Valuing Breeding Traits for Appearance and Structural

Timber in Radiata Pine

A thesis submitted in partial fulfillment of the

Requirements of the Degree

of Doctor of Philosophy

in the University of Canterbury

by Rosa M. Alzamora

University of Canterbury

2010

Abstract

The aims of this thesis were; firstly, to obtain economic values for radiata pine traits to produce appearance and structural lumber, and secondly to analyze the selection of efficient logs and profitable trees to substantiate the development of breeding objectives for solid wood quality.

The thesis included three approaches to value wood attributes: hedonic models, partial regressions and stochastic frontiers. Hedonic models generated economic values for pruned and unpruned log traits to produce appearance grades. Values for small end diameter were 0.33, 0.19 and 0.10 US \$/mm, and for form 2.6, 1.4 and 0.63 US \$ for the first, second and third log respectively. The value of mean internode length was 0.19 US \$/cm. Branch size traits were non-significant to explain the log conversion return ($p > 0.05$).

The economic value of log traits to produce structural lumber with stiffness of 8, 10 and 12 GPa was estimated with a partial regression. The 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. Small end diameter and stiffness explained 73% of the variation of log conversion return. The economic values for structural attributes were also derived from a Cobb Douglas stochastic frontier, resulting in 2.1 NZ \$/cm for small end diameter and 15.8 NZ \$/GPa for stiffness. The change of values between approaches can be attributed to differences of model formulation. The stochastic frontier used aggregate volume of lumber with stiffness of 8 GPa or higher. The partial regression used the economic value of every lumber product derived from the logs, making it more sensitive to changes in wood quality.

Data envelopment analysis (DEA) used structural traits and their economic values to assess the technical and economic efficiency of logs to produce lumber with stiffness of 8, 10 and 12 GPa. The most efficient logs had 1:4 ratios between stiffness and small end diameter, whereas logs that did not generate structural lumber had ratios closer to 1:8. Trait economic values from the partial regression analysis were used as attribute prices to estimate cost efficiency. Efficiency measures were significantly correlated with stiffness and log conversion return; however, they were non-significantly correlated with small end diameter and log prices. The technical efficiency of logs to produce structural lumber was also determined using a Cobb Douglas stochastic frontier which determined that the most efficient logs were characterized by a 1:5 ratio between stiffness and small end diameter.

Selection of trees for deployment was analyzed with a portfolio model, where risk was represented as the mean absolute deviation of tree returns due to the variability of volume, stiffness and resin defects. Under high variability (risk), the model selected structural trees with large stiffness and high return. These results suggest an opportunity for narrowing genetic variability (via clonal or family forestry) to make the returns from radiata pine structural grades lumber less risky.

As variability decreased the portfolio model opted for trees that produced appearance and structural lumber. These trees had a stabilizing effect on their returns, as there were phenotypic tradeoffs between stiffness and volume under optimistic and pessimistic growing scenarios. These results showed the benefits of product diversification at the tree level.

Todas las teorías son legítimas y ninguna tiene importancia. Lo que importa es lo que se hace con ellas.

Jorge Luis Borges

 "say it in words." Don't be satisfied with a formal argument if you don't understand it.

Joan Robinson

Dedicated to Maria Mallea, for her precious sacrifice and Antonio for his love and patience.

Acknowledgments

In first place I would like to record my gratitude to my senior supervisor Dr. Luis A. Apiolaza for his support, advice, guidance and invaluable patience from the very beginning of my work. Thanks for encouraging me Luis! I realize it has not been easy, but all sacrifices have been rewarded with lots of learning.

Thanks to the Radiata Pine Breeding Company (RPBC) because this research would not have been possible without their financial support. Thanks also to the Wood Quality Initiative and Mr Marco Lausberg for providing me with information and advice.

I am also grateful to Dr. David Evison and Dr. Bruce Manley for their support, help and comments on my doctoral work. I must also acknowledge Professor John Walker, Dr Richard Woollons, Mr Don McConchie, Dr. Tim Coelli, Dr. Satish Kumar and Dr. Euan Mason who provided me with help, information and advice along the way. My appreciation also goes out to Mr Jeff Tombleson for his help and suggestions with my manuscripts and to Jeanette Allen who provided me with timely help and guidance in times of need. My thanks go out to Mario Meneses, Victor Mena Jean P. Lasserre for their help and advice from Chile.

My deepest thanks and love to my devoted husband Antonio, for his love, patience, mathematical help and constant support in all my endeavors.

A very special thanks goes out to Lithos, Marcela and Orlando, dear friends, family, and English teachers that helped me settle in this new environment in order to carry out my research. I am also very grateful to Kelita for her constant help and for making me feel as loved as a real daughter.

Thanks to my friends at *Casa Piedra* in Valdivia: Hernán, Alejandra, Carolina, Teresa, Elke, Claudia, Piky and Gonzalo. A special thanks also goes out to Boris, Lucy, Naty, and to my loyal friends Paula, Jaime, Marcela Paz, Cristian, Kena, Carlos y Lulo.

Last but not least I wish to acknowledge my parents; my father, who understands nothing about Universities or theses, however he has been able to show me the virtues of being educated. Most especially I want to acknowledge my mother's memory because she has been my hero, and my inspiration of life and sacrifice to achieve my goals.

Table of Contents

List of Figures

Chapter 4

List of Tables

Declaration

I declare that the information, models and material in this thesis are my own work, excepting for the following assistance:

    i. My senior supervisor provided statistical advice in chapter 3.

    ii. The publication given as chapter 3 was written by me and my senior supervisor.

    iii. All chapters of this thesis were written by me with a critical and helpful review from my senior supervisor.

1 General Introduction

Breeding objectives define the direction of breeding programs by providing the characteristics to improve and their economic values, which depend on the production systems and the end products being targeted by the breeding strategy (Apiolaza 2000). A breeding objective defines the net genetic merit of individuals which considers the breeding value of the trait, and its economic weight due to one-unit change in the breeding value considering all other traits unchanged (Hazel 1943).

Defining breeding objectives in forestry is not trivial; there are difficulties associated with the tradeoffs between objective traits, the complexity of the processing systems, the technical relationships between wood traits and volume and quality of end products, and the long rotation that generates uncertainty about the trees use (Apiolaza and Greaves 2001). On the other hand, when having clear objectives that integrate the economic value of growth and wood quality traits, the programs will be working according to the industry expectations of efficiency and competitiveness.

Wood production based on radiata pine 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 such as basic density and stiffness (Cotterill and Jackson 1985; Carson 1987; Shelbourne et al. 1989; Shelboume et al. 1997; Shelbourne 1997; Watt et al. 2000; Apiolaza and Garrick 2001; Jayawickrama 2001b, a; Kumar et al. 2002; Kumar 2004; Ivković et al. 2006). On the other hand, economic weights have received less study and their estimation has been based on a single approach such as bioeconomic models.

Hazel (1943) demonstrated the incorporation of economic values into a breeding objective to calculate phenotypic selection indexes and estimate aggregate breeding values in livestock. When multiple traits are used to define the breeding objective, index selection has been shown to be more efficient than other forms of selection choosing genetically superior animals (Hazel 1943; Hazel and Terrill 1946). In this sense, economic values should be estimated for all attributes based on their contribution to increase the volume and the quality of final products.

Bioeconomic models consider that the value of one trait corresponds to the change in profitability of a production system, due to a change in the trait (e.g., Borralho et al. 1993;

Greaves et al. 1997b; Apiolaza and Garrick 2001; Ivković et al. 2006). These models have been suitable to estimate economic weights in vertically integrated firms; however, their representativeness is limited to those systems. As a result, the issue of the distribution of an economic weight between forest and mill has not been well solved. On the other hand, the bioeconomic approach has been useful to assess the convenience of investing in breeding, since the model of a vertically integrated firm considers all stages of production, from the acquisition of logs to the retailing of the final product.

Although bioeconomic models have showed plausible results, the economic theory offers more alternatives to value a product's traits. Thus, we have partial regressions which link logs traits with volume and value of products obtained at the mill. Partial coefficients derived from the model correspond to the economic weights (Talbert 1984; Cotterill and Jackson 1985; Ernst and Fahey 1986; Aubry et al. 1998). The major limitation of the method 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 give the best information to obtain economic weights.

Economic weights can be addressed 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 estimating economic weights of radiata pine wood traits, the main restriction for using hedonic models is that traits are not reflected in log prices. Some factors involved in this situation are monopsony power in log purchasing, information asymmetries on log quality between growers and processors, and the transaction costs involved in assessing logs quality. Signaling and screening are reported as solutions to these problems. In signaling, the part with higher information signals their preferences as a way to transfer information to the other part (Spence 1973). Sawmills have signaled their preferences on log diameter and form with differentiated prices. However, traits such as wood stiffness have been signaled in terms of restrictions; thus, logs are purchased as long as they fulfill a stiffness threshold. Screening consists in that the underinformed part induces the other part to reveal their preferences by providing a list of choices in such a way that the selected option depends on the private information of the informed part (Stiglitz 1975).

Vertical integration has been also proposed as a solution of information problems; however, this solution could result in having monopolistic and monopsonic markets which has been shown to affect the economic surplus on log demand and lumber supply.

However, since those traits are observable, measurable and directly related to the quality and value of end products, an alternative approach of log value could be used in order to apply those models. Thus, Alzamora and Apiolaza (2010) used the conversion return instead of the log price to estimate a hedonic model to value pruned and unpruned log traits for radiata pine appearance grades. Bloomberg et al. (2002) also used this approach to study price differences of radiata pine logs in terms of traits in four regions in New Zealand.

The production theory also offers a suitable framework to value wood traits. By this approach the traits would have a measurable physical contribution that can be modeled by production functions (e.g., Ladd and Martin 1976; Melton et al. 1994). A production function is a mathematical model of inputs that give the maximum output feasible to obtain, given the current technology. The economic value is estimated as the change in the marginal physical product of the attribute valued at the market price of the final good, which corresponds to the value of the marginal product (Beattie and Taylor 1985). In modeling a production function, the approach of the stochastic frontier allows generating a parametric production frontier as well as technical efficiency measures (Aigner et al. 1977; Meeusen and van den Broeck 1977; Coelli et al. 2005). By this method the input-output observations are converted to a frontier, accounting for technical inefficiency and random noise.

Linear programming also provides algorithms to solve the problem of economic weights. The goal is to obtain shadow prices for the traits which represent the maximum willingness to pay for an extra unit of the trait. The explicit consideration of constraints and alternative production possibilities is the main advantages of this method which has been occasionally applied on animal and agricultural breeding to obtain economic weights (Ladd and Gibson 1978; Jansen and Wilton 1984; Armstrong et al. 1990; Harris and Freeman 1993). Linear programming is also the base of methods that have been used to reveal the pattern of traits that distinguishes an optimal log to produce given lumber grade. Thus, Todoroki and Carson (2003) used Data envelopment analysis (DEA) to identify the most efficient logs to produce appearance grades looking for attributes that should be manipulated in tree breeding programs. DEA derives efficiency measures by comparing production units with optimal units generated by linear programming algorithms.

The aim of this thesis is to perform alternatives approaches to value radiata pine traits for appearance and structural lumber as well as to show their potential role in selecting logs and trees under efficiency and profitability criteria. Regarding economic weights, chapter 2 describes several methods that could be used to value wood attributes and chapter 3 presents a

hedonic model to value pruned and unpruned log traits (small-end diameter, form and internode length) for appearance grades, including Moulding & Better, Shop and Industrial Finger Joint. Models are also built at the tree level to explore the effect of selection as conducted by breeders. This chapter demonstrates that the log conversion return is a plausible measure of value when the log prices do not consistently reflect the value of traits.

In keeping with economic weights, chapter 4 deals with a DEA efficiency analysis and a partial regression to obtain economic weights for structural logs traits. The main purpose of this chapter is to reveal the relative magnitude of traits that characterize the most efficient logs from a technical and economic point of view. Thus, economic weights derived from the partial regression are used as traits prices to perform the cost efficiency. In keeping with the production approach, the chapter 5 presents the estimation of economic weights for structural logs attributes by using a stochastic frontier. The technical relationship between structural lumber, log small end diameter, wood stiffness and largest branch was modeled by using a Cobb-Douglas function which allowed obtaining the model coefficients as well as measures of the logs productive efficiency. The economic weights correspond to the value of the marginal product of each trait. That analysis also generated productive efficiency measures to characterize the most efficient logs. Chapters 4 and 5 are compared in depth because they have the same theoretical platform, and they are performed with the same information.

The chapter 6 contains an application of a portfolio selection to demonstrate that trees and silvicultural regimes can be approached as investment problems, and how the risk due to wood traits variability can affect decisions about the tree that should be targeted by radiate pine silviculture.

Finally, chapter 7 has a general discussion whose focus are, i- the plausibility of the economic weights estimated in chapters 3, 4 and 5 as well as the feasibility of obtaining the economic weights distribution, between forest and mill, when performing a bioeconomic model, and ii- the potential role of both, traits and economic weights, to assess and select logs and trees for improving the production of wood quality.

2 Review: Production and hedonic approaches to estimate economic weights of radiata pine wood attributes

2.1 Abstract

This review presents two approaches to value wood attributes for the purpose of deriving economic breeding weights. The first one, dubbed a production approach, is based on deriving values from lumber production using bioeconomic models, partial regressions, linear programming and stochastic frontiers. The second approach is based on hedonic prices which derives the value of wood traits from log prices. Bioeconomic models are suitable for vertically integrated forest companies; however, bioeconomic modeling can be expensive to apply and commonly includes numerous assumptions that may limit their application. Partial regressions produce results that are highly plausible but are also costly to obtain. Linear programming is appropriate when log processors face similar production constraints. Stochastic frontiers give consistent values and allow for characterization of the logs' technical efficiency, however, modeling production functions can be a highly complex activity. Hedonic prices are the most suitable method to value product characteristics; however, they require that market log prices reflect trait values of interest, which may not always occur. Log prices based on wood quality traits such as stiffness and internode length that better reflects the variable log resource is likely to enable improved estimation of economic weights.

Keywords: economic weights, breeding objectives, wood attributes, *Pinus radiata.*

2.2 Introduction

Forest management and processing depend on multiple tree characteristics that influence the quantity and quality of end products. This situation is explicitly recognized by breeders who practice multivariate selection, aiming to maximize industry profit. The direction of the breeding efforts is embodied in a *breeding objective*: the enumeration of biological traits under selection and their relative economic weights.

Ponzoni and Newman (1989) formalized the steps to define a breeding objective as i- identification of the sources and flows of income and cost, ii- identification of the biological traits that affect efficiency of production and iii- calculation of the economic weight for each objective trait. Although conceptually simple these steps are fraught with implementation

problems, mostly due to the complexity of the production systems and poorly described relationships between raw materials and final products (Apiolaza and Garrick 2001). This review concerns itself only with Ponzoni's third step: eliciting values for each objective trait. Furthermore, although the methodologies presented in this review apply to any tree species, the bibliography on specific wood traits refers mostly to radiata pine (*Pinus radiata* D. Don) aiming to support successive chapters.

Natural input-traits are commonly evaluated by their performance to generate specific goods or services. Many forest tree species are multipurpose and feed fiber, structural and appearance wood markets, with different wood trait requirements. For example, for radiata pine appearance wood is influenced by traits such as volume, internode length and resin defects. Structural wood is mostly determined by modulus of elasticity (stiffness), volume, branch size and wood density. Fiber production relates to basic density, fiber length and chemical composition (Zhang 1997; Walker and Nakada 1999; Tsehaye et al. 2000b; Tsehaye et al. 2000a; Xu 2002; Kumar 2004; Xu and Walker 2004; Tsuchikawa 2007). Most of these characteristics are heritable and amenable to breeding; a subset can also be tackled through silviculture. Either way there is a need for a hierarchy of traits to guide tree (and log) improvement to profitably meet consumers' requirements.

