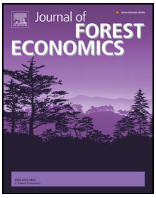
Journal of Forest Economics 19 (2013) 221–233

Contents lists available at ScienceDirect

Journal of Forest Economics

journal homepage: www.elsevier.com/locate/jfe



A DEA approach to assess the efficiency of radiata pine logs to produce New Zealand structural grades

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ARTICLE INFO

Article history:
Received 23 July 2010
Accepted 31 January 2013

JEL classification:
C1
D11

Keywords:
Log efficiency
DEA
Pinus radiata
Economic weights
Structural lumber
Breeding objectives

ABSTRACT

An efficiency analysis revealed the relative magnitude of wood traits that distinguishes efficient radiata pine logs to produce New Zealand structural grades. Technical and cost efficiencies were obtained by using data envelopment analysis (DEA). Wood trait prices used to perform the cost efficiency corresponded to economic weights derived from a partial regression. These values were 1.1, 29.7, 0.3 and −0.4 NZ $/m^3 for small end diameter (cm), stiffness (GPa), basic density (kg/m^3) and largest branch (mm) respectively. The most efficient logs were those with the highest difference between recovery value and price. There were positive and significant correlations between technical efficiency and wood stiffness (0.46, $p < 0.05$) and between cost efficiency and log recovery value (0.85, $p < 0.05$). The most efficient logs had a ratio of 1:4 between stiffness and small end diameter whereas logs that did not generate structural lumber presented ratios close to 1:8. This information will inform the development of breeding objectives, and help segregating and pricing logs by using traits patterns that result in efficient logs for the production of structural wood.

Introduction

Lumber specifications present important challenges to breeders, who must focus on multiple attributes to achieve the quality thresholds required by consumers. For instance, improving wood

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http://dx.doi.org/10.1016/j.jfe.2013.01.003

stiffness has become imperative in New Zealand since the introduction of the standard NZS3622:2004, which demands verification of structural lumber properties. Consequently, in recent years the New Zealand radiata pine (*Pinus radiata* D. Don) breeding program has emphasized work on traits such as stiffness (Shelbourne, 1997; Jayawickrama and Carson, 2000; Kumar et al., 2002). Furthermore, growers are also looking for combinations of genetic material and silvicultural regimes that improve the structural characteristics of logs according to market demands (Waghorn et al., 2007a). Tree breeders are expected to increase wood quality, defined as the relative magnitude of log traits that generate high value lumber. Breeding could then be approached as a production system where the inputs are both wood traits and the relationships among them, while the outputs are logs that generate a high recovery value at the mill. Under this framework the relative contribution of traits would be a key element in assessing the productive efficiency of logs. A log would be an efficient unit of lumber production as long as its traits were able to generate a high recovery of the most valuable lumber.

The efficiency of units of production, such as logs, can be analyzed by the efficiency frontiers approach which includes two methods, data envelopment analysis (DEA) which is a non-parametric deterministic model, and the stochastic frontier which is a parametric production function (Coelli et al., 2005; Van Biesebroeck, 2007).

DEA analyses the efficiency of a production unit in using and combining inputs to produce a given level of output (Farrell, 1957; Charnes et al., 1978; Färe et al., 1985; Xue and Harker, 1999; Coelli et al., 2005). DEA has been usually applied to decision-making units such as firms to detect inefficiencies and reduce them by adjusting the use of inputs (e.g., Carter and Cubbage, 1995; Chakraborty et al., 2002). Estimating the efficiency of logs to produce lumber may seem unusual, since it is not possible to have control over their use of inputs. Nevertheless, breeding and silviculture can be used to change the relative magnitude of wood traits by targeting the genetic material to be deployed, stocking and site selection (e.g., Jayawickrama, 2001; Lasserre et al., 2004; Waghorn et al., 2007b).

Furthermore, there are examples of using efficiency frontiers to characterize radiata pine logs. Thus, Todoroki and Carson (2003) used DEA to identify the most efficient logs to produce appearance grades looking for traits that could be manipulated in a breeding program. Alzamora and Apiolaza (2012) applied a stochastic frontier to analyze the mix of wood traits in the most efficient logs to produce structural grades.

DEA generates measures of technical, allocative and economic efficiencies. Technical efficiency is concerned with producing the maximum output with the available inputs, or minimizing the use of inputs to achieve a given output level. Allocative efficiency deals with the optimal combination of inputs, given the input prices. Economic efficiency, or cost efficiency, represents the total efficiency of a production system (Farrell, 1957; Färe et al., 1985; Jahanshahloo et al., 2008).

