produce structural lumber.

Materials and methods

The New Zealand wood quality initiative provided data from a sawing study with a sample of 71.5 m long unpruned logs (35 second logs and 36 third logs) from 36 trees. Trees were sourced from two forests: Compartment 8 at Crater Block in the Kaingaroa Timberlands estate (28 years) and Compartment 111/3 at Tarawera (26 years). There were 18 selected trees for each forest, to represent a range in attributes (standing trees acoustics, diameter at breast height, branching, earthwood, etc.). A second log was omitted from the study due to transportation limitations (Jones & Emms 2010).

A subset of the log attributes assessed in this study have been identified as breeding objective-traits to produce structural lumber grades from Radiata pine (e.g. Shelbourne 1997; Kumar 2004; Ivković et al. 2006). Log SED is often used to classify and price logs. STF corresponds to Young's modulus of elasticity, which describes the resistance of an object to be deformed elastically, and it is considered a determining wood property to produce structural lumber (Evans & Ilic 2001; Xu & Walker 2004; Chauhan 2006). STF was predicted using the sound velocity reading assessed using a Director HM200 tool. LBR corresponds to the diameter of the LBR of the log. Branches tend to have a negative influence on the recovery of structural lumber grades from logs (Grant et al. 1984; Xu 2002). Table I shows a summary of the logs attributes.

The objective of the sawing study was to maximize the recovery of New Zealand structural grades. Table II presents details of the log outturn.

Methodological background

The SF is a method to model parametric production frontiers aiming to derive measures of productive or TE (Aigner et al. 1977; Meeusen & van den Broeck 1977; Coelli et al. 2005). Analysis of the SF allows estimating the marginal product of inputs, which are then multiplied by end-products prices in order to obtain the VMP. VMP is a measure of the income

Table I. Descriptive statistics by log class.

Variable	Second log ($N=35$)	Third log ($N=36$)
Mean small end diameter (SED, cm)	44.91	39.77
Maximum SED	62.50	53.90
Minimum SED	32.00	23.30
Standard deviation	8.42	7.71
Mean wood stiffness (STF, GPa)	7.97	7.97
Maximum STF	11.59	10.60
Minimum STF	5.63	5.40
Standard deviation	1.47	1.26
Mean largest branch (LBR, cm)	6.03	7.33
Maximum LBR	11.00	3.50
Minimum LBR	2.50	12.50
Standard deviation	2.10	2.66

supplied by the last unit of a productive input employed (Beattie & Taylor 1985; Varian 1992). The advantages of deriving log attributes' values using a SF are its economic plausibility (since the valuation of inputs is based on the neoclassical model of the firm) and the explicit consideration of technical inefficiencies, which allows identifying the wood trait pattern in the most efficient logs to generate specific lumber grades. SF studies in forestry have mainly focused on obtaining TE of lumber and pulp production, as well as on harvesting and sawmilling systems (e.g. Carter & Cubbage 1994; Löthgren 1997; Yin 2000; Helvoigt & Adams 2009; Niquidet & Nelson 2010).

Equation 1 presents a production SF where Q_i is the total output from the ith production system and x_i is the vector of j inputs in the ith production system.

$$Q_i = x_i^{'}\beta + v_i - u_i \quad i = 1, \ldots n \tag{1}$$

The symmetric random error v_i accounts for statistical noise and can take positive or negative values, following an independent and identical distribution $N(0,\sigma_v^2)$. The random error u_i is a nonnegative variable, which accounts for technical inefficiency. Commonly, the distributional specifications of u_i are assumed to be half-normal $N^+(0,\sigma_u^2)$ and truncated-normal $N^+(\mu,\sigma_u^2)$; although exponential and gamma distributions are also used. Nevertheless, truncated-normal and gamma distribution have shown to be more flexible to represent the distribution of the inefficiency error (e.g. Carter & Cubbage 1994, 1995; Yin 2000; Helvoigt & Adams 2009).

SF is often fitted using ordinary least squares (OLS), corrected OLS or maximum likelihood (ML). This study used the software FRONTIER version 4.1-c to model the SF. FRONTIER initially obtains OLS estimates for the parameters, which are then used as starting values for a ML estimation. The ML estimates are used to calculate the efficiency parameter gamma (γ), which is $\sigma_u^2(\sigma_v^2+\sigma_u^2)$. Gamma varies between 0 and 1, where values close to 1 indicate that the efficiency effect dominates the noise effect and, consequently, the deviations from the SF would be mainly due to productive inefficiencies (Löthgren 1997; Coelli et al. 2005).