Obtaining wood traits information from logs is not simple; logs are naturally heterogeneous, which creates problems for product differentiation and the definition of quality grades and standards. Fortunately, there have been significant advances to identify and measure wood properties such as stiffness from trees and logs (Harris and Andrews 1999; Walker and Nakada 1999; Lindström et al. 2002; Matheson et al. 2002; Lasserre et al. 2004; Lasserre et al. 2005; Lasserre et al. 2007; Waghorn et al. 2007a; Waghorn et al. 2007b). There are also methods to segregate pruned logs in order to minimize defects such as resin pockets on appearance lumber (e.g., Somerville 1997; Ridoutt et al. 1999; McConchie 2002; McConchie and Turner 2002). Near Infrared Spectroscopy (NIR) has become popular for quick screening properties that have a strong chemical basis (e.g., Raymond and Schimleck 2002; Schimleck et al. 2002; Tsuchikawa 2007). Nevertheless, information about the economic value of wood quality traits is a topic that has not been developed to an equal extent.

Valuing input-traits has been conducted mainly on agriculture and animal production (Ladd and Martin 1976; Ladd and Suvannunt 1976; Ladd and Gibson 1978; Ethridge 1982; Brascamp et al. 1985; Stewart et al. 1990; Espinosa and Goodwin 1991; Amer and Fox 1992; Bowman and Ethridge 1992; Beckman and van Arendonk 1993; Amer et al. 1996; Goddard

1998; Dalton 2003). In forestry, this issue has been applied primarily to value breeding objective-traits and to build selection indices. (Borralho et al. 1993; Greaves et al. 1997b; Shelbourne 1997; Apiolaza and Garrick 2001; Ivković et al. 2006; Berlin et al. 2009). The economic weight of a trait is defined as the change in economic outcome of a production system caused by a change in the genetic value of the trait (Hazel 1943). These values have been habitually obtained using bioeconomic models. By this approach, the trait value corresponds to the change in profitability of a production system due to a change in the attribute (e.g., Apiolaza and Garrick 2001; Ivković et al. 2006).

In addition to bioeconomic models economic theory offers other approaches to estimate values of input-traits without market prices. For example, the theory of revealed preferences developed by Samuelson (1948, 1953) presents an appropriate framework to value wood attributes. This theory states the possibility of discerning consumer behavior on the basis of variable prices, revealing consumers' preferences by their purchasing habits. Approaches derived from this theory have also been useful to value non-market environmental resources (Adamowicz and Graham-Tomasi 1991; Freeman and Harrington 2001; Hassan et al. 2005).

A general value approach derived from this theory is the *productivity change*, which has been applied to value non-market inputs that contribute to the production of commercially traded goods. This is an indirect approach because input-trait values are obtained through market prices of end-products (Freeman and Harrington 2001; Freeman 2003). There are several methods that may fall under this description, including bioeconomic models, partial regressions, linear programming and stochastic frontiers. Values derived from these methods are interpreted as the maximum willingness to pay for having an extra input-trait to produce lumber.

The other approach is hedonic prices which basic premise is that the price of a marketed good is related to its characteristics (Griliches 1961; Lancaster 1966; Griliches 1971; Rosen 1974; Lucas 1975; Palmquist and Smith 2001). This approach has been extensively applied to estimate non-market attributes; however, it requires that the value of the characteristic is reflected in the product price (Haab and McConnell 2003; Lambert and Wilson 2003; Lambert 2009).

This chapter reviews alternative methods to derive economic values for log traits considering production and hedonic approaches. The advantages and limitations of the methodologies are discussed considering complexity, information requirements and economic plausibility.

2.3   Production approach

Under a production perspective log attributes have the role of input-traits related to lumber production. Groen (2003) stated that "The economic value of a trait expresses to what extent economic efficiency of production is improved at the moment of expression of one unit of genetic superiority for that trait". Therefore, having extra units of log traits generates quantitative and qualitative changes on lumber production, which can be monetarized following methodologies like bioeconomic models, partial regressions, linear programming and stochastic frontiers.

2.3.1   Bioeconomic models (BM)

These models are used to integrate biophysical and economic processes within a production structure. BM can be viewed as complementary to the concept of cost-benefit analysis (Amer et al. 1994; Amer et al. 1997; Conington et al. 2000; Jones et al. 2004). BM model the effects of input-traits changes on the profitability of a whole production system and are useful to understand the interactions between elements of complex systems.

BM have been extensively used in animal breeding and they have been reported as being efficient tools to describe complex production systems (e.g., Dekkers 1991; Amer et al. 1994; Koots and Gibson 1998). One advantage of BM is that they consider genetic aspects, management decisions and economic factors to provide economic values in various traits. In addition, BM offer a framework to assess the impact of breeding decisions across the production chain; facilitating conducting sensibility analyses with several elements of the system (Amer et al. 1997; Jones et al. 2004). Nevertheless, most radiata pine BM have been applied to scenarios that consider a single grower and one processing system. Additionally, a large part of the model is based on assumptions (Borralho et al. 1993; Greaves et al. 1997a; Chambers and Borralho 1999; Apiolaza and Garrick 2001; Ivković et al. 2006; Berlin et al. 2009). Using assumptions is a common exercise in economic evaluations, especially when dealing with complex production systems; however, they can reduce model plausibility.

A more realistic production scenario for BM was proposed by Ivković et al. (2006) for the production of radiata pine structural lumber in Australia. This model included mean annual stem diameter increment, stem sweep, branch size, and modulus of elasticity. Economic weight estimates were based on the impact of improving a trait on overall profitability of three production systems: grower, sawmill, and integrated firm. Despite careful modeling there were economic weights with counter-intuitive values, such as the negative value for mean

annual diameter increment at the sawmill. Log diameter is intimately related to wood recovery during log processing; consequently, increasing this trait should be beneficial. In addition, there was no equivalence between trait values at the forest or the mill levels, and the corresponding value for the integrated system. Trait values should be congruent across BM production systems. Applying concepts derived from the residual-value appraisal to estimate stumpage, such as conversion return, and margin for profit and risk, would allow obtaining the expected trait signs as well as a congruent distribution of trait value between forest and mill (Davis and Johnson 1987).

Profit functions are analogous to BM, although they are usually presented as a different method (Groen 2003). The main distinction is that a profit function refers to a single equation while BM comprise a set of equations (Borralho et al. 1993; Krupova et al. 2008). A single profit equation is not adequate to describe physical and economic interactions when the production system is complex. In contrast, BM are more flexible to capture such interactions. Profit equations have been extensively used to derive economic weights in animal breeding (Brascamp et al. 1985; Ponzoni 1986; Stewart et al. 1990; Beckman and van Arendonk 1993; Weller 1994). In forestry, Borralho et al. (1993) used profit equations to estimate economic weights for volume, basic density and pulp yield in a *Eucalyptus globulus* kraft pulp production system.

Although BM are suitable to estimate economic weights, their modeling requirements are complex and costly; for this reason a substantial part of BM in forestry have been based on many assumptions. In addition, the yet unresolved distribution of an economic weight between forest and mill becomes relevant when independent growers make the decision to purchase genetically improved material.

2.3.2   Partial regressions (PR)

PR consider measuring wood attributes from logs or trees and recording volume and value of products obtained at the mill, with regressions linking log attributes to log recovery value, which corresponds to the conversion return or maximum willingness to pay for logs delivered to the sawmill (Davis and Johnson 1987). The partial coefficients estimated by the regressions correspond to the economic weights (Talbert 1984; Cotterill and Jackson 1985; Ernst and Fahey 1986; Aubry et al. 1998).

Partial regressions are intimately related to the definition of breeding objective because their structure mimic Hazel's (Hazel 1943) model of total genetic superiority. Hazel defined the

aggregate genetic-economic value as a linear combination of additive genetic values of two or more attributes weighted by their economic relative values:

$$H = v_1 a_1 + v_2 a_2 + ... v_n a_n = v'a \qquad (2.1)$$

where H is aggregate or total genetic-economic value, v and a are vectors of economic weights and objective traits respectively. An economic weight represents the benefit of one unit improvement of the attribute without altering the other traits present in the objective (Hazel 1943).

The major limitation of PR is the high cost of sawing studies; however, approaches based on recovery studies provide the best information to obtain economic weights (Ernst and Fahey 1986; Aubry et al. 1998). Trait values should express the benefits for improving the economic efficiency of production of end-products (Groen 2003). On the other hand, since economic weights could vary with milled products, grading systems and lumber prices, it is important to use plausible information to represent current and future production scenarios (Aubry et al. 1998).

There have also been other studies linking trees and logs attributes with the resulting volume and value recovery but that have not explicitly calculated economic weights for the attributes (e.g., Zhang 1997; Beauregard et al. 2002; McConchie and Turner 2002).

2.3.3 Linear programming (LP)

Linear programming also provides algorithms to solve the problem of economic weights. The goal is to obtain shadow prices for the traits which represent the maximum willingness to pay for an extra unit of the trait. Solving a linear programming problem implies to select actions in such a way as to obtain an optimal plan which maximizes the objective function and is feasible for satisfying the constraints (Sivarajasingam et al. 1984). Thus, the explicit consideration of constraints and alternative production possibilities is the main advantage of this method which has been occasionally applied on animal and agricultural breeding to obtain economic weights.

In animal breeding, Ladd and Gibson (1978) applied LP to derive economic weights for livestock. These values are obtained by profit changes for having genetically superior strains of livestock. Harris and Freeman (1993) used LP to obtain economic values for yield traits and herd life from a farm system under different economic scenarios and production quotas. Similarly, Jansen and Wilton (1984) utilized LP to derive economic weights for livestock

selection. These authors contrasted the LP model performance with a profit equation. Thus, the explicit consideration of constraints and alternative production possibilities would be the main advantages of LP over the approach of profit equations. In the same way, Armstrong et al. (1990) utilized LP to compare feed intake, weaning weight and net returns for four breeding systems. Authors concluded that although the LP approach is more complex than profit equations, the former is more practical because it can deal with components of an entire beef production system.

Regarding agricultural input-traits, Ladd and Martin (1976) used the LP framework of blending problems to estimate economic weights of corn. Two LP formulations are presented according to different production approaches. In addition, the study presented the dual formulation of each problem in order to clarify the concept of shadow price as economic value for input-traits.

LP is also the base for methods that have been used to reveal the pattern of traits that distinguishes an optimal log to produce a desired lumber grade. Thus, Todoroki and Carson (2003) used data envelopment analysis (DEA) to identify the most efficient logs to produce appearance grades looking for attributes that could be manipulated in tree breeding programs. DEA derives efficiency measures by comparing production units with optimal units generated by linear programming algorithms (Coelli et al. 2005; Van Biesebroeck 2007).

A possible LP formulation to estimate economic weights for log traits would consider a processor whose goal is to minimize log cost subject to satisfying demands of specific lumber products. The processors willingness to pay depends on the expected lumber recovery value, which varies with log quality. The log quality can be assessed by external and internal traits which allow segregation the logs in *j* groups. In keeping with this scenario, the formulation of the primal and dual LP problem is presented as follows:

$$Min \sum_{j=1}^{J} r_j \, x_j \qquad\qquad Max \sum_{j=1}^{J} \sum_{i=1}^{I} \lambda^{T}_{ji} \, c_{ji}$$

Subject to $\qquad\qquad\qquad\qquad$ Subject to

$$b_{ji} \, x_j \geq C_{ji} \quad : \lambda_{ji} \quad \forall_{ji} \qquad\qquad \sum_{i=1}^{I} b_{ji} \, \lambda_{ji} \leq r_j \quad : x_j \quad \forall_{j}$$

$$x_j \geq 0 \qquad\qquad\qquad\qquad\qquad \lambda_{ji} \geq 0$$

The objective function of the primal problem corresponds to log cost minimization, where r_j represents the willingness to pay for a log type j ($/m^3$), x_j is volume of logs type j (m^3), b_{ji} is the average value of the i-th log trait type j, and C_{ji} is the requirement of the i-th trait in log type j. The restriction shows that the i-th trait contained in log type j multiplied by the volume of logs j must be greater or equal than a threshold C_{ij}. Thus, the shadow price of the restriction λ_{ji} is the log cost reduction for having a marginal decrease in the average of the i-th and would represent the economic value of the characteristic. There will be as many shadow prices as traits and logs considered in the model. Additional restrictions should be added to this formulation in order to represent a real production scenario. On the other hand, having too many constraints to describe the optimization problem would make the LP formulation excessively specific and unable to represent other production systems.

2.3.4   Stochastic Frontier Functions (SF)

Stochastic frontiers require modeling production functions which represent the inputs that give the maximum feasible output given current technology. Since wood traits have the role of inputs in lumber production, it is possible to find a technical relationship between lumber production and log characteristics.

SF allow generating a parametric production frontier as well as technical efficiency measures. SF have been broadly used to measure productive efficiency since they were proposed by Aigner and Lovell (1977) and Meeusen and van den Broeck (1977). These functions convert the input-output observations to a frontier, accounting for technical inefficiency and random noise.

Equation (2.2) presents a stochastic production frontier where Q_i is lumber volume from the i-th log and x_i is the vector of attributes measured from i-th log and $i = 1\ldots n$.

$$Q_i = x_i`\beta + v_i - u_i \tag{2.2}$$

The symmetric random error v_i, which accounts for statistical noise and can take positive or negative values, is assumed to be independently distributed N(0,σ_v^2). The positive random error u_i accounts for technical inefficiency. This error has similar properties to v_i, except that u_i has non-zero mean. Errors v_i and u_i are also assumed to be independent of each other.

The distributional specifications of u_i are commonly assumed to be half-normal or truncated-normal, although, exponential and gamma distributions are also used. Truncated-normal and gamma distribution allow more flexibility in the distributional shape of u_i; however, they are

more computationally demanding than the half-normal distribution (Coelli et al. 2005; Greene 2000).

SF models are usually fitted by maximum likelihood representing the error variance ratio by a parameter Gamma ($\gamma = \sigma_u^2/(\sigma_v^2+\sigma_u^2)$) which varies between 0 and 1. Values close to 1 indicate that the efficiency effect dominates the noise effect (Coelli et al. 2005).

Most of the reported SF are one-output; however, it is possible to model multi-output models by using the stochastic ray approach which consists in transforming a firm outputs into a composite output vector. The estimation of the output mix vector is based on the Euclidean vector norm (Löthgren 1997). Niquidet and Nelson (2010) used Cobb-Douglas and Translog ray frontiers to model the production of both lumber and chips in sawmills in the interior of British Columbia.

Usually Cobb-Douglas and Translog functional forms are recommended for SF modeling. The Cobb-Douglas model takes the form $Q=\beta_0 \prod_{n=1}^{N} X^{\beta_n}$ where Q is the total product and X_s are the production factors. The β_n exponents correspond to product elasticities, which indicate the percentage change of total product when an input is increased by one percent. The sum of product elasticities results in the scale elasticity (Coelli et al. 2005). The limitations of the Cobb-Douglas function are presenting constant product and substitution elasticities. The elasticity of substitution indicates in what grade an input can be replaced by another one holding the output constant (Varian 1992). A more flexible function is the transcendental logarithmic or Translog. This model permits the elasticity of substitution between inputs to vary; additionally, with this function the elasticity of scale can vary with output and factor proportions.