Obtaining cost efficiency requires input prices; however, this information is not commonly available for wood traits. Instead, economic weights used by breeders to develop breeding objectives and to build selection indices can be used as plausible prices. The economic weight of an attribute is defined as the net increase in production system profit for each unit of improvement of the attribute (Hazel, 1943). Economic weights would represent the implicit cost of traits when breeding efficient logs. Thus, based on efficiency criteria, breeders should produce logs that maximize the value of output with a given level of input. Accordingly, breeding programs should target those logs that achieve the highest efficiency scores. The relative magnitude of traits in those logs could be useful information to improve silvicultural regimes as well as to design protocols for segregation and classification of logs.

Bioeconomic models and partial regressions are two common approaches for the estimation of economic weights (e.g., Borralho et al., 1993; Greaves et al., 1997; Aubry et al., 1998; Apiolaza and Garrick, 2001; Berlin et al., 2009). Bioeconomic models consider the value of a trait as the change in profitability of a forest production system due to a change in that trait. The modeling requirements for Bioeconomic models are complex and costly, for this reason a substantial part of the models has been based on large numbers of assumptions. On the other hand, Bioeconomic models offer a framework to assess the impact of breeding decisions across all the production chain, allowing analyze the sensitivity of several system elements (Amer et al., 1997; Jones et al., 2004).

Partial regressions link wood traits from logs with volume and value of products obtained at the mill. Partial coefficients derived from partial regressions correspond to the economic weights (Talbert, 1984; Cotterill and Jackson, 1985a,b; Ernst and Fahey, 1986; Aubry et al., 1998). The major limitation of partial regressions is the high cost of running a product recovery study; however, Ernst and Fahey (1986) and Aubry et al. (1998) assert that approaches derived from recovery studies provide the best information to obtain economic weights.

Economic weights can be also estimated by using hedonic prices which correspond to the implicit prices of traits and are revealed to economic agents from observed prices of differentiated products and the specific amounts of traits associated with them (Lancaster, 1966; Rosen, 1974). In forestry, Alzamora and Apiolaza (2010) presented a hedonic approach to value log attributes for radiata pine appearance grades.

This study provides estimates of log efficiency of wood traits usage to produce structural lumber. The application is performed by using an input-oriented DEA based on a sample of 71 radiata pine logs. Economic weights derived from a partial regression are used as input prices to estimate cost efficiency. We hypothesize that there should be a high correlation between structural grades recovery and log technical efficiency; that logs with the highest cost efficiency should also present the highest value recovery; and that stiffness and efficiency will be highly correlated with log recovery value, but not with log prices.

Materials and methods

Data set

Data were provided by the New Zealand Wood Quality Initiative, as a sample of 71 (35 second logs and 36 third logs) 5 m long unpruned logs from two forests: Compartment 8 at Crater Block in the Kaingaroa Timberlands estate (28 years) and Compartment 111/3 at Tarawera (26 years). Table 1 presents a summary of log attributes.

The attributes assessed in the study have been suggested as breeding objective traits to produce structural products from radiata pine (e.g., Shelbourne, 1997; Ivković et al., 2006). Log small end diameter is commonly used to classify and price logs. Taper is a measure of form that corresponds to the degree to which the tree stem (or log) decreases in diameter as a function of its height. Small end diameter and taper are intimately related to lumber recovery during log processing. Largest branch is the diameter of the largest branch of the log. Branches have a negative influence in the production of structural grades, where high branch angle and diameter reduce the quality of structural products (Grant et al., 1984; Xu, 2002). Basic density 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. Wood stiffness corresponds to Young's modulus of elasticity, which describes the capacity of an object to be deformed elastically, but not permanently, when it receives a force (Chauhan, 2006). The acoustic measurements of logs to estimate stiffness were collected using a Director HM200 tool.

In general terms, breeders have aimed at increasing small end diameter, basic density and stiffness, reducing taper and limiting the knot size (small largest branch).

The strategy to process the log sample was to cant saw, maximizing the recovery of 100 × 50 mm structural lumber. Broken full-length boards were kept but short boards and 25 mm boards were excluded from the study. The resulting 1300 boards were machine stress graded twice. The stress grader captured all the grading information at 152 mm increments along the lumber with the first and

Table 1
Mean values and standard deviations of second and third log attributes.

Variable	Second log		Third log	
	Mean	Standard deviations	Mean	Standard deviations
Small end diameter (cm)	44.91	8.41	39.77	7.71
Stiffness (GPa)	7.97	1.47	7.97	1.26
Basic density (kg/m^3)	382.34	28.69	377.97	28.70
Largest branch (mm)	60.29	20.97	73.33	26.59
Taper (mm/m)	8.25	3.20	10.06	3.16

last 700 mm of the lumber being ungraded. Lumber was identified as structural grades 6, 8, 10 and 12, where the number is the wood stiffness in GPa.