Stochastic production frontier modeling. Modeling production functions requires information on inputs and outputs; however, it is also necessary to meet assumptions of essentiality, monotonicity, and quasi-concavity in order to generate plausible models. Essentiality indicates that the existence of inputs implies the existence of output, monotonicity implies that additional units of an input will not decrease output whereas the global quasi-concavity implies the parameters of the model are positive (Henderson & Quandt 1980; Coelli et al. 2005; Niquidet & Nelson 2010).

In this study the output is an aggregate product, log volume of lumber with stiffness of 8 GPa or higher (MSG8+), a threshold often applied to structural lumber (Chauhan 2006). The inputs are SED, STF, and LBR.

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

	MSG6	MSG8 +	Reject	Total yield (%)	MSG8+yield (%)
Second logs					
Mean value	0.221	0.163	0.056	0.500	0.212
Maximum value	0.630	0.594	0.614	0.502	0.470
Minimum value	0.020	0.000	0.000	0.500	0.000
Standard deviation	0.167	0.164	0.112	0.000	0.147
Third logs					
Mean value	0.190	0.106	0.040	0.500	0.173
Maximum value	0.515	0.514	0.361	0.501	0.500
Minimum value	0.000	0.000	0.000	0.500	0.000
Standard deviation	0.129	0.117	0.076	0.000	0.135

Note: MSG machine stress grade and the number corresponds to lumber stiffness in GPa.

We used Cobb–Douglas and Translog functional forms for the production function, and the distributional specifications of u_i were assumed to be half-normal and truncated-normal. The Cobb–Douglas function is frequently used to model technical relationships between outputs and inputs and takes the following form:

$$Q = \beta_0 \prod_{k=1}^{m} X_k^{\beta_k} \quad k = 1, \ldots, m$$

where Q is the total product and X_k are factors of production. The β_k corresponds to product elasticities, which indicate the percentage change on total product for a 1% change of input k. The sum of product elasticities results on the scale elasticity (Coelli et al. 2005). The Cobb–Douglas function assumes that the product elasticities are constant and that the elasticity of substitution is one (Varian 1992; Greene 2000).

The Translog is a more flexible production model, permitting variable elasticity of substitution between inputs, and varying elasticity of scale with output and input proportions. Nevertheless, the generality of the Translog functional form has adverse effects, such as this model is neither monotonic nor globally convex as is the Cobb–Douglas (Weaver 1983; Fried et al. 2008). The Translog takes the following functional form:

$$\ln Q = \beta_0 + \sum_{k=1}^{m} \beta_k \ln X_k + 1/2 \sum_{k=1}^{m} \sum_{l=1}^{m} \beta_{kl} \ln X_k \ln X_l$$

where Q is the total product, X_k are factors of production, and β_k correspond to the model coefficients.

Derivation of economic weights. The economic values of the attributes are estimated as the change in the profit per log for an extra unit of the attribute at the mill. Let us consider that the structural lumber production from log i can be represented by a short-term production function of the type presented in Equation 2:

$$Q_i = Q\left(\overline{L}, \overline{K}, T_1, T_2, \ldots, T_m\right) \quad i = 1, \ldots, n \tag{2}$$

where Q_i is the volume of structural lumber (MSG8+) from log i for which L and K are labor and capital, respectively, and T_j are log traits with $j = 1, \ldots, m$. Further assume that:

- L and K are fixed in the short run.
- The marginal physical product of all input-traits is positive.
- The mill that processes the log is a competitive lumber price-taker.