The economic values of input-traits are derived from their contribution to the final production of goods (Varian 1992). The physical contribution of inputs is measured by the marginal product, which corresponds to total product change from a marginal increment of the input. The input value is represented by the value of the marginal product which, under competitive markets assumptions, is obtained multiplying the marginal product of the input by the price of the end product (Beattie and Taylor 1985).

Most applications of stochastic frontiers in forestry relate to the production of timber and pulp and have compared production systems in terms of their technical efficiency (e.g., Carter and Cubbage 1995; Munn and Palmquist 1997; Yin 2000; Siry and Newman 2001). However, Helvoigt and Adams (2009) reported that most stochastic frontiers applied to wood

production had problems meeting the properties of the production function, used insufficient factors of production and generated unexpected magnitudes of efficiency. That review suggested that modelers should consider and analyze the theoretical and statistical considerations that characterize a well-behaved stochastic frontier.

The advantages of using SF to estimate economic weights include economic plausibility and the possibility of deriving values of traits from an efficiency point of view. However, traits with a counter-productive role such as branches or taper could not be included in a production SF because they are not proper inputs. On production theory, inputs are supposed to contribute to the production, which is known as the monotonicity condition (Henderson and Quandt 1980; Varian 1992).

Finally, approaching logs as conventional production systems could generate problems with distinguishing statistical noise from the efficiency error. Nonetheless, the inefficiency of logs is mostly a variability issue and the focus of the analysis is on selecting the best logs rather than on identifying the error components.

2.4   Hedonic models approach

This approach is derived from Lancaster's consumer theory which states that utility is derived from the properties or characteristics of a good (Lancaster 1966; Lancaster 1971; Lancaster 1991). Hedonic prices (HP) are defined as 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. Rosen (1974) and Palmquist (1984) showed that when characteristics are objectively measured and mapped to observed equilibrium market prices in a competitive economy, the marginal implicit value of traits can be derived from HP functions. Most applications of Rosen's model have dealt with differentiated consumer goods; however, Palmquist (1989) adapted Rosen's work to form a theoretical hedonic model for land as a production factor.

Information of product attributes and market prices is required to build a hedonic model. HP also needs that attribute values are reflected in product prices. Haab and McConnell (2003) stated that HP models fall under the rubric of non-market valuation because goods and services occasionally have qualities that are not provided by the market. Actually, this requirement has been the boundary to apply HP to those agricultural inputs with characteristics that are not revealed in market prices (Lambert and Wilson 2003; Baker and Babcock 2008).

Several applications of HP have been used to estimate the relationships between prices and attributes in competitive markets (e.g., Butler 1982; Jones 1988; Brasington and Hite 2005; Ready and Abdalla 2005). Hedonic models have been applied to obtain marginal values of attributes of natural input-traits like agricultural products (Ladd and Martin 1976; Ladd and Suvannunt 1976; Ladd and Gibson 1978; Ethridge 1982; Espinosa and Goodwin 1991; Bowman and Ethridge 1992; Parker and Zilberman 1993). The study by Waugh (1929) concerning the value of vegetable quality is a key contribution to value input-traits. Following Waugh's arguments Ladd and Martin (1976) verified the hypothesis that the price paid for an input is equal to the sum of the hedonic prices of the input's attributes multiplied by the marginal yield of those characteristics.

The application of HP models in forestry has dealt mainly with factors explaining stumpage price (Puttock et al. 1990), the value of forest land (Roos 1995, 1996; Hardie and Parks 1997; Snyder et al. 2007) and the impact of environmental amenities on forest land prices (Munn and Rucker 1994; Bastian et al. 2002; Snyder et al. 2007). Concerning radiata pine traits, Bloomberg (2001) applied hedonic models to study price differences of logs in terms of attributes in four regions in New Zealand.

Econometrics provides the framework to model HP functions. Suitable functional forms can be selected using statistical tools such as the Box-Cox transformation which also helps to reduce anomalies such as non-additivity, non-normality and heteroscedasticity (Box and Cox 1964 cited by Sakia 1992). A common problem for HP modeling is collinearity between explanatory variables; only variables with a large weight for product value should be included in HP models (Butler 1982). Many critiques of HP relate to the economic rigor applied in the formulation of current hedonic models. Ekeland and Heckman (2002) stressed the abuse of linearization strategies, which are applied to simplify estimations and to justify the application of instrumental variables that produce identification problems. However, econometricians are constantly developing procedures to fit well-behaved models, this can be observed in several works related to automobiles and housing (Atkinson and Halvorsen 1984; Palmquist 1984; Gilley and Pace 1995; Clapp 2004)

In spite of the difficulties that have been previously mentioned; it is possible to use a hedonic approach to value wood attributes by using an alternative log economic value such as the conversion return (Davis and Johnson 1987) which reflects the value of logs in terms of the end products prices, which are assumed to be competitive.

2.5   Discussion

2.5.1   Final evaluation

All methodologies presented in this review are appropriate to estimate economic weights for log traits; however, each methodology has strengths and weaknesses depending on the analysis scenario. In addition, the best approach from a theoretical point of view could be too costly to implement. The following discussion considers compatibility with the problem, representativeness of results and economic plausibility; because methodologies should operate within the boundaries of economic theory.

Bioeconomic models are suitable to estimate economic weights in vertically integrated firms. However, forest bioeconomic models have not deal with the issue of the distribution of an economic weight between forest and mill, which becomes relevant when the log producers are independent growers. Additionally, these models often consider the whole value chain, making attribute values highly dependent on other markets besides the lumber market. On the other hand, bioeconomic models are suitable to assess the convenience of doing breeding today, given that the results would be reaped in the long term. It is important to emphasize that tree breeders have been concerned about the value of wood attributes for a long time and that their work with bioeconomic models provides the current benchmark on economic weights for wood attributes.

Linear programming presents economic plausibility since it is supported by the principles of Lagrange and Kuhn Tucker (Chiang 1984; Hillier and Lieberman 2001). However, the results are highly dependent on the production scenario; thus, linear programming results would be representative as long as other firms face similar production restrictions.

Stochastic frontiers also satisfy all requirements to estimate plausible values for log traits. In addition, they also allow characterizing logs by their technical efficiency to produce lumber. However, this is a single product model which precludes its application to multi-product systems; in addition, this approach is complex due to the economic requirements involved in its estimation.

Hedonic prices fulfill the suitability and plausibility criteria; however, they cannot be directly applied because log prices are not representative of log values. Logs, in common with many commodities, are priced considering basic characteristics that do not match the economic value of products that they generate (e.g., Lambert and Wilson 2003; Baker and Babcock

2008). Nevertheless, technology is creating tools that can reveal traits from trees and logs, making possible to perform forest transactions based on wood quality attributes such as stiffness. This should promote markets with more competitive logs prices that, in turn, would make easier obtaining wood traits economic weights by using the hedonic approaches.

2.5.2   The role of forest appraisal in log values

Logs prices are mainly derived from forests transactions which in turn, depend upon the volume and quality for specific wood products in the forest (Davis and Johnson 1987). If there is information on tree quality, logs should be priced according to quality standards determined by the market. In New Zealand the log market is strongly based on detailed forest inventory, and segregation and pricing follows log size and some quality features (Gordon 2005; Manley 2005). However, the modest premiums paid for some quality characteristics, such as stiffness, may not reflect value recovery; hence the use of such log prices to estimate economic weights may result in underestimation of economic values.

Many factors preclude the log market generating prices that consistently reflect the value of wood quality traits; however, transaction costs derived from identifying wood quality and power asymmetries between growers and processors are major influences on maintaining a log market mainly based on volume and form (Treolar 2005). On the other hand, technology has provided tools and protocols to segregate and classify logs based on wood quality. Sawmills apply these methods with a view to improving log processing. Additionally, there have been some transactions that consider traits beyond volume and form mostly dealing with high quality forests. These examples illustrate the feasibility of incorporating aspects of wood quality in forest appraisal in order to promote logs prices that reflect the value of forming wood quality at the forest.

Growers can gain a better understanding of the quality of their forests by observing tree attributes such as volume, form and internode length on unpruned logs. Knowledge of the silvicultural regime also helps in the assessment of wood quality; for example, timings of pruning and thinning are predictors of pruned log quality (e.g., Knowles et al. 1987). The transaction could be finalized at this point, in which case standing tree quality and the relative power of the negotiating parties will be key elements in deciding the stumpage. A forest transaction could also use a sample of logs to estimate pruned log index (PLI), internode length indices and stiffness of unpruned logs for structural purposes, improving the accuracy of value estimates. This would imply using expertise that may not be available to growers, but

high quality forests would justify the costs to obtain the additional information. Under this scenario, it is possible to conjecture that in the long term there would be differentiated prices with quality thresholds, as well as non-differentiated values for logs with poor wood quality. This situation would act as an incentive to invest in silviculture and genetically improved material.

2.5.3 Final remarks

Some of the methodologies presented in this review, have been jointly applied. Munn and Palmquist (1997) applied stochastic frontier analysis to hedonic models to explain stumpage in cases of uncertainty by sellers and buyers. Smith et al. (1991) estimated the travel cost function for each recreationist as a technically efficient frontier. Fernandez-Castro and Smith (2002) showed the high theoretical consistency of Lancaster's characteristic model and hedonic prices with data envelopment analysis in order to assess decisions relating to multi-attribute products selection. These applications illustrate the appropriateness of combining hedonic prices, linear programming and efficiency frontiers to obtain the economic value of attributes.

This review encourages the use of alternative economic methods, i.e. beyond bioeconomic models, to determine the value of wood attributes for the purpose of estimating economic weights for tree breeding. The joint application of two or more methodologies to enrich the decision making process is also highlighted.

3   A hedonic approach to value Pinus radiata log traits for appearance-grade lumber production

3.1   Abstract

This study used a hedonic approach to estimate the economic value of radiata pine log attributes (small-end diameter, form and internode length) for appearance grade lumber, including Moulding & Better, Shop and Industrial Finger Joint. Models were also built at the tree level to investigate the effect of selection as conducted by breeders. A Chilean sawing study provided information on wood traits and log outturn for 156 logs divided into three classes: pruned butt log, second log and third log. The conversion return of logs, instead of log prices, was used as the measure of log economic value. The economic values of log small-end diameter were 0.33, 0.19 and 0.10 US $/mm for the first, second and third log respectively. Concerning form, those values were 2.6, 1.4 and 0.63 US $ for a marginal improvement of this characteristic. The value of mean internode length was 0.19 US $/cm for second unpruned logs. Values for other internode length indices are also presented in this paper. Branch variables were not statistically significant in explaining the log recovery value. Finally, log recovery value was found to be elastic to the changes in small-end diameter and form, but inelastic to changes in the mean internode length.

Key words: wood attributes; hedonic values; Pinus radiata; appearance lumber; breeding objectives.

3.2   Introduction

Log attributes, including volume and form, have a large influence on the yield and quality of lumber. Most attributes can be identified and measured, but their economic values are not well understood, nor are they frequently reported. For example, advances in the assessment of wood stiffness and resin defects of appearance products have contributed to improved log segregation practices (Ridoutt et al. 1999; Walker and Nakada 1999; Lindström et al. 2002; Lasserre et al. 2005; McConchie and Cown 2008). The economic value of wood

characteristics has received less study. However, knowing the value of wood traits is very important if growers are to improve the quality of the forest crop.

Economic values are particularly important to tree breeders, as they require this information to define breeding objectives and to build selection indices. Commonly, bioeconomic models have been used to obtain those values, modeling the effects of trait changes on the profitability of a production system (Borralho et al. 1993; Apiolaza and Garrick 2001; Ivković et al. 2006). Other approaches used to obtain economic values of traits have been linear programming (Ladd and Gibson 1978), efficiency measures on production systems (e.g., Lambert and Wilson 2003; Todoroki and Carson 2003) and hedonic models (e.g., Bloomberg 2001).

Hedonic values are defined as the implicit prices of traits and they are revealed by observed prices of differentiated products and the specific amounts of traits associated with them (Lancaster 1966; Rosen 1974). In the case of agricultural commodities, hedonic models have been applied to determine the marginal value of quality traits (Ladd and Martin 1976; Ethridge 1982; Angel et al. 1990; Espinosa and Goodwin 1991; Bowman and Ethridge 1992; Parker and Zilberman 1993; Nerlove 1995; Carew 2000; Walburger 2002).

When developing breeding objectives for specific wood attributes, comparable approaches to hedonic models have been occasionally applied under the name 'value regressions'. For instance, Ernst and Fahey (1986) stated that regressions of value on wood traits, coming from product recovery studies, would provide the way to estimate economic weights for tree breeders. Similar studies have been documented by Cotterill and Jackson (1985) and Aubry et al. (1998). Forest hedonic models have mostly been concerned with the impact of environmental amenities on land prices (Munn and Palmquist 1997; Bastian et al. 2002; Snyder et al. 2007) and also with factors that explain stumpage price (e.g., Puttock et al. 1990).

This paper presents an application of hedonic models to value log and tree wood attributes for appearance lumber of *Pinus radiata* D.Don in Chile. The log recovery value is used as response variable instead of log prices. Finally, the sensitivity of the log value to wood attribute changes is analyzed using an elasticity approach.

3.3   Materials and methods

The data for this project came from a Chilean sawing study that included 156 radiata pine logs from three stands. At the time of sampling the stands were 19, 22 and 34 years old with Site Indices of 31, 28 and 27 m, respectively. These radiata pine stands are representative of the site quality available for clear wood production. The stands were thinned and pruned to different stocking intensities, but all of them targeted a 5 m long pruned log. Trees used in the current study, were chosen considering representativeness in the diameter distribution as well as stem quality to generate sawlogs. The log sample contained a minimum small-end diameter of 20 cm and most trees contained three 5 m logs. Table 1 summarizes quality information at the log level.

Table 3.1 Average value of log descriptors segregated by log class.

Variable	Pruned butt log	Second log	Third log
Number of logs	54	57	45
Log length (LL, cm)	505	505	410
Small-end diameter (SED, mm)	385.15	358.60	335.09
Log volume (VOL, m^3)	0.73	0.55	0.43
Form (FORM)	0.73	0.79	0.79
Defect core diameter (DCD, mm)	240.69		
Pruned log index (PLI)	4.83		
Branch index (BI, mm)		44.95	50.46
Largest branch (LB, mm)		56.64	66.55
Base internode length (BIL, cm)		71.31	52.42
Mean internode length (MIL, cm)		71.44	58.12
Internode index base 80 cm (II$_{80}$, %)		33.04	23.49
Internode index base 60 cm (II$_{60}$, %)		46.77	32.16

3.3.1   Definition of tree and log variables

SED, presented in Table 3.1, is the small-end diameter of the log. FORM corresponds to the relationship Cvol/Lvol, where Cvol is the common volume (m^3) equivalent to the maximum cylinder contained in the log, and Lvol is the under bark log volume. SED and FORM are related to the recovery of solid wood during log processing. 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. Defect core

diameter (DCD) corresponds to the diameter with defects after pruning. The prune log index (PLI) is an indicator that expresses the potential of a pruned log to produce long clear wood pieces, such as Moulding & Better (Park 1989). *PLI* is estimated by the following relationship:

$$PLI = (D1.3 - DCD)^{0.5} * (D1.3/DCD) * FORM^{1.6} \tag{3.1}$$

where D1.3 is the diameter at 1.3 m of log. Usually, the DCD is known after processing the log; nevertheless, it can be previously estimated using *PLI*, or by statistical models that consider variables related to the silvicultural regime of the stand (Knowles et al. 1987).