Economic weights

Economic weights were derived from a partial regression that considered log recovery value, or conversion return (Davis and Johnson, 1987), as the response variable, and small end diameter, taper, largest branch, basic density and stiffness as explanatory variables. Log recovery value (LRV) corresponds to the total value of lumber contained in one cubic meter of logs minus the total log processing cost:

$$\mathrm{LRV} = \sum_{i=1}^{n} p_i \times L_i - \mathrm{PC} \tag{1}$$

where p_i is the price of lumber type i, L_i is the volume of lumber type i contained in one cubic meter of logs, and PC is the processing cost of one cubic meter of logs. The partial regression model to estimate the economic weights for the attributes is:

$$\mathrm{LRV} = \sum_{i=1}^{n} \beta_i \times t_i \tag{2}$$

where LRV is the log recovery value of the logs (NZ $\$/\mathrm{m}^3$), t_i is the total amount of trait i contained in one cubic meter of log and β_i corresponds to the economic weight of trait i.

Information to calculate LRV (Eq. (1)) was obtained from New Zealand firms. The prices for 100 × 50 mm lumber were 2.5, 3.2 and 4.1 NZ $/linear m for structural grades 6, 8 and 10 respectively, while the processing cost was 180 NZ $\$/\mathrm{m}^3$. Processing cost depends on log diameter but we are assuming that it does not vary significantly in this log sample. The price for structural grade 12 was estimated as 4.8 NZ $/linear m by assuming that the differential price between grades 8 and 10 would be the same as between grades 10 and 12. Reject products were priced at 1.3 NZ $/linear m.

Efficiency analysis

Data envelopment analysis (DEA) is a method to estimate non-parametric efficiency frontiers in multi-product and multi-input systems. DEA involves the use of linear programming to build a non-parametric surface over the data; thus, efficiency measures are calculated relative to this surface or frontier (Coelli et al., 2005; Van Biesebroeck, 2007; Jahanshahloo et al., 2008). Input-oriented DEA estimates technical efficiency, which determines how much can inputs be proportionally reduced in order to achieve the same output level. Technical efficiency is represented by an input/output ratio constrained to be between zero and one, defining a frontier with the logs that present the lowest ratios. Logs located in the frontier obtain a technical efficiency score of one; less efficient logs, located below the frontier, obtain scores lower than one.

There will be as many linear programming problems as logs are analyzed. For each problem, a fully efficient comparison point (technical efficiency = 1) is obtained by projecting the log on the frontier using a linear combination of the closest efficient logs. The proportional distance from the log to the fully efficient point on the frontier corresponds to that log's technical efficiency.

Preliminary results from the partial regression analyses suggested focusing on three traits: small end diameter, wood stiffness and basic density. Without losing generality, the technical efficiency of log i to produce volume of structural grades 8 (SG8), 10 (SG10) and 12 (SG12), using small end diameter (SED), wood stiffness (STF) and basic density (BD), was formulated as follows:

$$\begin{aligned}
&\text{Minimize } \tau \\
&\tau, k \\
&\text{subject to,} \\
&\begin{bmatrix} \text{SED}_1 & \text{SED}_2 & \cdots & \text{SED}_n \\ \text{STF}_1 & \text{STF}_2 & \cdots & \text{STF}_n \\ \text{BD}_1 & \text{BD}_2 & \cdots & \text{BD}_n \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \le \tau \begin{bmatrix} \text{SED}_i \\ \text{STF}_i \\ \text{BD}_i \end{bmatrix} \\
&\begin{bmatrix} \text{SG8}_1 & \text{SG8}_2 & \cdots & \text{SG8}_n \\ \text{SG10}_1 & \text{SG10}_2 & \cdots & \text{SG10}_n \\ \text{SG12}_1 & \text{SG12}_2 & \cdots & \text{SG12}_n \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \ge \begin{bmatrix} \text{SG8}_i \\ \text{SG10}_i \\ \text{SG12}_i \end{bmatrix}, \\
&\begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \ge 0
\end{aligned}$$

where the decision variables are τ, which represents technical efficiency, and the vector of constants k. The matrix of log traits contained the attributes, one row per log, while the matrix of log products contained the volume of structural grades, one row per log.