Under those conditions, the profit achieved from the log i would be represented by Equation 3:

$$\pi_i = P\ Q\left(\overline{L}, \overline{K}, T_1, T_2, \ldots, T_m\right) \tag{3}$$

where π_i corresponds to profit per log, and P represents the net price of lumber (MSG8+) discounting processing costs, in order to obtain a value that reflects the maximum willingness to pay for an extra unit of the attribute at the mill. The P value corresponds to the log conversion return (CR) or log recovery value (Davis & Johnson 1987). Accordingly, the first order conditions for profit maximization are:

$$\frac{\partial \pi_i}{\partial T_j} = P\ \frac{\partial Q\left(\overline{L}, \overline{K}, T_1, T_2, \ldots, T_m\right)}{\partial T_j} \tag{4}$$

From Equation 4, the profit increase due to a marginal change on the trait is represented by the product between the marginal product of T_j and the lumber price, which corresponds to the VMP of the attribute.

Lumber prices and processing costs were obtained from New Zealand firms. The price for 100 × 50 mm MSG8 lumber was 3.2 NZ$/linear m, while the cost for processing one cubic meter of logs was 180 NZ$. All these values were transformed to values per cubic meter of end-product in order to obtain P for Equation 4.

Results

The response variable for the production function was the volume of lumber with stiffness of 8 GPa or higher (MSG8+). About 60 out of the 71 logs met the MSG8+ criterion; satisfying the basic assumption of essentiality.

A linear production model was used for exploratory data analysis, showing that there were no significant collinearity problems and that all predictors but LBR were significant ($p < 0.05$).

Differences for intercept and slope between second and third logs were tested using dummy variables, which were not significant ($p > 0.05$); thus, production modeling considered second and third logs as a single sample.

Economic values for log attributes derived from the SFs

Table III presents the parameter estimates for the Cobb–Douglas production frontier, where all coefficients are exponents of explanatory variables. Significance tests were performed using Likelihood Ratio Tests, which showed that coefficients for SED and STF were significant ($p < 0.05$) and with signs

Table III. Parameter estimates for the Cobb–Douglas production frontier.

$\ln(\mathrm{MSG8+}) = \beta_0 + \beta_1 \ln\mathrm{SED} + \beta_2 \ln\mathrm{STF}$

Parameter	Estimate	Standard error	Prob.
Log β_0	−16.793	1.395	<0.05
β_1	2.161	0.085	<0.05
β_2	3.576	0.517	<0.05

according to expectations; however, the LBR was no-significant ($p > 0.05$).

Likelihood ratio tests were also performed to analyze the differences between models estimated by using truncated-normal or half-normal distribution for the inefficiency error. As a result there was nonsignificant difference between log likelihood function values of these models and we reported those results derived from half-normal assumption for u_i.

The Cobb–Douglas model satisfied the monotonicity condition, which implies that additional units of an input will not decrease output, as shown by the positive marginal products of inputs. There was a significant correlation between observed and predicted values of MSG8+ with the Cobb–Douglas frontier (0.64, $p < 0.05$). The Cobb–Douglas also met the global quasi-concavity assumption; however, coefficients associated with SED and STF were higher than 1; thus, the production of logs capable of producing structural (MSG8+) sawn timber would be in a stage of increasing marginal productivity. Lumber production was SED and STF elastic, as the product elasticities (represented by the coefficients β_1 and β_2) for the traits were >1. In consequence, a simultaneous increase in SED and STF would increase the production of structural lumber more than proportionally. Furthermore, the sum of parameters was also >1, implying that, at the present production stage, this frontier presents increasing returns to scale.

Table IV shows the parameter estimates for the Translog frontier. The coefficients of this frontier were significant ($p < 0.05$).

There was a significant correlation between observed and predicted values of MSG8+ with the Translog frontier (0.66, $p < 0.05$). The product point elasticities for the attributes SED and STF were estimated resulting in 1.94 y 2.38, respectively. Thus, the Translog also showed that the production of structural lumber is SED and STF elastic. In addition, the sum of parameters was >1, implying that this production SF also presents increasing returns to scale when having simultaneous increase in SED and STF.

Table V presents the economic values of wood attributes obtained from the marginal product (VMP) for each attribute by using the Cobb–Douglas and Translog frontier. The first row presents the mean value of VMP, whereas the second row shows the VMP evaluated in the mean value of the attributes. The third row depicts the VMP for the log with the highest TE (TE = 1). All values represent log profit increase for an extra unit of the attribute.