Internode length is an important characteristic in determining the outturn of Shop and Finger Joint grades. The mean internode length (MIL) is the sum of length (m) of internodes in branched section of the log divided by the number of internode lengths in branched section of the log (Watt et al. 2000). Internode index (II_b) is the sum of internode lengths greater than a given base (b) divided by the log length. This study considered bases of 60 and 80 cm. Further details relating to the above traits are described in the literature by Park (1989), Grace and Carson (1993), Carson and Inglis (1988) and Jayawickrama et al. (1997). The base internode length (BIL) corresponds to the minimum internode length that is contained in 50 percent of the log length. Meneses and Guzman (2003) developed this index for unpruned logs based on the Internode index (II_b). Thus, BIL represents that minimum internode length (b) that generates an II_b equal to 0.5.

II_b, MIL and BIL give complementary information about internode length. MIL describes the average internode length of a log, tree or stand while II_b provides an indication of variability but it is usually estimated for specific internode lengths, which limits the possibilities of processing to a limited set of products. BIL is more flexible and is associated to the length of clear pieces that could be obtained from the logs, which is useful for matching stands of varying internode length to product requirements (Meneses and Guzmán 2003).

The variables included in the models correspond to log traits that are important in the recovery of radiata pine appearance grades (e.g., Zhang 1997; Beauregard et al. 2002; Young et al. 2004). In addition, these attributes have been proposed as breeding-objectives to produce solid wood due their influence on log value recovery (e.g., Shelboume et al. 1997; Shelbourne 1997; Ivković et al. 2006).

Table 3.2 Descriptive statistics of lumber volume (m^3) by product.

Pruned butt log	Moulding & Better (m^3)	3rd Clr (m^3)	Shop 1 (m^3)	Shop 2 (m^3)	Shop 3 (m^3)	Finger Joint Blocks (m^3)	Finger Out (m^3)
Average	0.179	0.002	0.036	0.045	0.070	0.020	0.022
Maximum	0.613	0.052	0.135	0.191	0.167	0.111	0.063
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Standard deviation	0.147	0.009	0.041	0.046	0.038	0.029	0.024
Second log							
Average	0.027	0.005	0.035	0.083	0.103	0.016	0.030
Maximum	0.371	0.091	0.233	0.388	0.296	0.142	0.095
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Standard deviation	0.069	0.018	0.058	0.089	0.056	0.028	0.282
Third log							
Average	0.001	0.001	0.014	0.137	0.086	0.032	0.026
Maximum	0.025	0.037	0.221	0.413	0.267	0.123	0.065
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Standard deviation	0.005	0.006	0.043	0.11	0.059	0.033	0.020
Tree							
Average	0.239	0.010	0.096	0.208	0.244	0.068	0.075
Maximum	1.009	0.091	0.442	0.632	0.507	0.178	0.203
Minimum	0.000	0.000	0.000	0.000	0.078	0.000	0.000
Standard deviation	0.211	0.022	0.114	0.193	0.099	0.056	0.057

3.3.2 Sawmill product evaluation

Once the standing trees and logs were assessed in the field, the logs were processed at the mill. The aim of processing was to maximize the recovery of lumber in the Moulding & Better grades from the pruned logs and Shop grades from unpruned logs, as described by the Western Wood Products Association for the USA market (WWPA 1995). An additional low quality product called Finger Out was generated by the sawing study and included in the analysis. Lumber grade recovery for each log type is shown in Table 3.2.

3.3.3 Model components

Hedonic models (HM) disaggregate the price of a product into the value of its component traits to obtain the contributory value of each attribute (Rosen, 1974).

Logs are required by processors because they contain wood traits to produce specific lumber. In keeping with HM theory, the log is a differentiated product with attributes can be identified and measured and, therefore monetarized.

We assume competitive markets, and the models developed by Ladd and Martin (1976) and Espinosa and Goodwin (1991) are used as a theoretical framework. We also consider a single product firm where specific log attributes, such as small-end diameter, form and internode length, are arguments in the appearance-grade lumber production function $G(t)$.

If the log processor is assumed to maximize profit subject to the production function $G(t)$, the first order conditions of the profit maximization generate Equation (2) which represents a hedonic price function. Lumber production is a function of the log trait use, which is a function of the log use; thus, the differentiation of a compound function (function that operates on another function, often represented as nested functions, e.g. f(g(x))) is used to derive Equation(3.2).

$$p_z = p * \sum_{t_i=1}^{n} \frac{\partial G}{\partial t_i} * \frac{\partial t_i}{\partial z} \tag{3.2}$$

where p_z is the price paid for the input (log) and p is the price received for the product (appearance-grade lumber). Variable z corresponds to the quantity of the input log used in the production of lumber, t_i is the amount of trait i provided by one unit of input z, $\frac{\partial t_i}{\partial z}$ is the marginal yield of trait t_i in the production of lumber from input z, and $p * \frac{\partial G}{\partial t_i}$ is the value of the marginal product of trait t_i, which represents the marginal implicit price (hedonic price) paid for the trait t_i because of its contribution to lumber production. Thus, Equation (3.2) states that the price paid for the input log is equal to the sum of the hedonic prices of the log traits multiplied by the marginal yield of those traits.

Equation (3.2) may be simplified with the assumption that the marginal product of the trait t_i and $\frac{\partial t_i}{\partial z} = T_i$ are constant. This simplification implies that each additional unit of input z contributes the same amount of the *t-th* trait to the function $G(t)$. Thus, Equation (3.2) can be written as the following single linear hedonic price function:

$$p_z = \sum_{t_i=1}^{n} \beta_{t_i} * T_i \tag{3.3}$$

These assumptions have been consistent with many natural commodity traits (Ladd and Martin 1976; Espinosa and Goodwin 1991). Nevertheless, this study is open to estimate nonlinear functional forms according to the model specification tests.

Linking log prices with their attributes by regressions allows obtaining the parameters of Equation (3.2), which is the foundation of hedonic models.

If attributes are not reflected in prices, but they are observable, measurable and directly related to the quality and value of final products, an alternative approach of value could be used in order to estimate the parameters of Equation(3.2). For example, log internode length is a trait intimately related to quality and prices of Shop products. Thus, longer internodes generate longer Shop pieces with higher prices. However, the log market does not explicitly value this characteristic in unpruned log prices.

This study proposes the use of a log recovery value called *conversion return* (CR), which represents the theoretical maximum willingness to pay for logs in US $/m^3 delivered to the sawmill (Davis and Johnson 1987). The suitability of product recovery studies to value wood traits for breeding purposes has been reported by other studies (e.g., Ernst and Fahey 1986; Aubry et al. 1998). This indicator corresponds to the residual value of the log after processing, and it is estimated as follows:

$$CR = \sum_{i=1}^{N} p_i L_i - PC \tag{3.4}$$

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. Prices of lumber corresponding to the "Industrials, Specialties, and other items" section in the Random Lengths Report (Random Lengths 2008), were directly provided by Random Lengths publications. These corresponded to the monthly prices series 1995-2008, which were expressed in 2008 using the USA CPI (base 1982-1984:100). The average values of these series were used to estimate the CR. Table 3.3 presents prices and shipping costs of products, as well as log processing costs (Jean P. Lasserre, pers. comm., Forestal Mininco-Chile, March 20, 2008).

Table 3.3 Prices and shipping costs for products and processing costs for logs.

Moulding & Better [US $/m³]	3rd Clr [US $/m³]	Shop 1 [US $/m³]	Shop 2 [US $/m³]	Shop 3 [US $/m³]	Finger Joint Blocks [US $/m³]	Finger Out [US $/m³]	Shipping cost [US $/m³]	Log processing cost [US $/m³]
584	394	373	328	266	367	257	60	70

Explanatory variables were measured and estimated from logs and trees. The information at the log level includes SED, FORM, internode indices (MIL, BIL, II_{60}, II_{80}) and branch measures. However, our hypothesis was that branches would have only a minor influence on the quality and value of appearance products, because the knots are removed as part of the production process − i.e. a remanufacturing plant will use chop saws to remove all knots. Thus the size of knots has a much lower effect than the distribution of knots, which is considered by the internode index. In fact, the requirements for radiata pine appearance lumber relate only to the length of the clear piece (Kretschmann and Hernandez 2006). If there were specific stiffness or strength requirements, the situation would be different because in that case knots derived of branches would cause downgrade in lumber, as it happens with structural lumber (Chauhan 2006a).

At the tree level, the explanatory variables were diameter at breast height (DBH) and internode length indices. Tree form, BI and products volume per tree were obtained by aggregating the logs for each tree, which meant rebuilding forty trees.

The suitability of a linear functional form for the hedonic models was assessed by the Box-Cox transformation (1964). The objective of this transformation is to identify an appropriate exponent lambda (λ) to obtain the best transformation to achieve data normality. The Box-Cox transformation takes the following form:

$$y(\lambda) = \begin{cases} \dfrac{y^{\lambda} - 1}{\lambda}, & \text{if } \lambda \neq 0; \\ \log y, & \text{if } \lambda = 0. \end{cases} \qquad (3.5)$$

The resulting functional form will depend on the value of λ. For instance, if λ is equal to one the transformation is linear.

The hedonic model approach allows estimation of elasticities to assess the sensitivity of log value to changes in wood attributes. The changes in log value and attributes were expressed as

percentages of the average log value and average trait. The elasticity of log value (ε) is the change in *CR* divided by the change in the attribute, multiplied by the level of the attribute divided by the level of *CR*. In this way, the elasticity depends on the attributes levels considered in its estimation. Elasticity of log value (ε) is estimated as follows:

$$\varepsilon_i = \frac{\partial CR}{\partial t_i} * \frac{t_i}{CR} \tag{3.6}$$

where t_i is a trait in the hedonic model and *CR* is the conversion return of the log. If this elasticity is lower than one (inelastic), there will be a less than proportionate change in relative log value for any change in the wood trait. The opposite is true if the elasticity is greater than one (elastic), when the proportionate change in relative log value is greater than the change in the trait. Thus, it is desirable that the log attributes that contribute to log value, such as SED, FORM and internode length, have elasticity values greater than one.

3.4   Results and discussion

Hedonic models were fit at the log level and tree level, considering attributes of form, diameter, internode length and branches, as well as of silviculture. The hedonic value of a given attribute was calculated as the partial derivative of *CR* on that attribute. Models presented at the tree level aim to understand the effect of improving wood quality as done by tree breeders in the development of breeding objectives. Furthermore, there is rarely an opportunity in radiata pine to process 14 m of tree for the same end-product. This information could help to assess the effect of improvement at the tree-level on profitability at the log-level.

3.4.1   Log level models

The conversion return averaged 114, 66 and 54 US $/m^3 for first, second and third logs respectively. Log recovery values were consistent with the amount of highest priced lumber that they generated. Thus, the butt log presented the highest value due to its high volume of Moulding & Better products. However, higher differences in value between butt log and second log have been reported (e.g., Beauregard et al. 2002). The smaller difference obtained in this study was due to small piece size, large defect core size, and the associated low PLI (4.8). BI for the second log was 45 mm, lower than for the third log (50 mm). However, the largest branch was found in the second log (158 mm). Similar results were obtained by

Woollons et al. (2002) in a study for developing a branch model for New Zealand radiata pine. In addition, the author highlights the variability of branch size observed for this species. The high variability of radiata pine branching traits, within trees and among trees, was also reported by Bannister (1962).

Branch size depends on initial spacing and site index (Tombleson et al. 1990). In addition, the combined effects of thinning and pruning, could increase branch sizes above the last pruned section (Jacobs 1938 cited by Shirley 1974). This situation could occur when wider spacing is left after thinning, especially in direct sawlog regimes (Chauhan 2006a).

Branch data for second and third logs showed a weak (not significant) correlation between BI and MIL, of 0.02 and 0.16 for the second and third log respectively. Considering LB these correlations increased slightly. Our data set does not support the positive relationship between internode length and branch size reported by other studies (e.g., Burdon et al. 1992; Watt et al. 2000). In contrast, Woollons et al. (2002) obtained a low correlation (around 0.1) between the size of the maximum branch and internode length. Nevertheless, our data showed a positive correlation between BI and SED, 0.53 and 0.47 for second and third log respectively.

Longer internodes were observed in the second log, a result that agrees with the trend depicted by the model of Grace and Carson (1993) and with the results obtained by Tombleson et al. (1990).

There were six hedonic models fitted at the log level: one for the first pruned log, four for the second unpruned log and one for the third unpruned log. The explanatory variables for the first log were FORM, SED and DCD. For the second log the variables were SED, FORM, BI and one internode measure at the time: MIL, BIL, II_{80} and II_{60}. Finally, the third log model considered SED, FORM and BIL as independent variables.

The functional form of the hedonic models was assessed by the Box-Cox transformation, obtaining $\lambda=1$ for all models and making a linear functional form suitable.

Models were not found to be heteroskedastic using the White Test, at a significance level of 0.01. The normality of the data was also tested using the Shapiro-Wilk test. Results indicated that there was no evidence to reject the null hypothesis of normally distributed data. Collinearity between explanatory variables was tested by the condition index (CI). This index is a measure of the relative amount of variance associated with an eigenvalue; consequently, a big CI indicates a high level of collinearity (Rawlings et al. 1998; Quinn and Keough 2002).

Table 3.4 indicates the presence of collinearity, especially with variables related to branches and internode length

Table 3.4 Condition index (CI) to test collinearity in models at the log level.

Variables	Model Log 1	Model 1 Log 2	Model 2 Log 2	Model 3 Log 2	Model 4 Log 2	Model Log 3
	CI	CI	CI	CI	CI	CI
INTERCEPT	1.000	1.000	1.000	1.000	1.000	1.000
SED	9.624	5.195	4.040	4.424	4.519	4.156
F	19.713	7.541	7.320	7.968	7.021	9.742
DCD	34.347					
BI		30.329	29.898	30.245	29.733	
MIL		12.400				
BIL			12.2881			35.524
II_{60}				12.338		
II_{80}					12.154	

The first approach to reduce collinearity was to eliminate those variables with highest values of CI. However, collinearity persisted with the internode length variables, which presented a CI close to 27 in the unpruned log models. Instead, models were fitted centering the explanatory variables, expressing them as deviations from their mean values. Using this approach, the CI for explanatory variables was reduced to less than three, which would suggest no collinearity problems. This centering process does not affect residual standard deviations, goodness of fit, coefficient values or standard error of the interactions, but its main effect is that the coefficients are now interpretable based on a comparison to the mean of the data (Gelman and Hill 2007).

Models were also tested with the Durbin-Watson statistic (d) to detect autocorrelation in the residuals. The statistic d was greater than 2 for all log models suggesting that there are no autocorrelation problems.

Table 3.5 Hedonic model results, first, second and third log.