The total economic efficiency, or cost efficiency, is derived from an optimization problem that generates the minimum cost of traits per log; logs for which their current cost equals the optimal cost generate the cost efficiency frontier. The cost efficiency of log i corresponds to the ratio between its projected cost in the frontier and its observed cost; when this ratio is 1, the log i is cost efficient (Färe et al., 1985; Coelli et al., 2005). The cost efficiency frontier model was formulated as follows:

$$\begin{aligned}
&\text{Minimize : cost} \\
&k,\ \text{SED}_i^*,\ \text{STF}_i^*,\ \text{BD}_i^* \\
&\begin{bmatrix} \text{pSED}_i & \text{pSTF}_i & \text{pBD}_i \end{bmatrix} \begin{bmatrix} \text{SED}_i^* \\ \text{STF}_i^* \\ \text{BD}_i^* \end{bmatrix} \\
&\text{Subject to,} \\
&\begin{bmatrix} \text{SG8}_1 & \text{SG8}_2 & \cdots & \text{SG8}_n \\ \text{SG10}_1 & \text{SG10}_2 & \cdots & \text{SG10}_n \\ \text{SG12}_1 & \text{SG12}_2 & \cdots & \text{SG12}_n \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \ge \begin{bmatrix} \text{SG8}_i \\ \text{SG10}_i \\ \text{SG12}_i \end{bmatrix} \\
&\begin{bmatrix} \text{SED}_1 & \text{SED}_2 & \cdots & \text{SED}_n \\ \text{STF}_1 & \text{STF}_2 & \cdots & \text{STF}_n \\ \text{BD}_1 & \text{BD}_2 & \cdots & \text{BD}_n \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \le \tau \begin{bmatrix} \text{SED}_i^* \\ \text{STF}_i^* \\ \text{BD}_i^* \end{bmatrix} \\
&\begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \ge 0
\end{aligned}$$

Then, the cost efficiency (CE) of the i-th log is calculated as:

$$\mathrm{CE}_i = \frac{\begin{bmatrix} \mathrm{pSED}_i & \mathrm{pSTF}_i & \mathrm{pBD}_i \end{bmatrix} \begin{bmatrix} \mathrm{SED}_i^* \\ \mathrm{STF}_i^* \\ \mathrm{BD}_i^* \end{bmatrix}}{\begin{bmatrix} \mathrm{pSED}_i & \mathrm{pSTF}_i & \mathrm{pBD}_i \end{bmatrix} \begin{bmatrix} \mathrm{SED}_i \\ \mathrm{STF}_i \\ \mathrm{BD}_i \end{bmatrix}}$$

where pSED_i, pSTF_i and pBD_i correspond to the prices of small end diameter, wood stiffness and basic density, respectively. For this study, those values were estimated, as economic weights, from the partial regressions approach.

For both analyses, technical efficiency and cost efficiency, there will be as many linear programming problems as logs are analyzed.

DEA also derives measures of allocative efficiency which represents the ability of a production unit in using the optimal set of inputs for a given set of input prices. Allocative efficiency is estimated as the ratio between cost efficiency and technical efficiency. Extending the interpretation of this concept to logs is difficult, as the allocative efficiency of logs is the result of natural processes and silvicultural actions rather than a deliberate decision by logs. Therefore, this study will not report allocative efficiency results.

The efficiency analysis was run using the software DEAP version 2.1 (Coelli et al., 2005), which can run input-oriented and output-oriented DEA. In addition, DEAP allows the estimation of returns to scale of the logs. Our hypothesis was that logs would have constant returns to scale, which is plausible when production units are operating in an optimal scale (Coelli et al., 2005). Log production is controlled by the economic rotation age (Chang, 1998), and since the logs of this study are economically mature, we would be located in the economic stage of the production that includes the point of optimal scale.

DEA was also run considering structural lumber with stiffness of 8 GPa or higher (SG8+) as a single generic product. That analysis would be suitable for growers because they want to achieve a profitable wood quality threshold, without considerations about particular structural grades.

Results and discussion

In the first section we present the effect of log attributes on recovery of structural grades and economic return and build a linear regression to explain recovery of SG8+ products. This is followed by the estimation of economic weights using a partial regression. Finally DEA integrates the previous results to determine, from both technical and economic viewpoints, the relative mix of traits that characterizes an efficient log to produce SG8, SG10, SG12 as well as SG8+.

Relationships between log traits and structural volume

The correlations between log attributes agreed with results reported by Cotterill and Jackson (1985a,b), Beauregard et al. (2002), Chauhan and Walker (2006) and Ivković et al. (2006). There was a negative and significant correlation between stiffness and small end diameter (−0.49, $p < 0.05$). The correlation between stiffness and basic density was also significant (0.72, $p < 0.05$); nevertheless, this association would be much weaker for young trees at the time of selecting for breeding (e.g., Chauhan and Walker, 2006). The relationships between largest branch and small end diameter, as well as between largest branch and stiffness were also in accordance with other published values (Grant et al., 1984; Tombleson et al., 1990; Watt et al., 2000; Jayawickrama, 2001; Xu, 2002; Kumar, 2004; Apiolaza, 2009). Details of this information are presented in Table 2.