There was a significant correlation between the VMP of SED and STF (0.84, $p < 0.05$) with the Cobb–Douglas model; in addition, the CR of logs was highly correlated with the VMP of attributes (0.74 and 0.95, $p < 0.05$) for SED and STF, respectively. Similar trends were obtained with the Translog frontier; thus, the VMP of SED and STF were highly correlated (0.87, $p < 0.05$) and logs CR had a significant correlation with the VMP of the attributes (0.74 and 0.95, $p < 0.05$) for SED and STF, respectively. Thus, for the production stage considered in this study, SED and STF were significant traits to improve value recovery above MSG8+.

TE of logs to produce MSG8+

The existence of inefficiency in the Cobb–Douglas and Translog frontiers was tested using an likelihood ratio test (LRT) that rejected the null hypothesis ($p < 0.05$) of $\gamma = 0$. The models presented a γ around 0.9, which indicated that the inefficiency effect dominated the noise effect. The mean TE of logs derived from the Cobb–Douglas was 0.54 whereas

Table IV. Parameter estimates for the Translog production frontier.

$\ln(\mathrm{MSG8+}) = \beta_0 + \beta_1 \ln\mathrm{SED} + \beta_2 \ln\mathrm{STF} + 0.5\beta_3 \ln\mathrm{SED}^2 + 0.5\beta_4 \ln\mathrm{STF}^2 + \beta_5 \ln\mathrm{SED}\ln\mathrm{STF}$

Parameter	Estimate	Standard error	Prob.
Log β_0	34.658	7.123	<0.05
β_1	−24.726	3.523	<0.05
β_2	3.921	1.437	<0.05
β_3	5.533	1.125	<0.05
β_4	−5.764	1.455	<0.05
β_5	2.841	0.696	<0.05

Table V. Economic value of the marginal product of SED and STF.

	Cobb–Douglas		Translog	
Value of the marginal product (VMP)	SED (NZ$/cm)	STF (NZ$/GPa)	SED (NZ$/cm)	STF (NZ$/GPa)
Mean value for all logs	2.23	16.88	1.67	9.15
Evaluated in the mean value of SED and STF	1.86	15.66	1.58	9.91
Value in the most efficient log	3.01	17.60	3.75	24.87

with the Translog frontier was 0.59. The most efficient log presented an efficiency score of 1. A TE score lower than one implies that, potentially, the log would be able to generate more output with the same available inputs.

Log efficiency was highly correlated with MSG8 + volume (0.63, $p < 0.05$) and (0.79, $p < 0.05$) for the Cobb–Douglas and Translog frontiers, respectively. The ranking of logs efficiency between the two SF was very similar with a Spearman rank correlation coefficient of 0.89 ($p < 0.05$). Figure 1 shows the TE scores of logs obtained with the Cobb–Douglas and Translog frontiers.

Table VI shows a description of the logs with the highest TE scores (> 0.9) derived from Cobb–Douglas and Translog frontiers. The log CR of these logs was much larger than log prices, a common situation for logs with TE > 0.6.

At the analyzed production stage, the most efficient logs presented STF to SED ratios that ranged between 1:4 and 1:6, with a mean value of 1:5. There was a significant correlation between STF and TE (0.62, $p < 0.05$); however, when considering all logs, this correlation was low and nonsignificant (0.11, $p > 0.01$). The most efficient logs presented a stiffness > 7.5 GPa; furthermore, the most efficient log (TE = 1) had the highest stiffness, the largest CR, and the highest STF:SED ratio.

Discussion

The Cobb–Douglas and Translog frontiers generated plausible relative economic values of SED and STF for the production of structural grades. Thus, for the logs production stage, attributes SED and STF were relevant for improving log value recovery above MSG8 +.

Nevertheless, SED and STF display different coefficients of variation, degrees of genetic control and assessment costs, which will influence how much they can be improved through breeding.