Models	Parameter Estimate	Standard Error	R^2-adj
Pruned butt log			
$CR = \beta_0 + \beta_1 * SED + \beta_2 * FORM + \beta_3 * DCD$			0.65
Intercept	113.656***	2.103	
SED	0.339***	0.059	
FORM	257.900***	55.602	
DCD	-0.267***	0.090	
Second log, model 1			
$CR = \beta_0 + \beta_1 * SED + \beta_2 * FORM + \beta_3 * MIL + \beta_4 * BI$			0.66
Intercept	66.331***	2.690	
SED	0.189***	0.033	
FORM	145.515***	36.191	
MIL	0.187**	0.080	
BI	-0.043	0.172	
Second log, model 2			
$CR = \beta_0 + \beta_1 * SED + \beta_2 * FORM + \beta_3 * BIL + \beta_4 * BI$			0.68
Intercept	66.336***	2.628	
SED	0.191***	0.033	
FORM	142.491***	35.376	
BIL	0.159***	0.056	
BI	0.003	0.169	
Second log, model 3			
$CR = \beta_0 + \beta_1 * SED + \beta_2 * FORM + \beta_3 * II_{60} + \beta_4 * BI$			0.65
Intercept	66.299***	2.716	
SED	0.200***	0.034	
FORM	147.076***	36.544	
II_{60}	22.572**	10.833	
BI	-0.003	0.176	

Second log, model 4		
$CR = \beta_0 + \beta_1 * SED + \beta_2 * FORM + \beta_3 * II_{80} + \beta_4 * BI$		0.67
Intercept	66.271***	2.636
SED	0.191***	0.033
FORM	149.179***	35.486
II_{80}	27.518***	9.887
BI	-0.033	0.168
Third log		
$CR = \beta_0 + \beta_1 * SED + \beta_2 * FORM + \beta_3 * BIL$		0.38
Intercept	54.159***	2.109
SED	0.099***	0.025
FORM	62.880*	32.166
BIL	0.025	0.065

* Significant at 0.1 level; ** significant at 0.05 level; *** significant at 0.01 level

Table 3.5 presents the results of the final models. Given the linear functional form of the models, parameters correspond to the trait hedonic values.

The model for the pruned butt log presented an R^2-adj of 0.65 and all coefficients were significantly different from zero ($p<0.01$). As expected, FORM and SED had a positive contribution to log value, while DCD had a negative role. For this log, 50 percent of the CR variation was explained by SED ($p<0.01$), which supports the economic importance of log size. FORM and SED are inherent attributes of the logs, whereas DCD is a variable generated by silviculture. Despite this difference, DCD was considered in the model because it gives indirect information of the amount of knot-free wood, which is the objective product in the pruned log.

The hedonic values of SED and DCD were 0.33 and -0.27 US \$/mm respectively. These values would correspond to the marginal contribution to log recovery value for having an extra millimeter on SED and DCD, in which case they are expressed in US \$/m^3. The variable FORM is an index that ranges between 0 and 1, thus improving this index by 1 percent would result in an increment of 2.58 US \$/m^3 in the log conversion return.

The models for second logs presented high values for R^2-adj. (see Table 3.5). All parameters were statistically significant ($p<0.05$) and their signs were consistent across models. Additionally, the magnitude of the coefficients for internode indices followed the expected trend; the highest value is associated with II_{80} followed by II_{60}. Similar results were obtained

by Beauregard et al. (2002) but their model considers DBH, BI and II_{60} as explanatory variables and the resulting goodness of fit was 0.9. The authors did not report the regression coefficients; nevertheless, they pointed out that trees with small branches presented better grade recovery than trees with big branches.

In the second logs the hedonic values for FORM were consistent across models with values between 1.46 and 1.49 US $/m^3$. These values were lower than those observed in the first log. This result was expected, due to the higher economic value of the butt log. In fact, 65 percent of the tree value was contained in the first log. SED presented a consistent hedonic value around 0.19 US $/m^3$ across models, explaining 65 percent of variation of the CR (p<0.01).

Regarding the economic value of internodes, the first model fitted MIL with a hedonic value of 0.19 US $/cm. The hedonic value for BIL was 0.16 US $/cm. Internode indices II_{60} and II_{80} presented values corresponding to marginal contributions of 0.23 and 0.28 US $/m^3$ to the CR, respectively.

Branch variables did not provide a significant (p<0.1) explanation of recovery value for second logs for appearance lumber. Table 3.5 shows the information corresponding to BI; models were also tried with LB, which was not significant (p<0.1).

Concerning the third log, 32 percent of CR variation was explained by SED which supports the significant economic weight of this trait (p<0.01). Although, the goodness of fit was poor (R^2-adj 0.38) the intercept and parameters associated with SED and FORM were significant (p<0.1) and the corresponding hedonic values were lower than those obtained for the second log. The parameter associated to BIL was not significant; however, its sign was consistent with expectations. Additionally, this log presented the highest variability of quality and value amongst logs, which could be influencing fit.

3.4.2   Tree level models

Two models are presented in order to explain tree value in terms of wood attributes. The functional form of these models was also linear, with λ=1 for the Box-Cox transformation. These models did not present heteroskedasticity problems; nevertheless, there was collinearity between explanatory variables, which was avoided by centering the variables. Concerning autocorrelation, the Durbin-Watson statistic (*d*) was close to 1.9 for both tree models; which would indicate a mild presence of autocorrelated residuals.

The average conversion return was 175 US \$/tree. Models that explained CR at the tree level resulted in an improved fit compared to the models at the log level, with an R^2-adj. of 0.92 for both models. Table 3.6 presents the results of the hedonic models at the tree level.

Table 3.6 Hedonic models at the tree level

Models	Parameter Estimate	Standard Error	R^2-adj
Tree, model 1			
$CR = \beta_0 + \beta_1 * DBH + \beta_2 * FORM + \beta_3 * MIL_{511}$			0.92
Intercept	175.445***	5.786	
DBH	1.091***	0.092	
FORM	381.197**	144.251	
MIL_{511}	0.115	0.174	
DCD	-0.011	0.159	
BI	-0.115	0.366	
Tree, model 2			
$CR = \beta_0 + \beta_1 * DBH + \beta_2 * FORM + \beta_3 * BIL_2$			0.92
Intercept	175.44***	5.556	
DBH	1.049***	0.092	
FORM	374.453**	138.323	
BIL_2	0.213*	0.116	
DCD	0.054	0.158	
BI	-0.078	0.350	

* Significant at 0.1 level; ** significant at 0.05 level; *** significant at 0.01 level

The explanatory variables considered in these models were DBH, FORM, internode measures, DCD and BI. The pertinence of DBH and internode length for predicting appearance lumber quality from trees has been also reported by Gazo et al. (2000).

Concerning internode measures, model 1 considered the mean internode length between 5 and 11 m (MIL_{511}). The second model included the base internode length of the second log as explanatory variable (BIL_2).

The economic values of attributes derived from model 1 were 1.09 US \$/cm for DBH and 3.81 US \$ for FORM (the highest value for this variable). The value of MIL_{511} was not significant, although its magnitude and sign were as expected. In the same way, DCD and BI

were not significant to explain tree recovery value. In model 2, variables DBH and FORM had similar hedonic values to those generated by model 1. The parameter associated to BIL_2 was statistically significant (p<0.1) and higher than the corresponding value at the log level. This difference is due to the higher economic value of trees compared with the value of second logs. In contrast, DCD and BI were not significant and close to zero.

Although the value of trees could be debatable, they were estimated to show the joint value of the logs that potentially could be processed for appearance products. This information could be useful for breeders, particularly to assess single-purpose versus multi-purpose breeding programs.

3.4.3   Elasticity results

The sensitiveness of CR to log attributes changes can be analyzed using elasticity. Despite of the similarity between the elasticity of CR and the attribute economic value, they are different concepts. The value of an attribute obtained by hedonic models corresponds to the marginal contribution of the trait to the CR and it is expressed in absolute values (US $/m^3$). The elasticity of the CR with respect to one log trait is the percentage change in CR caused by a one percent change in the trait. The changes in CR and attributes are expressed as percentages of the average CR and average attribute. Elasticity is dimensionless and its interpretation depends on the resulting value being greater, equal or lower than one.

Table 3.7 presents the elasticities of the log recovery value estimated from two hedonic models. The first one corresponds to the model of the butt log, while the second one is model 1 for the second log (see Table 3.5). Elasticity of log recovery value was estimated for SED, FORM, DCD and MIL. The elasticity values for the pruned butt log indicate that the CR was SED and FORM elastic, but DCD inelastic. Thus, CR would increase by 1.2 percent if SED experiments a change of 1 percent, while CR would increase by 1.7 percent for FORM. Concerning DCD, a change in this variable would cause a less than proportional change in CR. Given that this variable has a negative contribution to the log CR, having elasticity lower than one is advantageous.

Table 3.7 Elasticities for log conversion return on attributes SED, FORM, DCD and MIL.

Models	Mean attributes values	Elasticity (%)
Pruned butt log model		
SED (mm)	385.148	1.149
FORM	0.730	1.656
DCD (mm)	240.685	-0.565
Second log, model 1		
SED (mm)	358.596	1.027
FORM	0.792	1.737
MIL (cm)	70.786	0.201

Concerning the second log, the CR resulted to be SED and FORM elastic, with similar elasticity values to the butt log. On the other hand, CR resulted to be MIL inelastic. Thus, the CR would increase just by 0.2 percent if the mean internode length increased by 1 percent.

Elasticity values could be useful complementary information to implement wood attribute rankings in breeding programs. For instance, if a wood attribute has high economic value and its log value elasticity is higher than one, then this characteristic will reward breeding effort, as it happens with SED and FORM.

3.5 Conclusions

The objective of this study was to estimate the economic value of wood traits of radiata pine logs for producing appearance lumber (Moulding & Better, Shop and Industrial Finger Joint). We used hedonic models to ascertain the economic values of wood attributes on pruned butt logs, unpruned logs and trees. Finally, an elasticity analysis was used to understand the magnitude and the direction of the log recovery value response due to changes in wood attributes.

The use of conversion return as response variable made it possible to capture and value marginal changes in wood traits. Thus, despite of its theoretical nature, conversion return is a plausible economic measure to assess wood traits at the log and tree level. Using conversion return, processors incorporate known information that is part of their decision making process when buying logs. However, we assumed that a single log CR is representative of the radiata pine solid timber industry which is debatable since there are differences on processing

technology and costs between mills. In spite of this assumption, we believe that the relative economic values of wood attributes will be consistent with those reported in this study.

SED and FORM were the characteristics with the highest economic value for the production of appearance lumber, as well as generating the highest log value elasticities. This result is consistent with the priorities observed in many breeding programs. The value of internode length indices highlighted their significant contribution to the value of logs destined to appearance lumber.

Branch variables did not contribute to explain the variation of CR for unpruned logs. These results supported the hypothesis asserted in this study. In this way, the wood quality of unpruned logs to produce appearance grades should be just focused on SED, FORM and internode length variables. In addition, appearance products have no requirements for stiffness and strength, a case in which knots generated by branches would negatively affect the log recovery value.

BIL showed a good performance at explaining log and tree recovery values. Thus, it would be advantageous to incorporate this alternative index to the information derived from radiata pine unpruned logs.

The elasticity analysis was useful to examine the responsiveness of log value to changes in wood characteristics. The elasticity of the conversion return, due to changes in log attributes could be complementary information for ranking trees in breeding programs.

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

4.1 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.

Keywords: log efficiency, DEA, *Pinus radiata*, economic weights, structural lumber, breeding objectives.

4.2 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 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 estimated by using data envelopment analysis (DEA). This approach 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 2001a; Lasserre et al. 2004; Waghorn et al. 2007b). Furthermore, there are examples of using DEA to identify the most efficient logs to produce appearance grades looking for traits that could be manipulated in a radiata pine breeding program (e.g., Todoroki and Carson 2003).

DEA generates measures of technical, allocative and cost 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. Cost efficiency corresponds to the product of technical efficiency and allocative efficiency and it represents the total efficiency of a production system (Farrell 1957; Färe et al. 1985).

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 (BM) and partial regressions (PR) are two common approaches for the estimation of economic weights (e.g., Borralho et al. 1993; Greaves et al. 1997b; 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. BM modeling requirements 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, BM 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 PR correspond to the economic weights (Talbert 1984; Cotterill and Jackson 1985; Ernst and Fahey 1986; Aubry et al. 1998). The major limitation of PR 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 (HP) 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 an HP approach to value pruned and unpruned 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.

4.3 Materials and methods

4.3.1 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 4.1 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 (SED) is commonly used to classify and price logs. Taper (TP) 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 (SED) and taper (TP) are intimately related to lumber recovery during log processing. Largest Branch (LBR) 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 (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. Wood stiffness (STF) 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 2006b). The acoustic measurements of logs to estimate STF 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).

Table 4.1 Mean values and standard deviations (SD) of second and third log attributes.

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

The strategy to process the log sample was to cant saw, maximizing the recovery of 100x50 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 last 700 mm of the lumber being ungraded. Lumber was identified as MSG6, MSG8, MSG10 and MSG12, where MSG stands for machine stress graded, and the number is the stiffness in GPa.

4.3.2 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 SED, TP, LBR, BD and STF 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:

$$LRV = \sum_{i=1}^{n} p_i L_i - PC \qquad (4.1)$$

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 regression model to estimate the economic weights for the attributes is:

$$LRV = \sum_{i=1}^{n} \beta_i t_i \qquad (4.2)$$

where *LRV* is the log recovery value of the logs (NZ \$/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* (Equation (4.1)) was obtained from New Zealand firms. The prices for 100x50 mm lumber were 2.5, 3.2 and 4.1 NZ \$/linear m for MSG6, MSG8 and MSG10 respectively, while the processing cost was 180 NZ \$/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 MSG12 was estimated as 4.8 NZ \$/linear m by assuming that the differential price between MSG8 and MSG10 would be the same as between MSG10 and MSG12. Reject products were priced at 1.3 NZ \$/linear m.

The functional form of Equation (4.2) was assessed using a Box-Cox transformation (Box and Cox 1964). The aim of this transformation is to identify a suitable exponent lambda (λ) to

obtain the best transformation to achieve data normality. The Box-Cox transformation takes the following form:

$$y(\lambda) = \begin{cases} \dfrac{y^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0; \\ log\ y & , \text{if } \lambda = 0. \end{cases} \qquad (4.3)$$

The resulting functional form of the model will depend on the value of λ. For instance, if λ is equal to one the transformation is linear. The fitted model used centered explanatory variables, expressing them as deviations from their mean values. Centering does not affect goodness of fit, residual standard deviations or coefficient values; however, the coefficients are now interpretable based on a comparison to the mean of the data (Gelman and Hill 2007).

4.3.3   Efficiency analysis

Data envelopment analysis (DEA) is a method to estimate non-parametric and deterministic 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). Input-oriented DEA estimates technical efficiency (TE), which determines how much inputs can be proportionally reduced in order to achieve the same output level. TE 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 TE score of one; less efficient logs, located below the frontier, obtain TE scores lower than one.

There will be as many linear programming problems as logs are analyzed. For each problem, a fully efficient comparison point (TE = 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: SED, STF and BD. Without losing generality, the technical efficiency of log i to produce volume of structural grades MSG8, MSG10 and MSG12, using SED, STF and BD was formulated as follows:

Minimize τ,

τ, k

        Subject to:

$$\begin{bmatrix} k_1 & k_2 & \cdots & k_n \end{bmatrix} \begin{bmatrix} SED_1 & STF_1 & BD_1 \\ SED_2 & STF_2 & BD_2 \\ \vdots & \vdots & \vdots \\ SED_n & STF_n & BD_n \end{bmatrix} \leq \tau \begin{bmatrix} SED_i \\ STF_i \\ BD_i \end{bmatrix}$$

$$\begin{bmatrix} k_1 & k_2 & \cdots & k_n \end{bmatrix} \begin{bmatrix} MSG8_1 & MSG10_1 & MSG12_1 \\ MSG8_2 & MSG10_2 & MSG12_2 \\ \vdots & \vdots & \vdots \\ MSG8_n & MSG10_n & MSG12_n \end{bmatrix} \geq \begin{bmatrix} MSG8_i \\ MSG10_i \\ MSG12_i \end{bmatrix}$$

$$\begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \geq 0$$

where the decision variables are τ, which represents TE, 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 cost efficiency (CE) 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 CE 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.