Significant correlations were found between second and third log attributes ($p < 0.05$); however, second logs had higher small end diameter, stiffness and basic density, and lower largest branch than third logs (results not presented). For instance, the maximum values of stiffness and largest branch for second and third logs were 11.6 and 10.6 GPa, and 110 and 125 mm, respectively. These results

Table 2
Pearson correlation coefficients between log attributes and lumber grade recovery.

	Small end diameter	Stiffness	Basic density	SG6	SG8	SG10	SG8+
Small end diameter				0.73*	0.19	−0.07	0.05
Stiffness	−0.49*			−0.66*	0.23*	0.59*	0.60*
Basic density	−0.17	0.72*		−0.37*	0.32*	0.52*	0.59*
Largest branch	0.43*	−0.49*	−0.14	0.56*	−0.07	−0.32*	−0.29*

* Significant at 0.05 level.

are similar to those obtained by comparable logs recovery studies (e.g., Gazo et al., 2000; Beauregard et al., 2002; Xu and Walker, 2004).

Products with stiffness of 8 GPa or higher were generated in 86% of the second logs, and 83% of the third logs. SG10 was generated in 66% of the second logs and 56% of the third logs whereas SG12 was produced in 37% of second logs and 6% of the third logs. There was a high correlation between small end diameter and SG6 (0.73, $p < 0.05$); nonetheless, the correlation between this product and stiffness was negative. SG6 was positively correlated with largest branch, which was also expected due to the positive relationship between small end diameter and both, branch size and SG6. However, when the lumber stiffness requirements increased, these correlations reversed their signs. Thus, the correlations of stiffness with both SG8 and SG10 were positive and significant (0.23 and 0.59 respectively, $p < 0.05$). Consequently, SG10 was negatively correlated with largest branch. The correlations between log traits and SG8+, i.e., lumber volume with stiffness of 8 GPa or higher, followed the same trend as for SG10.

The high significance of the correlations between structural volume and log traits supported building models to explain the recovery of SG8+. Different intercepts and slopes for second and third logs were tested using dummy variables, which were not significant ($p > 0.05$); thus, all logs were considered as a single population. There were no significant collinearity or heteroskedasticity issues.

The model had moderate goodness of fit (R^2-adj 0.57). The coefficients for small end diameter, stiffness and basic density were significant ($p < 0.05$); however, the coefficient for largest branch was not significantly different from zero. Branching has shown to have a negative effect on the recovery of structural grades (e.g., Grant et al., 1984; Xu, 2002) and was expected to display a significant effect on SG8+. Table 3 shows details of the model.

Log recovery value and economic weights

LRV averaged 111 and 95 NZ $/m^3 for second and third logs respectively, and the average for all logs was 103 NZ $/m^3. The highest LRV coincided with the highest stiffness for second and third logs; however, these logs did not have the largest small end diameter. In fact, the logs with the highest LRV and stiffness had a small end diameter of less than 41 cm. Product SG10 volume showed the highest correlation with LRV (0.79, $p < 0.05$). A high correlation was also found between LRV and stiffness (0.85, $p < 0.05$), as well with basic density (0.69, $p < 0.05$). Correlations between LRV and largest branch (−0.43, $p < 0.05$), and LRV with small end diameter (−0.29, $p < 0.05$) were also significant, but moderate. Similar results had been documented by Cotterill and Jackson (1985a,b) and Beauregard et al. (2002).

Table 3
Models to explain volume recovery of SG8+ in terms of log traits.

	Coefficients	Standard error	*P*
Intercept	0.332*	0.014	<0.05
Small end diameter	0.008*	0.002	<0.05
Stiffness	0.074*	0.020	<0.05
Largest branch	−0.001	0.001	>0.05
Basic density	0.002*	0.001	<0.05
Taper	0.007	0.005	>0.05
R^2-adj	0.57		

* Significant at 0.05 level.

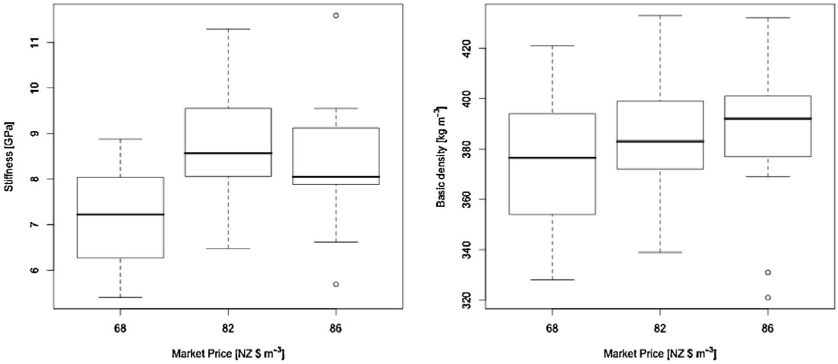

Fig. 1. Relationship between wood stiffness and basic density with log prices.