The economic values for SED were similar to figures reported by other studies (Ivković et al. 2006; Alzamora & Apiolaza 2009). However, the economic value of STF was smaller than the value estimated by Alzamora and Apiolaza (2009) when using a partial regression with a comparable data-set. The differences between those values can be explained by the nature of each methodology. The SF is a production function that provides physical outputs; in contrast, partial regressions relate the economic value of logs to their attributes. In addition, we approached the frontier as a single product modeling system, which corresponded to MSG8 +. On the other hand, partial regression used the economic value of every lumber product derived from the logs; hence, it is more sensitive than SF to changes in wood quality. Nevertheless, the economic value of STF was similar

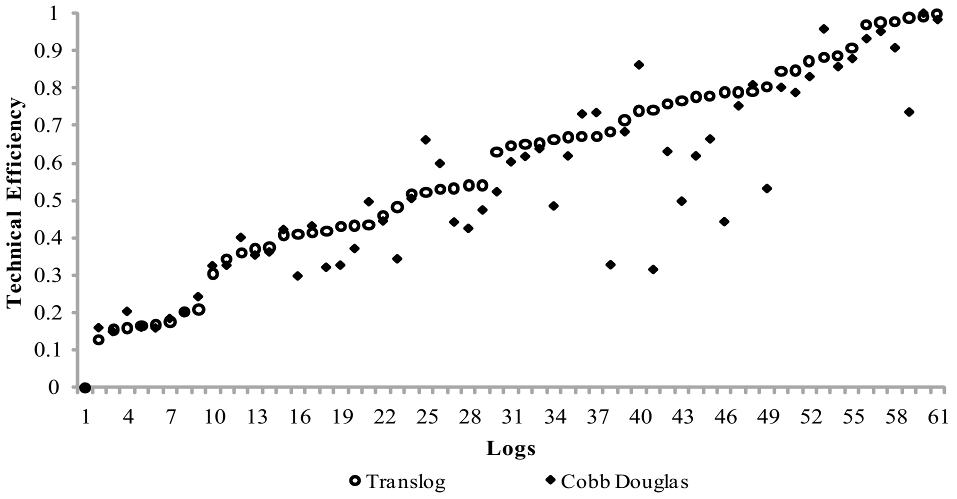

Figure 1. TE scores derived from the Cobb–Douglas and Translog frontiers.

Table VI. Traits and economic values of the most efficient logs to produce MSG8+.

Log class	TE Cobb–Douglas	TE Translog	SED (cm)	STF (GPa)	LBR (cm)	CR (NZ$/m^3)	Log price (NZ$/m^3)	Ratio STF:SED
3rd	0.99	0.96	50.6	8.04	7.0	151.43	68	0.16
3rd	1.00	1.00	31.7	8.98	5.0	193.22	82	0.28
2nd	0.94	0.98	43.8	7.53	11.0	145.55	68	0.17
2nd	0.93	0.98	40.9	7.99	5.0	133.16	86	0.20
2nd	0.92	0.91	48.3	8.05	5.0	152.75	86	0.17

to the value reported by Ivković et al. (2006) by using a bioeconomic model for the production of Radiata pine structural lumber in Australia.

The value of LBR was not significant, which could be due to the variability of branch size in the logs sample. In contrast, studies based on partial regressions, bioeconomic models and sawing studies have reported negative effects of branching on the recovery of structural grades from unpruned Radiata pine logs (Xu 2002; Ivković et al. 2006; Alzamora & Apiolaza 2009).

VMP of SED and stiffness obtained with the Translog frontier were lower than those estimated with the Cobb–Douglas. This could be due to the interactions among production factors allowed in the Translog model. Since the interaction between SED and STF was shown to be competitive, we could expect lower VMP than those estimated with a model without interactions such as the Cobb–Douglas. However, in comparing absolute economic values, the Translog generated values close to those reported by Ivković et al. (2006).

SED and STF presented increasing returns in the production of MSG8+ (coefficients >1). For SED, this result is understandable since a sawmill will only purchase logs within a feasible range of diameters, determined by the sawmill design. Within that range, larger SED logs will yield higher production levels, and since log volume increases as the square of diameter, it is reasonable to expect a coefficient >1 for that variable. About STF, the result could be explained in the same way; thus, as the log STF increases there will be more proportion of structural volume, because this is the most influential trait to produce structural grades (Walker & Nakada 1999; Xu 2002; Ivković et al. 2006). In addition, this is a case study referred to a short run profit function – the data come from only one mill, and the only factor of production that is variable is quality of the log input. In this case, increasing returns to the traits SED and STF may be a plausible result.