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 (CRS), 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 (MSG8+) 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.

4.4 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 MSG8+ 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 structural grades MSG8, MSG10, MSG12 as well as MSG8+.

4.4.1 Relationships between log traits and structural volume

The correlations between log attributes agreed with results reported by Cotterill and Jackson (1985); Beauregard et al. (2002); Chauhan and Walker (2006) and Ivković et al. (2006). There was a negative and significant correlation between STF and SED (-0.49, $p<0.05$). The correlation between STF and BD 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 LBR and SED, as well as between LBR and STF were also in accordance with other published values (Grant et al. 1984; Tombleson et al. 1990; Watt et al. 2000; Jayawickrama 2001a; Xu 2002; Kumar 2004; Apiolaza 2009). Details of this information are presented in Table 4.2.

Table 4.2 Pearson correlation coefficients between log attributes and lumber grade recovery.

	SED	STF	BD	MSG6	MSG8	MSG10	MSG8+
SED				0.73[*]	0.19	-0.07	0.05
STF	-0.49[*]			-0.66[*]	0.23[*]	0.59[*]	0.60[*]
BD	-0.17	0.72[*]		-0.37[*]	0.32[*]	0.52[*]	0.59[*]
LBR	0.43[*]	-0.49[*]	-0.14	0.56[*]	-0.07	-0.32[*]	-0.29[*]

*Significant at 0.05 level

Significant correlations were found between second and third log attributes ($p < 0.05$); however, second logs had higher SED, STF and BD, and lower LBR than third logs (results not presented). For instance, the maximum values of STF and LBR for second and third logs were 11.6 and 10.6 GPa, and 110 and 125 mm, respectively. These results 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. MSG10 was generated in 66% of the second logs and 56% of the third logs whereas MSG12 was produced in 37% of second logs and 6% of the third logs. There was a high correlation between SED and MSG6 (0.73, $p < 0.05$); nonetheless, the correlation between this product and STF was negative. MSG6 was positively correlated with LBR, which was also expected due to the positive relationship between SED and both, branch size and MSG6. However, when the lumber stiffness requirements increased, these correlations reversed their signs. Thus, the correlations of STF with both MSG8 and MSG10 were positive and significant (0.23 and 0.59 respectively, $p < 0.05$). Consequently, MSG10 was negatively correlated with LBR. The correlations between log traits and MSG8+, i.e. lumber volume with STF of 8 GPa or higher, followed the same trend as for MSG10.

The high significance of the correlations between structural volume and log traits supported building models to explain the recovery of MSG8+. 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. The functional form of the model was evaluated with a Box-Cox transformation that resulted in a lambda of 0.5; thus, the response variable was transformed using square root. There were no significant collinearity or heteroskedasticity issues.

The model had moderate goodness of fit (R^2-adj 0.57) (see Table 4.3). The coefficients for SED, STF and BD were significant ($p < 0.05$); however, the coefficient for LBR 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 MSG8+.

Table 4.3 Model to explain volume of MSG8+ in terms of log traits.

	Coefficients	Standard error	P
Intercept	0.332[*]	0.014	<0.05
SED	0.008[*]	0.002	<0.05
STF	0.074[*]	0.020	<0.05
LBR	-0.001	0.001	>0.05
BD	0.002[*]	0.001	<0.05
TP	0.007	0.005	>0.05
R^2-adj	0.57		

*Significant at 0.05 level

4.4.2 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 STF for second and third logs; however, these logs did not have the largest SED. In fact, the logs with the highest LRV and STF had SED smaller than 41 cm. Product MSG10 volume showed the highest correlation with LRV (0.79, p<0.05). A high correlation was also found between LRV and STF (0.85, p<0.05), as well as BD (0.69, p<0.05). Correlations between LRV and LBR (-0.43, p<0.05), as well as SED (-0.29, p<0.05) were also significant, but moderate. Similar results had been documented by Cotterill and Jackson (1985) and Beauregard et al. (2002).

In spite of the importance of STF 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 SED and LBR (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 (NZ $ 86/m^3) had negative LRV. As STF is not included in formal pricing criteria, there is a wide range of STF 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 Figure 4.1 which shows the relationships between log prices and traits not included in the log pricing criteria, such as STF and BD. There was a large overlap of STF across log prices and an even more dramatic trend is observed for BD, where there was almost complete overlap across price classes.
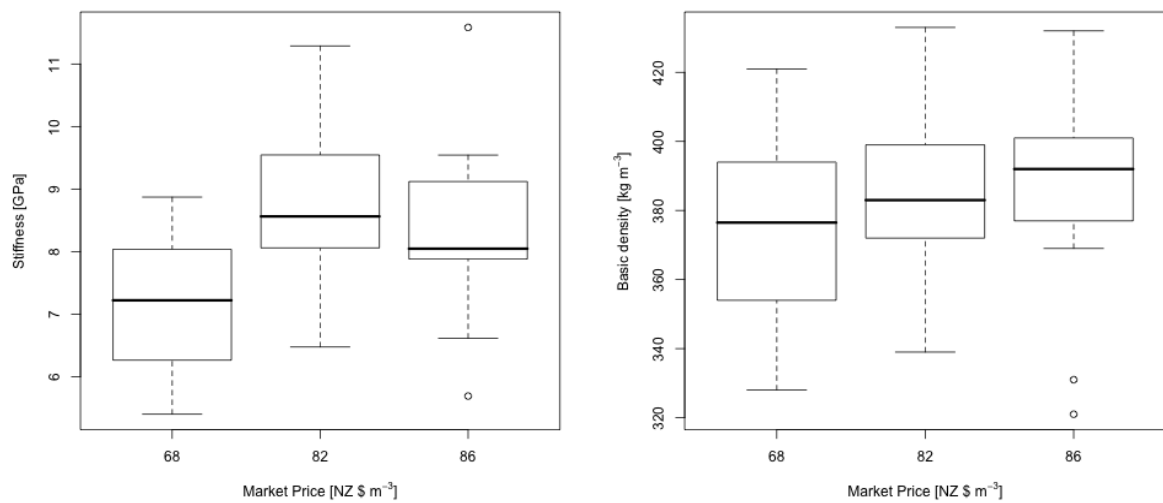
Figure 4.1 Relationship between wood stiffness and basic density with log prices.

Log prices should reveal the processors willingness to pay for structural wood quality which has been shown to be strongly correlated with STF; however, this concept has not been internalized in the log market. This lack of price incentives for growers could generate a market biased towards 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 MAF (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 4.4 presents the regression of log recovery value on log traits, where the Box-Cox evaluation suggested a linear functional form. 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 SED, STF and LBR were significant ($p<0.05$) and the goodness of fit was high (R^2-Adj 0.75). BD did not provide a significant explanation of log recovery value ($p<0.05$). SED and STF were the most important predictors, accounting for 73 % of the LRV variation.

Table 4.4 Regression of log recovery value on log traits; regression coefficients are also the economic weights.

Variable	Coefficients	Standard Error	P
Intercept	102.966[*]	3.247	<0.05
SED	1.056[*]	0.479	<0.05
STF	29.681[*]	4.657	<0.05
BD	0.330	0.184	>0.05
TP	2.256[*]	1.099	<0.05
LBR	-0.362[*]	0.176	<0.05
R^2-adj	0.75		

*Significant at 0.05 level

Given the linearity of the model, the regression coefficients correspond to the economic weights. Economic weights derived from a partial regression rely on the linearity of profit increase due to changes on wood attributes; however, traits such as STF are non-linearly related with profit as they depend on a categorical price structure (Burdon 1990; Apiolaza and Garrick 2001; Apiolaza and Greaves 2001). However, a log generates a mix of products and increasing a log wood quality attribute redistributes lumber grades, changing total value linearly with the attribute change.

The economic value of SED was 1.1 NZ $/cm, which represents the marginal contribution of SED to LRV. Having an extra GPa of stiffness would increase the log recovery value by 29.7 NZ $. The value of LBR was negative; thus, an extra millimeter of LBR would decrease LRV by 0.4 NZ $. In contrast, Alzamora and Apiolaza (2010) reported that LBR was not relevant to explain the economic value of unpruned logs for appearance timber. Furthermore, these authors reported an economic value for SED 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 STF requirements for appearance products; in contrast, STF is a key quality trait for structural lumber (Evans and Ilic 2001). In addition, SED has a direct relationship with the recovery of appearance grades; but it has shown to be negatively correlated with the recovery of structural lumber.

4.4.3 DEA and wood traits performance on the most efficient logs

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

Considering MSG8, MSG10 and MSG12 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, which represents the total economic 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 technically and allocative efficient logs.

Although it is not possible to improve logs 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 TE and a single product was with MSG10 (0.72, $p<0.05$); in contrast, the associations between TE and MSG6 as well as non-structural products were negative and significant ($p<0.05$). TE was directly correlated with STF (0.46, $p<0.05$); however, there was not significant correlation with SED. 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, STF has been shown as the most relevant trait to produce structural lumber (e.g., Dickson and Walker 1997a; Evans and Ilic 2001; Apiolaza 2009). As a result, the most technically efficient logs had SED smaller than 41 cm, but their STF were greater than 8 GPa (see Table 4.5 Achieving structural production goals with smaller SED implies that the rotation age could be reduced.

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

Figure 4.2 illustrates the efficiency for second and third logs. Results are presented in ascending CE order for illustration purposes only. There was a high variability between logs for TE and CE; in addition, some logs showed significant differences between TE and CE. The latter was frequent in logs with SED greater than 40 cm and MSG8+ lower than 15% of log volume. Those logs were inefficient because they had a very low MSG8+ in comparison with the magnitude and cost of their traits.
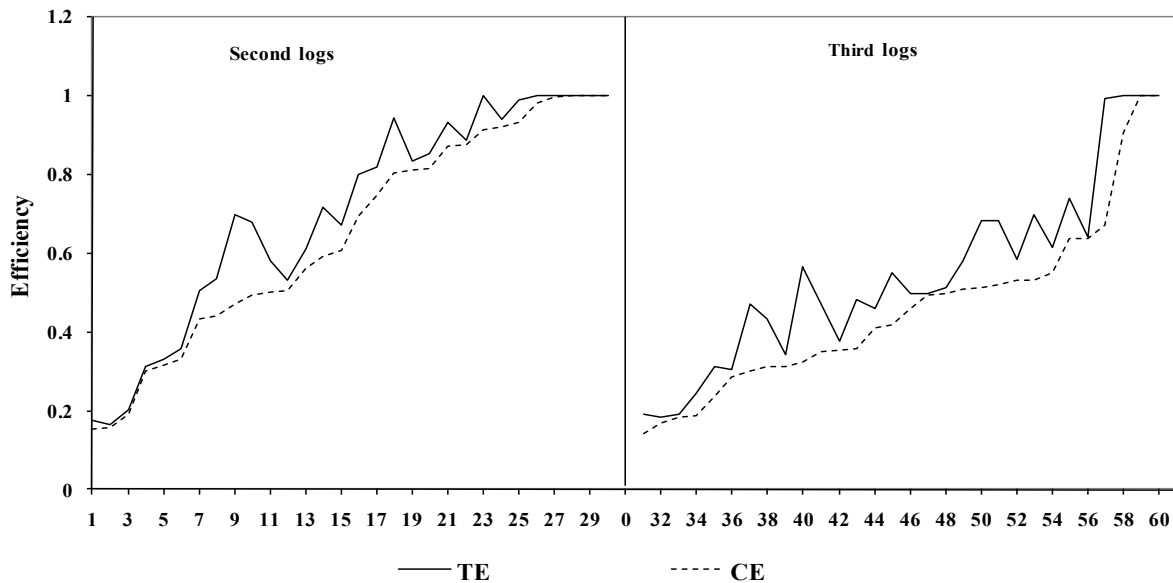
Figure 4.2. Technical efficiency (TE) and cost efficiency (CE) by log.

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 performing better than the average of second logs. Xu and Walker (2004) obtained similar trends when studying the longitudinal STF profile in radiata pine trees.

DEA was also performed considering the aggregate of MSG8+ as a single product. The average efficiencies for second and third logs were respectively 0.56 and 0.43 for TE and 0.46 and 0.34 for CE. These values are lower than those obtained with three separate products; however, the TE and CE trends for logs were similar to those showed in Figure 4.1.

Similarly to three-product DEA there were also high and significant correlations between LRV and TE (0.83) and between LRV and CE (0.88). Only one log scored 1 for TE and CE when aggregating MSG8+ products.

A high and significant correlation was found between TE and MSG8+ (0.96, p<0.05); a similar trend was observed for total efficiency (CE). STF was directly correlated with TE (0.59, p<0.05); however, the correlation between TE and SED was non-significant. There was also a high correlation between TE and CE (0.93, p<0.05).

 In general, analyzing MSG8+ as an aggregate or as three separate products resulted in constant returns to scale (CRS). 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 CRS 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.

Table 4.5 Traits and LRV of the most efficient logs to produce MSG8, MSG10 and MSG12

Log Class	SED (cm)	STF (GPa)	BD (kg/m³)	LRV (NZ $/m³)	Log Price (NZ $/m³)	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
3[dr]	31.7	9.0	379	193.2	82	0.28

Table 4.5 shows trait values for the six logs that scored 1 on TE and CE 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 STF (11.6 GPa), the second highest BD, the highest percentage of MSG12 product, and the highest difference between LRV (234 NZ $/m³) and price (86 NZ $/m³). This log was characterized by a STF to SED ratio 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 a STF:SED ratio of 1:8. This suggests that any increase in SED should occur along an increase of STF, with a STF:SED ratio 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).

4.5   Conclusions:

STF, SED and LBR 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 STF 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 STF 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 STF and log recovery value. In addition, DEA allowed deriving information about the relative mix of traits that distinguishes the most efficient logs. A STF to SED ratio of 1:4 characterized the most efficient and profitable logs. Both STF and SED 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 STF 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 STF should be formally included in the segregation and pricing of logs to incentivize a market with high quality logs for structural purposes.

5 Using a stochastic frontier to estimate economic weights for radiata pine structural attributes

5.1 Abstract

We modeled the technical relationships between volume of *Pinus radiata* structural lumber (with stiffness greater than 8 GPa) and log attributes using a stochastic frontier approach. The production frontiers were Cobb Douglas and Translog functions, while the log attributes were small end diameter (SED), wood stiffness (STF) and largest branch (LBR); however, LBR was a non-significant trait (p>0.05). The economic values of the attributes were represented by their values of marginal product (VMP). The mean VMP was 2.11 NZ \$/cm for SED and 15.75 NZ \$/GPa for STF. The coefficients for the Cobb Douglas frontier were statistically significant and the model met the monotonicity assumption; however, it did not meet the concavity assumption. The Translog frontier coefficients were non-significant (p>0.05). Technical efficiency results derived from the stochastic frontier allowed to identify the best logs to produce structural grades with stiffness of 8 GPa or higher. Those logs were characterized by a ratio of 1:5 between STF and SED.

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

5.2 Introduction

Wood quality results from physical and chemical characteristics that enable it to meet the requirements for different end products (Mitchell 1961). Accordingly, demand for logs depends on a set of wood attributes to target particular lumber grades. Tree breeding is constantly targeting the improvement of attributes to satisfy processing requirements. Under this scenario, wood attributes could be considered as inputs for lumber production and tree breeding as an option to obtain them.