In spite of the importance of stiffness to explain quality and value of logs for structural purposes, it is not included in the current classification to price logs in New Zealand. Unpruned log prices are basically defined in terms of small end diameter and largest branch (MAF, 2009a) and do not consistently represent the value of structural lumber contained in logs. As a result, 5% of those logs with the highest price (86 NZ $/m^3) had negative LRV. As stiffness is not included in formal pricing criteria, there is a wide range of stiffness for any given log price, which is particularly evident for those logs with the highest price (86 and 82 NZ $/m^3). That situation is illustrated in Fig. 1 which shows the relationships between log prices and traits not included in the log pricing criteria, such as stiffness and basic density. There was a large overlap of stiffness across log prices and an even more dramatic trend is observed for basic density, where there was almost complete overlap across price classes.

Log prices should reveal the processors willingness to pay for structural wood quality which is strongly correlated with stiffness; however, this concept has not been internalized in the log market. This lack of price incentives for growers could generate a market biased toward low quality logs, homologous to the problem pointed out by Akerlof (1970), where information asymmetries would damage no just growers but also processors.

This study is based on log prices reported by Ministry of Agriculture and Forestry (MAF, 2009a), which do not consider a price for stiffness. However, there are unpublished transactions where a premium is paid for stiffness. For example, some sawmills in the New Zealand's North Island only buy structural logs that meet a threshold of acoustic measures.

Table 4 presents the partial regression of log recovery value on log traits. This model also fitted centered predictors, expressing them as deviations from their mean values (Gelman and Hill, 2007). All variables presented the expected behavior in relation to log recovery value, with the exception of taper that displayed a positive rather than a negative coefficient. Coefficients associated with small end diameter, stiffness and largest branch were significant ($p < 0.05$) and the goodness of fit was high (R^2-adj 0.75). Basic density did not provide a significant explanation of log recovery value ($p < 0.05$).

Table 4
Regression of LRV on log traits; regression coefficients are also the economic weights.

Variable	Coefficients	Standard error	*P*
Intercept	102.966*	3.247	<0.05
Small end diameter	1.056*	0.479	<0.05
Stiffness	29.681*	4.657	<0.05
Basic density	0.330	0.184	>0.05
Taper	2.256*	1.099	<0.05
Largest branch	−0.362*	0.176	<0.05
R^2-adj	0.75		

* Significant at 0.05 level.

Small end diameter and stiffness were the most important predictors, accounting for 73% of the LRV variation.

Given the linearity of the model, the regression coefficients correspond to the economic weights. The economic value of small end diameter was 1.1 NZ $/cm, which represents the marginal contribution of small end diameter to LRV. Having an extra GPa of stiffness would increase the log recovery value by 29.7 NZ $. The value of largest branch was negative; thus, an extra millimeter of largest branch would decrease LRV by 0.4 NZ $. In contrast, Alzamora and Apiolaza (2010) reported that largest branch was not relevant to explain the economic value of unpruned logs for appearance timber. Furthermore, these authors reported an economic value for small end diameter three times higher than the value obtained in this study. These divergences would be due to the different requirements for appearance and structural products: there are no stiffness requirements for appearance products; in contrast, stiffness is a key quality trait for structural lumber (Evans and Ilic, 2001). In addition, small end diameter has a direct relationship with the recovery of appearance grades; but it has shown to be negatively correlated with the recovery of structural lumber.

DEA and wood traits performance on the most efficient logs

The efficiency analysis considered small end diameter, stiffness and basic density as inputs to produce structural grades. The products corresponded to lumber with stiffness of 8 GPa or higher (SG8+), which left 60 logs for the analyses. An 8 GPa threshold is commonly used to distinguish structural wood quality of radiata pine (Chauhan, 2006).

Considering SG8, SG10 and SG12 products, the mean technical efficiencies were 0.70 and 0.54 for second and third logs respectively. A technical efficiency of 0.7 implies that the log could reduce the use of traits by 30% and still achieve the same output. Cost efficiency was 0.65 for second logs, and 0.46 for third logs. This means that the cost of traits per output unit could be reduced by 35% when using fully efficient logs.

Although it is not possible to improve log efficiency by reducing attributes; instead, we could derive information about the wood traits patterns that characterize those most efficient logs. Thus, there would be a different approach to better define the wood quality standards that should be targeted by breeding programs.