As Groen (2003) states, economic weights should express the benefits for improving the economic efficiency of production of end-products. Accordingly, the SF uses the same principle of classical methods, such as partial regressions and hedonic models, to derive economic weights. These approaches are based on measuring traits from logs or trees and recording volume and value of end-products obtained at the mill, with models linking those traits to log recovery grades (SF), log prices (hedonic models), or log recovery value (partial regressions). Furthermore, the information derived from recovery studies has been reported to provide the best input to obtain economic weights (Ernst & Fahey 1986; Aubry et al. 1998). In addition, when comparing the relative importance of SED and STF, the values derived from the SF are not so different to those estimated by complex methods such as bioeconomic models. Nevertheless, the work so far is the beginning of future modeling that considers a long term approach as well as sensibility analyses to examine, on the model's results, the impact of changing variables and production scenarios. Moreover, this work could be improved upon by including several sawmills to better represent the production of lumber including inputs such as capital, technology, and labor.

In general, logs had low efficiency represented by the inefficiency component of the composite error. TE of the most efficient logs was significantly correlated with stiffness; however, this was not observed with diameter. Alzamora and Apiolaza (2009) reported comparable TE results when using a nonparametric and deterministic frontier, such as data envelopment analysis (DEA), for the same product (MSG8+).

DEA and the SF are expected to generate comparable results on TE, as long as the inefficiency effects prevail over statistical noise (Löthgren 1997; Coelli et al. 2005), which has been supported by this study. Todoroki and Carson (2003) also used DEA to identify efficient Radiata pine logs for appearance lumber, looking for the traits that should be targeted by breeding programs. The main advantage of DEA over the SF is that the former does not impose any assumptions on the functional form of the frontier; on the other hand, DEA precludes the estimation of production measures, such as the marginal product. Furthermore, as DEA is a deterministic frontier, all the distance to the frontier is assumed to be due to inefficiency (Coelli et al. 2005; Van Biesebroeck 2007).

Using a single product, such as MSG8+, could be debatable because logs generate a mix of lumber products; however, since lumber production per log is only known after processing, it is plausible to think that the processor plans production according to a minimum wood quality threshold, such as MSG8+, rather than particular lumber grades. Furthermore, in New Zealand the logs for structural purposes are purchased as long as they achieve a minimum threshold of stiffness (Treolar 2005); however, there are no premium prices when they present STF beyond the threshold. In the same way, there is not lumber price differentiation for those products with stiffness >10 GPa; thus, growers' expectations are just based in obtaining logs that fulfill a quality threshold imposed by the market.

The natural heterogeneity of logs made difficult to use the SF approach to explain the productive inefficiency of logs. There is a much larger component of inefficiency associated to natural log variability than when studying conventional production systems such as firms, making the interpretation difficult. As a counterexample, Yin (2000) reported a TE above 99% when using a SF to assess the efficiency of wood pulp producers. The author suggested that the lack of variation due to the homogeneous nature of the pulp production process could account for those results.

Conclusions

The Cobb–Douglas model met the theoretical properties of a well-behaved production model; however, since the coefficients for SED and STF were >1, the economic values for SED and STF were estimated in a nonoptimal production stage. The Translog frontier also was a plausible production model. The VMP generated with the Translog frontier were lower than those estimated with the Cobb–Douglas model, which could be due to the interaction effects, between SED and STF, modeled in the Translog. However, absolute values derived from the Translog were very similar to those reported by a bioeconomic model.

Results about economic weights values indicate that SED and STF for improving recovery above a certain grade are both statistically significant determinants of value in the production of structural lumber. However, the trait-specific variability, heritability and assessment costs have to be taken into account when deciding the selection emphasis for each trait.

The relative economic value for SED was comparable to other studies; nevertheless the value of STF was smaller than the one estimated by a partial regression. This difference was likely due to the SF considers a single product, which limits its application to specific wood quality thresholds. Thus, the SF would be a plausible approach to derive economic values of attributes in scenarios where the production is planned accordingly to a single wood quality threshold, such as MSG8+.

Efficiency measures were useful to characterize the most efficient logs, which presented a STF:SED ratio of 1:5; however, the plausibility of this ratio must be validated by testing a bigger data-set of logs.

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References

Acharya G. 2000. Approaches to valuing the hidden hydrological services of wetland ecosystems. Ecol Econ. 35(1):63–74.