Wood attributes do not have market prices; however, it is possible to derive their economic values from the lumber market. This approach is based on Samuelson's (1948, 1953) theory of revealed preferences, which states the possibility of discerning consumer behavior on the basis of variable prices, revealing consumers' preferences by their purchasing habits.

Obtaining economic values of wood attributes has been predominantly done by tree breeders. They require this information to define economic breeding objectives, which are in turn used to build selection 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 and Garrick 2001; Ivković et al. 2006). 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 and Jackson 1985; Ernst and Fahey 1986; Aubry et al. 1998). Other methods to derive economic values of attributes are linear programming (Ladd and Gibson 1978; Sivarajasingam et al. 1984) and hedonic models (Bloomberg et al. 2002; Alzamora and Apiolaza 2010). These two approaches are derived from Lancaster's characteristics model (1966; 1991) which is, in turn, founded on the theory of revealed preferences.

It is possible under revealed preferences to obtain economic values for wood traits by using production functions. 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 change in 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 (Beattie and Taylor 1985). This methodology is known as *change in productivity* or the *production function* method (Freeman and Harrington 2001; Freeman 2003).

Modelers have usually assumed that producers optimize their decisions, and have used production functions 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 production frontier is a method to model parametric production frontiers aiming to derive measures of productive or technical efficiency (Aigner et al. 1977; Meeusen and van den Broeck 1977).

Analysis of the stochastic frontier allows estimating the marginal product of inputs, which are then multiplied by end-products prices in order to obtain the value of the marginal product (VMP). VMP is a measure of the income supplied by the last unit of a productive input employed (Beattie and Taylor 1985). The advantages of deriving log attributes values using a stochastic frontier are i- its economic plausibility (since the valuation of inputs is based on the neoclassical model of the firm) and ii- the explicit consideration of inefficiencies, which allows the characterization of logs by their technical performance to generate specific lumber grades. Stochastic frontier applications in forestry have mainly focused on obtaining technical efficiency of lumber and pulp production, as well as on harvesting and sawmilling systems (e.g., Carter and Cubbage 1994; Carter and Cubbage 1995; Yin 2000; Helvoigt and Adams 2009).

Data envelopment analysis (DEA) is a non-parametric and deterministic frontier that has also been used in forestry to study the efficiency of production systems. For example, Todoroki and Carson (2003) 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 stochastic frontier is that the former does not impose any assumptions on the functional form of the frontier (Coelli et al. 2005; Van Biesebroeck 2007); 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).

This paper applies a stochastic frontier approach to value radiata pine logs attributes obtained from a sawing study for structural purposes. Cobb-Douglas and Translog frontier functions are used to model lumber production in terms of log small end diameter, log wood stiffness and largest branch. The economic values of attributes correspond to values of the marginal product derived from the stochastic frontier. In addition, efficiency results are used to identify the relative participation of attributes that distinguish the most efficient logs to produce structural lumber. Finally we discuss the difficulties of extending production efficiency theory to logs, which are natural and heterogeneous lumber producers.

5.3   Materials and Methods

The New Zealand Wood Quality Initiative provided data from a sawing study with a sample of 71 (35 second logs and 36 third logs) 5 m long unpruned logs. Logs 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). Table 5.1 presents a summary of log attributes.

Table 5.1 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	Cm	62.50	53.90
Minimum SED	Cm	32.00	23.30
Standard deviation	Cm	8.42	7.71
Mean Stiffness (STF)	GPa	7.97	7.97
Maximum STF	GPa	11.59	10.60
Minimum STF	GPa	5.63	5.40
Standard deviation	GPa	1.47	1.26
Mean Largest branch (LBR)	Cm	6.03	7.33
Maximum LBR	Cm	11.00	3.50
Minimum LBR	Cm	2.50	12.50
Standard deviation	Cm	2.10	2.66

The log attributes assessed in the 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 small end diameter (SED) is often used to classify and price logs. Largest Branch (LBR) corresponds to the diameter of the largest branch 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). Wood stiffness (STF) corresponds to Young's modulus of elasticity assessed using a Director HM200 tool. SED, STF and LBR also explain the value recovery of structural grades from radiata pine unpruned logs (Alzamora and Apiolaza 2009).

The objective of the sawing study was to maximize the recovery of New Zealand structural grades. Table 5.2 presents details of the log outturn, where MSG means machine stress grade and the number corresponds to lumber stiffness in GPa.

Table 5.2 Descriptive statistics of lumber grades volume (m^3) per log.

	MSG6	MSG8	MSG10	MSG12	Reject
Second log					
Mean value	0.221	0.078	0.064	0.021	0.056
Maximum value	0.630	0.218	0.227	0.149	0.614
Minimum value	0.020	0.000	0.000	0.000	0.000
Standard deviation	0.167	0.066	0.061	0.037	0.112
Third log					
Mean value	0.190	0.065	0.038	0.003	0.040
Maximum value	0.515	0.223	0.198	0.093	0.361
Minimum value	0.000	0.000	0.000	0.000	0.000
Standard deviation	0.129	0.054	0.047	0.016	0.076

5.3.1 Stochastic production frontier modeling

Modeling production functions requires information on inputs and outputs. In this study the output is an aggregate product, log volume of structural lumber with stiffness of 8 GPa or higher (MSG8+), while the inputs are small end diameter (SED), stiffness (STF) and largest branch. The latter is included in its inverse form (LBR^{-1}) because it has a negative influence on recovery of structural grades (Xu 2002).

We used a stochastic frontier approach to model the production function between log lumber and log attributes, converting the input-output observations to a frontier, and accounting for technical inefficiency and random noise (Coelli et al. 2005). Most efficiency studies have targeted production systems where the factors of production are labor, land, capital and raw materials; however, in this study we consider that the log is the production unit and that the inputs are log attributes.

Equation (5.1) presents a production stochastic frontier where Q_i is lumber volume from the ith log and x_i is the vector of j attributes in the ith log.

$$Q_i = x_i^{'}\beta + v_i - u_i \qquad i = 1,\ldots,n \qquad (5.1)$$

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 non-negative variable which accounts for technical inefficiency, u_i is commonly assumed to be independent and identically distributed $N(0,\sigma_u^2)$; in addition, v_i and u_i are assumed to be independent of each other.

The distributional specifications of u_i are assumed to be half-normal, truncated-normal, exponential and gamma distributions are also used. However, truncated-normal and gamma distribution have shown to be more flexible to represent the distribution of u_i (Coelli et al. 2005; Greene 2000).

Stochastic frontiers are often fitted using ordinary least squares (OLS), corrected ordinary least squares or maximum likelihood (ML). This study used the software FRONTIER version 4.1-c to model the stochastic frontier. FRONTIER initially obtains OLS estimates for the parameters, which are then used as starting values for a maximum likelihood (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 stochastic frontier would be mainly due to productive inefficiencies (Coelli et al. 2005).

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

$$Q = \beta_0 \prod_{k=1}^{m} X_k^{\beta_k} \qquad\qquad k = 1,...,m \qquad\qquad (5.2)$$

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 one percent 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. The elasticity of substitution indicates in which grade an input can be replaced by another one holding the output constant (Varian 1992; Greene 2000).

The Translog, or transcendental logarithmic, 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 or globally convex as is the Cobb-Douglas (Weaver 1983; Fried et al. 2008). The Translog presents the following functional form:

$$ln\ Q = \beta_0 + \sum_{k=1}^{m} \beta_k\ ln\ X_k + 1/2 \sum_{k=1}^{m} \sum_{l=1}^{m} \beta_{kl}\ ln\ X_k\ ln\ X_l \qquad\qquad (5.3)$$

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

5.3.2 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 (5.4):

$$Q_i = Q\left(\bar{L},\bar{K},T_1,T_2,...,T_m\right) \qquad i=1,...,n \qquad (5.4)$$

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 $j=1,...,m$. Further assume that:

- L and K do not change for a marginal increase of the input-traits per log.

- 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 (5.5):

$$\pi_i = P \; Q\left(\bar{L},\bar{K},T_1,T_2,...,T_m\right) \qquad (5.5)$$

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 or log recovery value (Davis and Johnson 1987). Accordingly, the first order conditions for profit maximization are:

$$\frac{\partial \pi_i}{\partial T_j} = P \; \frac{\partial Q\left(\bar{L},\bar{K},T_1,T_2,...,T_m\right)}{\partial T_j} \qquad (5.6)$$

From Equation (5.6) 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 value of the marginal product (VMP) of the attribute. The estimation of the economic values of wood attributes is based on the estimation of the VPM of SED, STF and LBR^{-1}.

Lumber prices and processing costs were obtained from New Zealand firms. The price for 100x50 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* (Equation (5.6)).

5.4   Results and discussion

The response variable for the production function was the volume of lumber with stiffness of 8 GPa or higher (MSG8+), a threshold often applied to structural lumber (Chauhan 2006b). Sixty out of the 71 logs met the MSG8+ criterion; satisfying the basic assumption of *essentiality,* whereas the existence of inputs implies the existence of output (Coelli et al. 2005).

A linear model was used for exploratory data analysis, showing that there were no significant collinearity problems and that all predictors but LBR^{-1} were significant ($p < 0.05$). Differences for intercept and slope between second and third logs were tested using dummy variables, which were not significant ($p < 0.05$); accordingly, production modeling considered second and third logs as a single sample. The coefficients of the Translog production function were non-significant ($p > 0.05$) and no further analyses were conducted for this functional form.

Table 5.3 presents the parameter estimates for the Cobb-Douglas production frontier, where all coefficients are exponents of explanatory variables. The coefficients for SED and STF were significant ($p < 0.05$) and with signs according to expectations; however, the inverse of LBR was not significant ($p > 0.05$).

Table 5.3 Parameter estimates for the Cobb Douglas production frontier.

Cobb Douglas frontier	Coefficients	Standard error	P
$ln(MSG8+) = \beta_0 + \beta_1\, ln\, SED + \beta_2\, ln\, STF + \beta_3\, ln\, LBR^{-1}$			
Log β_0	-16.0756	0.3293	<0.05
β_1	2.0784	0.0497	<0.05
β_2	3.3806	0.1340	<0.05
β_3	0.0017	0.0099	>0.05

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. The monotonicity property is particularly important for assessing technical efficiency because otherwise there would not be reasonable interpretation of the results (Henningsen and Henning 2009). There was a significant correlation between observed and predicted values of MSG8+ with the Cobb Douglas frontier (0.65, $p < 0.05$).

However, the Cobb Douglas model did not meet the quasi-concavity assumption, as the sum of the coefficients was greater than 1. For a continuously differentiable production function, quasi-concavity implies that all marginal products are non-increasing, which is known as the law of diminishing marginal productivity (Beattie and Taylor 1985; Varian 1992; Coelli et al. 2005). Since the assumption of quasi-concavity was not met and the coefficients of the Cobb Douglas model were higher than 1; the production of logs capable of producing structural (MSG8+) sawn timber would be in a stage of increasing marginal productivity that, from the production theory point of view, is not efficient (Beattie and Taylor 1985; Varian 1992).

Increasing returns to scale (coefficients greater than 1) is plausible for log SED. 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 greater than 1 for that variable.

Finally, this analysis refers only to a short run profit function—the data are on only one mill, and the only factor of production that is variable is quality of the log input. In this case, increasing returns to scale may be a plausible result.

Lumber production was SED and STF elastic, as the product elasticities for the traits were greater than 1. In consequence, a simultaneous increase in SED and STF would increase the production of structural lumber more than proportionally. Product elasticities showed a high sensitiveness of log structural volume (MSG8+) to stiffness, corroborating the relevance of this attribute to produce radiata pine structural lumber.
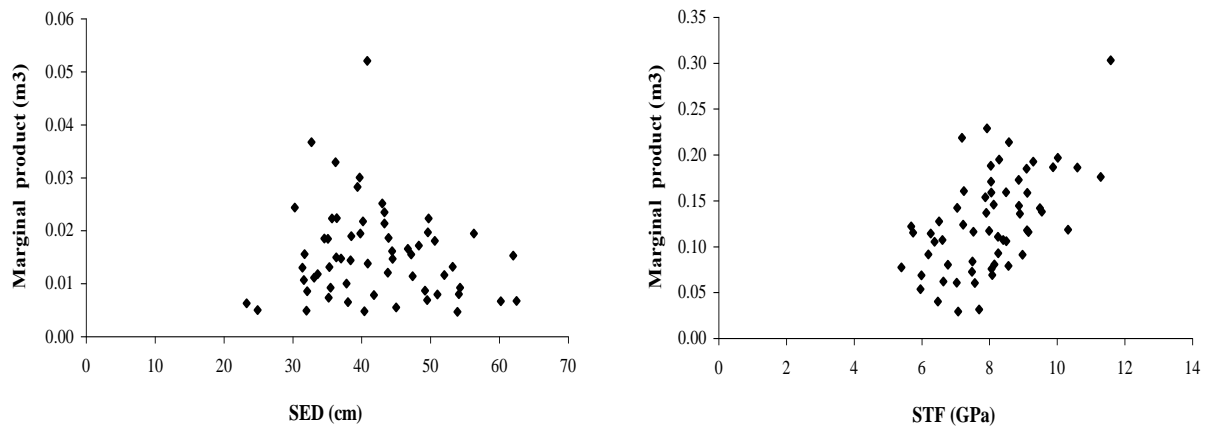
Figure 5.1. Marginal products for SED and STF derived from the Cobb-Douglas model.

Figure 5.1 illustrates the relationships between log traits (SED and STF) and their marginal products. The difference on magnitude of marginal products between the traits supports the superiority of STF to explain the yield of structural grades, which has been reported by comparables studies (Ivković et al. 2006; Alzamora and Apiolaza 2009). This figure also depicts the variability of the marginal products of the attributes between logs. There was a non-significant correlation between SED and marginal products ($p > 0.05$); in addition, logs with SED smaller than 40 cm achieved the highest marginal products. There was a positive and significant correlation between STF and marginal products (0.52, $p < 0.05$).

Table 5.4 Economic value of the marginal product of SED and STF.

Value of the marginal product (VMP)	SED (NZ \$/cm)	STF (NZ \$/GPa)
Mean value for all logs	2.11	15.75
Evaluated in the mean value of SED and STF	1.78	14.76
Value in the most efficient log	2.91	16.69
Mean value in second logs	2.47	18.89
Mean value in third logs	1.74	12.59

Table 5.4 shows the economic values of wood attributes obtained from the marginal product (VMP) for each attribute. 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 technical efficiency (TE equal 1). All values represent log profit increase for an extra unit of the attribute.

Table 5.4 also presents the average VMP of the attributes for second and third logs. As we see, the VMP of attributes were greater for second logs than for thirds logs, which was expected as second logs tend to present higher wood quality to produce structural grades (Xu and Walker 2004).

The Cobb-Douglas generated plausible economic values of SED and STF for the production of structural grades. However, the value of LBR^{-1} was not significant, which does not support the negative effect reported by Ivković et al. (2006) using a bioeconomic model.

The economic value for SED was similar to figures reported by other studies; however, the economic value of stiffness was smaller than the value estimated by Alzamora and Apiolaza (2009) when using a partial regression to estimate economic weights of structural attributes from unpruned logs. The differences between those values can be explained by the nature of each methodology. The stochastic frontier 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 stochastic frontier as a single product modeling system which corresponded to the log volume of structural lumber with STF of 8 GPa or higher. On the other hand, partial regression used the economic value of every lumber product derived from the logs; hence, it is more sensitive than stochastic frontier to changes in wood quality.