Considering all logs, the highest correlation between technical efficiency and a single product was with SG10 (0.72, $p < 0.05$); in contrast, the associations between technical efficiency and SG6 as well as non-structural products were negative and significant ($p < 0.05$). Technical efficiency was directly correlated with stiffness (0.46, $p < 0.05$); however, there was not significant correlation with small end diameter. By comparison, Todoroki and Carson (2003) reported an output-oriented model to assess the efficiency of radiata pine logs to produce appearance grades. As a result, in their work log volume was highly correlated with technical efficiency.

While volume is determinant in the quality of logs for appearance purposes, stiffness has been shown as the most relevant trait to produce structural lumber (e.g., Dickson and Walker, 1997b; Evans and Ilic, 2001; Apiolaza, 2009). As a result, the most technically efficient logs had small end diameter lower than 41 cm, but their stiffness were greater than 8 GPa (see Table 5). Achieving structural production goals with smaller small end diameter implies that the rotation age could be reduced.

A high and significant correlation was found between LRV and technical efficiency (0.80, $p < 0.05$), which was expected due to the direct relationship between LRV and stiffness. The cost efficiency highly correlated with LRV (0.85, $p < 0.05$); nevertheless, the correlations between cost efficiency and log prices were poor and non-significant (0.23, $p > 0.05$). Moreover, technical efficiency was highly correlated with cost efficiency (0.97, $p < 0.05$).

Fig. 2 illustrates the efficiency for second and third logs. Results are presented in ascending cost efficiency order for illustration purposes only. There was a high variability between logs for technical efficiency and economic efficiency; in addition, some logs showed significant differences between those efficiencies. The latter was frequent in logs with small end diameter greater than 40 cm and SG8+ lower than 15% of log volume. Those logs were inefficient because they had a very low SG8+ in comparison with the magnitude and cost of their traits.

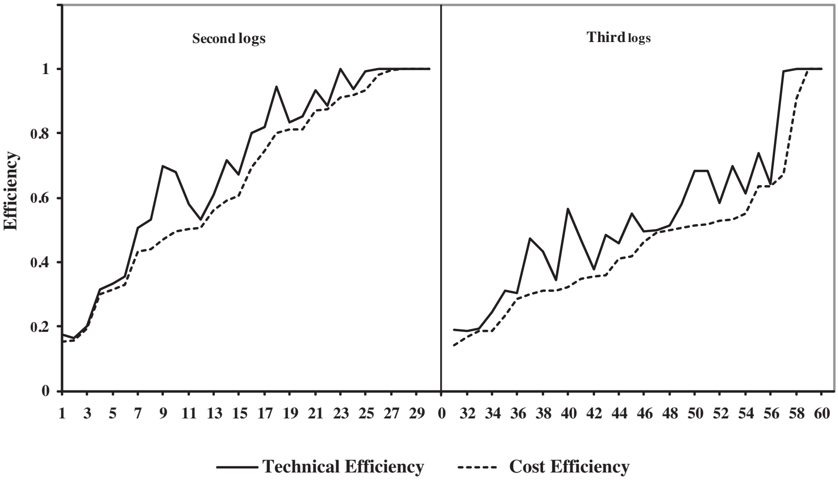

Fig. 2. Technical efficiency and cost efficiency by log.

Second logs presented a higher overall efficiency than third logs; however, trees of exceptional high quality had second and third logs with similar patterns of wood attributes. This resulted in some third logs outperforming the average of second logs. Xu and Walker (2004) obtained similar trends when studying the longitudinal stiffness profile in radiata pine trees.

DEA was also performed considering the aggregate of SG8+ as a single product. The average efficiencies for second and third logs were respectively 0.56 and 0.43 for technical efficiency and 0.46 and 0.34 for economic efficiency. These values are lower than those obtained with three separate products; however, the technical efficiency and cost efficiency trends for logs were similar to those showed in Fig. 1.

Similarly to three-product DEA there were also high and significant correlations between LRV and technical efficiency (0.83) and between LRV and cost efficiency (0.88). Only one log scored 1 for technical efficiency and cost efficiency when aggregating SG8+ products.

A high and significant correlation was found between technical efficiency and SG8+ (0.96, $p < 0.05$); a similar trend was observed for the cost efficiency. Stiffness was directly correlated with technical efficiency (0.59, $p < 0.05$); however, the correlation between technical efficiency and small end diameter was non-significant. There was also a high correlation between technical efficiency and cost efficiency (0.93, $p < 0.05$).

In general, analyzing SG8+ as an aggregate or as three separate products resulted in constant returns to scale. However, there were 4 logs that had decreasing returns to scale when working with separate products. In spite of this we run DEA models considering constant returns to scale because this was the general trend and it also let us to properly compare single-product to multi-product scenarios. In addition, output-oriented and input-oriented DEA provide comparable results on technical efficiency when using constant return to scale (Coelli et al., 2005). Thus, the most technically efficient logs in input minimization are also the most technically efficient logs in output maximization.