Aigner D, Lovell CAK, Schmidt P. 1977. Formulation and estimation of stochastic frontier production function models. J Econom. 6:21–37.

Alzamora RM, Apiolaza LA. 2009. Economic weights for structural wood attributes and characterization of efficient logs using DEA analysis. Radiata Pine Breeding Company (RPBC). Tech. Rep.

Alzamora RM, Apiolaza LA. 2010. A hedonic approach to value *Pinus radiata* log traits for appearance-grade lumber production. For Sci. 53(6):283–291.

Apiolaza LA, Garrick DJ. 2001. Breeding objectives for three silvicultural regimes of radiata pine. Can J For Res. 31: 654–662.

Aubry CA, Adams WT, Fahey TD. 1998. Determination of relative economic weights for multitrait selection in coastal Douglas-fir. Can J For Res. 28:1164–1170.

Beattie B, Taylor R. 1985. The economics of production. New York: John Wiley & Sons; p. 258.

Berlin M, Jansson G, Lönnstedt L, Danell Ö, Ericsson T. 2012. Development of economic forest tree breeding objectives: review of existing methodology and discussion of its application in Swedish conditions. Scand J For Res. iFirst article, 681–691.

Bloomberg M, Bigsby H, Sedcole R. 2002. Regional variation in radiata pine sawlog prices in New Zealand. N Z J For. 47(1):25–27.

Borralho NMG, Cotterill P.P., Kanowski PJ. 1993. Breeding objectives for pulp production of *Eucalyptus globulus* under different industrial cost structures. Can J For Res. 23: 648–656.

Carter DR, Cubbage FW. 1994. Technical efficiency and industry evolution in southern U.S. pulpwood harvesting. Can J For Res. 24:217–224.

Carter DR, Cubbage FW. 1995. Stochastic frontier estimation and sources of technical efficiency in southern timber harvesting. For Sci. 41(3):576–593.

Chauhan SS. 2006. Wood quality: multifaceted opportunities. In: Walker JCF, editor, Primary wood processing, principles and practice. New York: Springer; p. 170–175.

Coelli T, Rao D, O'Donell C, Battese G. 2005. An introduction to efficiency and productivity analyses. New York: Springer; p. 349.

Cotterill PP, Jackson N. 1985. On index selection I. Methods of determining economic weight. Silvae Genet. 34:2–3.

Davis LS, Johnson KN. 1987. Forest management. New York: McGraw-Hill; p. 789.

Dickson RL, Walker JCF. 1997. Selecting wood quality characteristics for pines. In: Timber management toward wood quality and end-product value. Québec City (Canada): IUFRO publications; p. 45–52.

Ernst S, Fahey TD. 1986. Changes in product recovery of Douglas-fir from old growth to young growth. In: Oliver CP, Hanley DP, Johnson JA, editors. Proceedings of Conference on Douglas-fir stand management for the future; 1985 June 18–20; Seattle (WA): University of Washington, p. 103–107.

Evans R, Ilic J. 2001. Rapid prediction of wood stiffness from microfibril angle and density. For Prod J. 51(3):53–57.

Freeman AM. 2003. The measurement of environmental and resource value: theory and methods. 2nd ed. Washington: Resources for the Future.

Freeman AM, Harrington W. 2001. Measuring welfare values of productivity changes. South Econ J. 56(4):892–904.

Fried HO, Lovell CA, Schmidt SS. 2008. The measurement of productive efficiency and productivity growth. New York: Oxford University Press, Inc.

Gaunt D. 1998. If you're not winning, change the rules. *Wood Processing Newsletter* Issue No. 23. Forest Research, Rotorua, New Zealand.

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.

Greene WH. 2000. Econometrics analysis. 4th ed. New Jersey: Prentice-Hall.

Groen AF. 2003. Breeding objectives and selection strategies for layer production. In: Muir, WM, Aggrey, SE, editors. Poultry genetics, breeding and biotechnology. Oxfordshire: CABI Publishing; p. 101–112.

Hazel LN. 1943. The genetic basis for constructing selection indexes. Genetics. 28:476–490.

Helvoigt TL, Adams DM. 2009. A stochastic frontier analysis of technical progress, efficiency change and productivity growth in the Pacific Northwest sawmill industry. For Policy Econ. 11(4):280–287.