Alzamora and Apiolaza (2012) reported comparable results when using a stochastic frontier to analyze a sample of radiata pine logs for the same aggregate product (SG8+). Results indicated the most technically efficient logs, were significantly correlated with stiffness; however, this was not observed with the small end diameter. In determining technical efficiency, the main advantage of DEA over the stochastic frontier is that the former does not impose any assumptions on the functional form of the production frontier (Coelli et al., 2005; Van Biesebroeck, 2007); however, as DEA is a deterministic frontier, the whole distance to the frontier is assumed to be due to technical inefficiency (Coelli et al., 2005; Van Biesebroeck, 2007; Jahanshahloo et al., 2008).

Table 5

Traits and LRV of the most efficient logs to produce SG8, SG10 and SG12.

Log class	Small end diameter (cm)	Stiffness (GPa)	Basic density (kg/m^3)	LRV (NZ $/m^3)	Log price (NZ $/m^3)	Ratio STF:SED
2nd a	36.4	9.5	383	210.8	82	0.26
3rd a	50.6	8.1	386	151.4	68	0.16
2nd b	40.8	11.6	432	234.0	86	0.28
3rd b	36.2	10.6	423	195.8	82	0.29
2nd	39.7	10.0	406	201.5	82	0.25
3rd	31.7	9.0	379	193.2	82	0.28

Table 5 shows trait values for the six logs that scored 1 on technical efficiency, and cost efficiency in the multi-product analysis (log numbers indicate class – second or third log – while letters denote logs that come from the same tree). The most profitable log was a second log that had the highest stiffness (11.6 GPa), the second highest basic density, the highest percentage of SG12 product, and the highest difference between LRV (234 NZ $/m^3) and price (86 NZ $/m^3). This log was characterized by stiffness to small end diameter ratio (STF:SED) greater than 1:4 whereas the mean ratio for the 60 logs was 1:5. In contrast, 80% of the logs that did not generate structural lumber presented STF:SED ratio of 1:8. This suggests that any increase in small end diameter should occur along an increase of stiffness, with a STF:SED ratio of 1:5 or greater in order to maximize log profitability.

The correlation between STF:SED ratio and LRV was significant (0.63, $p < 0.05$). In addition, modeling LRV in terms of basic density, largest branch and the STF:SED ratio, presented an R^2-adj of 0.61 and all coefficients were significantly different from zero ($p < 0.05$). We used the arcsin transformation to convert the ratio into a variable that was nearly normal (Greene, 2000).

Conclusions

Stiffness, small end diameter and largest branch had a significant contribution to explain the recovery value of logs to produce structural lumber grades. The magnitude and sign of the economic weights agreed with our expectations. As the structural quality requirements increased stiffness became the most relevant log attribute to explain structural volume and log value recovery for structural grades.

Our results do not support the assumption that published log prices consistently reflect the value of structural lumber contained in the logs. There was a wide range of stiffness included in any given log-price class; in addition, efficiency measures and structural volume had a poor correlation with log prices.

In general, logs were efficient in combining traits given their economic weights; however, most logs could reduce their use of traits and achieve the same output level or, conversely, achieve higher outputs with their current trait usage.

The efficiency approach has shown that, when analyzing wood production in a multi-trait and multi-product context, there are interactions between growth and wood quality traits that result in profitable wood production. Understanding these interactions would be useful to improve silvicultural decisions (such as stocking and rotation age) which have been mostly driven by individual attributes rather than by a combination of them.

Technical and cost efficiency were highly correlated with stiffness and log recovery value. In addition, DEA allowed deriving information about the relative mix of traits that distinguishes the most efficient logs. A stiffness to small end diameter ratio, STF:SED, of 1:4 characterized the most efficient and profitable logs. Both stiffness and small end diameter are inputs in the production of structural lumber and their complementarity ratio is useful information to support an efficient approach for breeding and selection purposes. Furthermore, this type of indicator could be useful as a fast log quality screening procedure.

Our results on the influence of stiffness on recovery of volume and value of structural grades, as well as the plausibility of the STF:SED ratio as an indicator of log quality, suggest that stiffness should be formally included in the segregation and pricing of logs to incentivize a market with high quality logs for structural purposes.

Acknowledgements

We want to thank Wood Quality Initiative New Zealand for providing access to the dataset. We also thank Antonio Pinto and Gonzalo Paredes for their helpful comments and suggestions. Finally, the authors acknowledge the constructive comments from two anonymous reviewers.

Rosa M. Alzamora and Luis A. Apiolaza were partly funded by the New Zealand Radiata Pine Breeding Company.

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