Henderson J, Quandt R. 1980. Microeconomic theory – a mathematical approach. Economics handbook series; United States of America. New York: McGraw-Hill, Inc. p. 420.

Ivković M, Wu HX, McRae TA, Powell MB. 2006. Developing breeding objectives for radiata pine structural wood production. I. Bioeconomic model and economic weights. Can J For Res. 36(11):2920–2931.

Jayawickrama KJS. 2001. Breeding radiata pine for wood stiffness: review and analysis. Aust For. 64(1):51–56.

Jones TG, Emms GW. 2010. Influence of acoustic velocity, density, and knots on the stiffness grade outturn of radiata pine logs. Wood Fiber Sci. 42(1):1–9.

Kumar S. 2004. Genetic parameter estimates for wood stiffness, strength, internal checking, and resin bleeding for radiata pine. Can J For Res. 34(12):2601–2610.

Ladd GW, Gibson C. 1978. Microeconomics of technical change: what's a better animal worth. Am J Agric Econ. 61:236–240.

Löthgren M. 1997. Generalized stochastic frontier production models. Econ Lett. 57:255–259.

Meeusen W, van den Broeck J. 1977. Efficiency estimation for Cobb-Douglas production functions with composed error. Int Econ Rev. 18:435–444.

Mitchell HL. 1961. A concept of intrinsic wood quality and nondestructive methods for determining quality in standing timber (Report No. 2233). Wisconsin, United States: Forest Products Laboratory, University of Wisconsin–Madison.

Niquidet K, Nelson H. 2010. Sawmill production in the interior of British Columbia: a stochastic ray frontier approach. J For Econ. 16:257–267.

Núñez D, Nahuelhual L, Oyarzún C. 2006. Forests and water: the value of native temperate forests in supplying water for human consumption. Ecol Econ. 58(3):606–616.

N.Z.F.O.A. 2010. New Zealand forest industry facts and figures (2010/2011); [cited 2012 Feb 10]. Available from: http://www.nzfoa.org.nz/images/stories/pdfs/fandf2011web.pdf

Shelbourne CJA 1997. Genetic of adding value to the end products of radiata pine. In Burdon RD, Moore JM, editors. IUFRO '97 Genetics of Radiata pine Conference: New Zealand FRI Bulletin 203; 1997 December 1–4; Rotorua (New Zealand): Forest Research Institute, p. 129–141.

Sivarajasingam S, Burnside EB, Wilton JW, Pfeiffer WC, Grieve DG. 1984. Ranking dairy sires by a linear programming dairy farm model. J Dairy Sci. 67:3015–3024.

Todoroki CL, Carson SD. 2003. Managing the future forest resource through designer trees. Int Trans Oper Res. 10:449–460.

Treolar C. 2005. Log grade revision: structural log grades. N Z J For. 49(4):33–34.

Van Biesebroeck J. 2007. Robustness of productivity estimates J Ind Econ. LV (3):529–569.

Varian HR. 1992. Microeconomic analysis. London: W. W. Norton & Company; p. 563.

Waghorn MJ, Mason EG, Watt MS. 2007. Influence of initial stand density and genotype on longitudinal variation in modulus of elasticity for 17-year-old *Pinus radiata*. For Ecol Manag. 252(1–3):67–72.

Walker JCF. 2010. Breeding – getting the most from radiata pine. N Z Tree Grower. 31(2):13–14.

Walker JCF, Nakada R. 1999. Understanding corewood in some softwoods: a selective review on stiffness and acoustics. Int For Rev. 1(4):251–259.

Watt MS, Turner JA, Mason EG. 2000. Genetic influence on second-log branching in *Pinus radiata*. N Z J For Sci. 30(3):315–331.

Weaver RD. 1983. Multiple input, multiple output production choices and technology in the U.S wheat region. Am J Agric Econ. 65:45–56.

Xu P. 2002. Estimating the influence of knots on the local longitudinal stiffness in radiata pine structural timber. Wood Sci Technol. 36(6):501–509.

Xu P, Walker JCF. 2004. Stiffness gradients in radiata pine trees. Wood Sci Technol. 38(1):1–9.

Yin RS. 2000. Alternative measurements of productive efficiency in the global bleached softwood pulp sector. For Sci. 46(4):558–569.