The existence of inefficiency in the Cobb Douglas frontier was tested using a likelihood-ratio test that rejected the null hypothesis ($p<0.05$) of $\gamma = 0$. The model presented a γ around 0.9, which indicated that the inefficiency effect dominated the noise effect (Coelli et al. 2005).

The natural heterogeneity of logs made difficult to use stochastic frontiers 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 technical efficiency above 99% when using a stochastic frontier 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.

The mean technical efficiency (TE) of logs was 0.54, while 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 (0.67, p<0.05).

Table 5.5 shows a description of the logs with the highest technical efficiency scores. The log conversion return (CR) of these logs was much larger than log prices, a common situation for logs with TE greater than 0.6.

Table 5.5 Traits and economic values of the most efficient logs to produce MSG8+.

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

Table 5.5 belonged to different trees and had 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). The most efficient logs presented a STF greater than 7.5 GPa; furthermore, the most efficient log (TE = 1) had the highest STF, the largest CR, and the highest STF:SED ratio.

In general, logs presented low efficiency represented by the inefficiency component of the composite error. The technical efficiency of the logs was highly correlated with stiffness; however, this was not observed with SED. Alzamora and Apiolaza (2009) reported comparable TE results in a single product DEA analysis for the same aggregate product (MSG8+). DEA and the stochastic frontier are expected to generate comparable results on TE, as long as the inefficiency effects prevail over statistical noise (Coelli et al. 2005), which has been supported by this study.

On the other hand, TE results obtained with the stochastic frontier were different to those obtained by Alzamora and Apiolaza (2009) when running a multiproduct DEA that included lumber grades of 8, 10 and 12 GPa. In this case, the most efficient logs were characterized by a STF:SED ratio of 1:4, whereas in applying a stochastic frontier that ratio was lower (1:5). This implies that when using one aggregate product the TE standards would be lower than for a mix of products. On the other hand, since the 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.

5.5   Conclusions

Using a stochastic production frontier allowed modeling technical relationships between lumber production and log attributes, as well as obtaining the productive efficiency of logs.

The Cobb Douglas model met the monotonicity assumption but it did not meet the concavity assumption, which indicates that the economic values for SED and STF were estimated in a non-optimal production stage.

This study supports the superiority of STF over SED to value logs for structural purposes. The economic value for SED was comparable to other studies; nevertheless the value of STF was smaller than the one estimated by other methods. This difference was likely due to the stochastic frontier considering a single product, which limits its application to specific wood quality thresholds. The stochastic frontier would be a plausible approach to derive economic values of attributes in scenarios where the production is planed 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. The efficiency analysis could be a useful tool to assess log quality with breeding purposes.

Technical efficiency results were comparable to those obtained by using a single product DEA (Alzamora and Apiolaza 2009). However, by including three lumber grades instead of one aggregate product, DEA generated a TE ranking based on a higher wood quality standard than the stochastic production frontier. As a result, the most efficient logs in DEA obtained an STF:SED ratio of 1:4, whereas for the stochastic production frontier that ratio was 1:5.

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.

6   Portfolio selection of radiata pine appearance and structural trees under variable expression of traits

6.1   Abstract

This study used portfolio theory to analyze the tradeoffs between returns and wood traits variability of *Pinus radiata*. We considered three groups of trees grown to produce appearance lumber, structural lumber, or both. Risk was based on the variability of tree returns in scenarios of changing volume, wood stiffness and presence of resin defects. The return of structural trees was highly variable with a mean of 3.11 NZ \$/stem/year, followed by appearance-structural trees (3.48 NZ \$/stem/year). In contrast, appearance trees had the lowest returns (1.99 NZ \$/stem/year) and variability. The portfolio model selected structural trees in high-risk scenarios, but as the risk decreased selection was apportioned between structural and appearance-structural trees. The model selected only appearance trees for high-risk aversion. The analysis also considered silvicultural regimes. In this case, the appearance-structural regime was selected under high variability. As risk decreased the appearance grades regime was also selected. The structural regime was rarely selected due to the variability of stiffness between trees. Using material genetically improved for stiffness could increase the expected value and reduce variability for structural purposes, making the structural regime more appealing.

Keywords: Portfolio selection, wood quality, *Pinus radiata*, breeding objectives, economic weights.

6.2   Introduction

Quantity and quality of radiata pine (*Pinus radiata* D.Don) appearance and structural lumber are highly dependent on several tree traits. Tree volume has the highest economic weight to produce appearance grades (Todoroki and Carson 2003; Alzamora and Apiolaza 2010), but recovery of clear pieces can be reduced by resin defects (e.g., McConchie and Turner 2002; Woollons et al. 2008). Volume and wood stiffness are the most important traits for structural lumber production (Evans and Ilic 2001; Jayawickrama 2001a; Kumar 2004; Xu and Walker 2004; Lindstrom et al. 2005; Ivković et al. 2006; Matheson et al. 2008). Volume relates to

total lumber recovery, while stiffness—the resistance of a material to deflection—affects structural grade recovery (Evans and Ilic 2001; Xu and Walker 2004; Chauhan 2006a).

The performance of trees depends on their genetic makeup (genotype), the environment where they are growing (which includes site and silviculture) and the interaction between genotype and environment. Several studies have shown variability for volume, stiffness and resin defects of radiata pine growing in different sites, silviculture and genetic material (e.g., Jayawickrama 2001a; McConchie and Turner 2002; Kumar 2004; Lasserre et al. 2004; Watt et al. 2005; Waghorn et al. 2007b; Woollons et al. 2008; Apiolaza 2009).

Radiata pine requires a minimum annual rainfall of 600 mm, with best development on sites with at least 750 mm (e.g., Hunter and Gibson 1984; Turner et al. 2001). Water use efficiency is a major determinant of growth under water-limited conditions (e.g., Nambiar 1995; Korol et al. 1999); water deficit also affects most wood properties. Trees have lower stiffness and higher propensity to develop resin problems when growing in low rainfall sites (e.g., Cown 1973; Tsehaye 1985; Walford 1985). Wind also affects wood properties, particularly in low stocking stands and trees growing in forest margins, where stem deflections induce reduced stiffness, compression wood and resin pockets (Telewski and Jaffe 1986; Zobel and Van Buijtenen 1989; Dunham and Cameron 2000; Moore and Quine 2000; Pruyn et al. 2000; Bascuñán et al. 2006).

Silvicultural decisions, such as stocking, affect volume and wood properties. Stocking reflects the extent to which trees use a site, affecting wood properties through impacts on growth rate, crown development and the availability of water and soil nutrients (Daniels et al. 1979; Zobel and Van Buijtenen 1989; Lasserre et al. 2004; Waghorn et al. 2007a). Increasing initial stoking decreases tree volume; however, average wood stiffness increases because the proportion of corewood (which has low stiffness) is reduced (e.g., Zhang et al. 2002; Lasserre et al. 2004; Lasserre et al. 2005; Watt et al. 2005). High stocking stands have fewer resin problems, probably due to better protection from wind as well as reduced water stress (Cown 1973; Woollons et al. 2008; Watt et al. 2009).

A further complication is the presence of genotype by environment interaction (GxE), which refers to changes of the relative performance of genotypes according to the environment where they are growing (Burdon 1977). In radiata pine most GxE studies deal with growth traits like stem diameter. For example, Johnson and Burdon (1990) found significant family x site interaction between pumice and clay sites in New Zealand while Matheson and Wu (2005) reported a high GxE for stem diameter and other traits on ten testing sites in Australia.

GxE information for wood properties is limited and mostly focused on basic density (e.g., Kumar 2004; Gapare et al. 2009).

Trait variability generates risk in decisions such as which clones (or families) should be deployed in a set of sites and silvicultural conditions to produce specific products. This problem is analogous to investment decisions in financial markets, where there are risks and returns across a set of correlated assets. Portfolio theory provides a framework to analyze return and risk for trees with values depending on variable traits.

Markowitz (1952) formulated portfolio selection as a quadratic programming problem, with the objective of either maximizing expected return for a given level of risk or minimizing risk for a given level of return. Risk was represented as the variance of the portfolio return. The solutions are a set of holdings (a portfolio), and an efficient frontier that defines the portfolios that have maximal expected return given an upper bound for the variance, or a minimal variance given a lower bound for the return.

Alternative models have been proposed to reduce numerical problems related to quadratic programming, including linear formulations (Sharpe 1971; Byrne and Lee 1997; Ruszczy ski and Vanderbei 2003; Stone 2009). Modeling risk as the mean absolute-deviation of the returns (MAD) is a popular linear approach, which is equivalent to the quadratic model when the returns are normally distributed (Konno and Yamazaki 1991). MAD and variance are comparable risk measures from a mathematical point of view although they are different in numerical terms (Konno and Koshizuka 2005). MAD models can be readily solved using linear programming, avoiding non-convexity problems sometimes present in nonlinear programming. In addition, there is no need to estimate the covariance matrix to set up the MAD model avoiding the difficulties of working with a non-singular covariance matrix (Byrne and Lee 1997).

Portfolio theory has been used in animal and crop breeding to select genetic material (e.g, Smith and Hammond 1987; Galligan et al. 1991; Shapcott 1992; Nash and Rogers 1996; Barkley and Peterson 2008; Nalley et al. 2009). In forestry the main applications have been at the forest level in land investment (e.g., Mills Jr and Hoover 1982; Zinkhan 1988; Heikkinen 2002; Clutter et al. 2005).

This study uses a MAD portfolio approach to analyze three sets of trees for i- returns from appearance and structural lumber production and ii- risks due to the variability of volume, stiffness and resin defects under different site and silviculture scenarios. Tree characteristics

are based on two sawing studies while the risk scenarios are derived from the natural variation of growing conditions for radiata pine. We assume that individual trees can be deployed using clonal forestry as the output of a breeding program.

6.3   Materials and methods

This research relies on two sawing studies: a Chilean study for appearance grades (Alzamora and Apiolaza 2010) and a New Zealand study for structural grades. The Chilean study included 156 logs from three stands that were 20, 23 and 34 years old with site indices 31, 34 and 28 m respectively. The stands were thinned and pruned at different stocking intensities, but all of them targeted a 5 m long pruned log. The New Zealand study included 18 stems from each of two forests that were 28 and 26 years old, producing 72 structural 5 m long second and third logs. Table 6.1 shows summary statistics for appearance and structural logs.

Small end diameter (SED) is commonly used to classify and price logs. FORM corresponds to the relationship Cvol/Lvol, where Cvol is the common volume (m^3) equivalent to the maximum cylinder contained in the log, and Lvol is the real log volume. LBR is the diameter of the largest branch of the log. Wood stiffness (STF), or modulus of elasticity, was estimated from acoustics assessments performed with a Director HM200.

Table 6.1 Average value of log descriptors for appearance and structural grades.

Production objective:	Appearance grades			Structural grades	
Variable	1st Log	2nd Log	3rd Log	2nd Log	3rd Log
Number of logs	54	57	45	35	36
Log length (LL, cm)	505	505	410	500	500
Small end diameter (SED, cm)	38.52	35.86	33.51	44.91	39.77
Log volume (VOL, m^3)	0.73	0.55	0.43	0.89	0.73
Form (FORM)	0.73	0.79	0.79	0.82	0.79
Largest branch (LBR, mm)		56.64	66.55	60.29	73.33
Defect cylinder diameter (DCD, mm)	240.69				
Pruned log index (PLI)	4.83				
Stiffness (STF, GPa)				7.97	7.97

In the Chilean study, the pruned butt log, and second and third unpruned logs were processed to obtain appearance products (W.W.P.A 1989). The objective was to maximize the production of Mouldings & Better from the pruned logs and Shop grades from unpruned logs.

The structural sawing study considered second and third unpruned logs and the goal was to produce New Zealand structural grades MSG6, MSG8, MSG10 and MSG12 where MSG means machine stress grade and the number corresponds to the stiffness in GPa.

None of the sawing studies used clonal material; however, for the purposes of this study it was assumed that the trees represented variation of a deployment population. The characteristics of each genotype (tree) could then be used in operational plantations through clonal deployment.

6.3.1   Completing trees for appearance and structural grades

The Chilean and New Zealand datasets did not include information for all logs of a tree, making necessary to estimate the volume of the rest of the tree up to 10 cm stem. Trees for appearance grades had log outturns for first pruned log, and second and third unpruned logs. The volume of the upper logs was recovered by using Ormond's model (1983) to determine tree height at 10 cm of stem diameter and then Bruce's taper model (1968) to obtain stem diameters at different heights. Using those diameters volume was estimated using Smalian's formula.

Trees for structural grades had information of log outturn for second and third unpruned logs, making necessary to estimate volume and log outturn for the first log and volume for the upper logs. Commercial heights, stem diameters and log volumes were estimated in the same way as for appearance grades. The first log outturn assumed stiffness similar to the second and third logs and following a vertical stiffness trend consistent with Xu and Walker (2004).

The first log was also modeled as a pruned log for appearance grades while maintaining the same volume and traits of the structural trees. This allowed generating a synthetic third tree (appearance-structural) with a pruned first log and two upper unpruned logs for structural purposes. The outturn of first log was modeled using only Chilean logs with PLI higher than 6, to account for New Zealand's longer rotations and lower stockings (Maclaren 1993). Table 6.2 shows a summary of the three types of trees included in this study.

Table 6.2 Descriptive statistics of lumber volume (m³) per tree

Mean values of trees		Appearance trees	Appearance-structural	Structural
DBH	cm	50.36	61.03	61.03
Total height	m	33.31	40.03	40.03
Defect core diameter	mm	246.33	281.37	
Log pruned index (PLI)		5.28	6.71	
Volume log 1	m³	0.78	1.08	1.08
Volume log 2	m³	0.59	0.90	0.90
Volume log 3	m³	0.42	0.72	0.72
Volume logs 4,5,6	m³	0.55	1.17	1.17
Pulp volume	m³	0.22	0.25	0.25

6.3.2 Economic return of trees

The return of the butt, second and third logs corresponds to the conversion return (*CR*) which represents the maximum willingness to pay for logs at the mill (Davis and Johnson 1987). *CR* corresponds to the total value of lumber in one cubic meter of logs minus the log processing cost:

$$CR = \sum_{i=1}^{n} p_i L_i - PC \qquad (6.1)$$

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. This value can be used when log prices do not consistently reflect the value of the wood attributes (Alzamora and Apiolaza 2010). We assumed that the quality of upper sawlogs and pulplogs is well represented by the market prices (MAF 2009).

Table 6.3 Prices and shipping costs for products and processing costs for logs.

Moulding & Better [NZ $/m³]	3rd Clr [NZ $/m³]	Shop 1 [NZ $/m³]	Shop 2 [NZ $/m³]	Shop 3 [NZ $/m³]	Finger Joint Blocks [NZ $/m³]	Finger Out [NZ $/m³]	Shipping cost [NZ $/m³]	Log processing cost [NZ $/m³]
812	548	518	456	370	510	357	83	97

Table 6.3 presents prices and shipping costs of products, as well as processing costs used to estimate log CR for appearance products. Information to estimate the conversion return of

structural logs was provided by the Wood Quality Initiative (WQI) and New Zealand sawmills. Prices for 100x50 mm lumber were 2.5, 3.2, 4.1, 4.8 NZ$/linear m for MSG6, MSG8, MSG10 and MSG12 respectively, while the processing cost was 180 NZ$/m^3.

6.4   Portfolio analysis

The portfolio model maximizes the expected return from investing in a set of trees. The model uses the mean-absolute deviation of the tree returns (MAD) as the risk measure (Konno 1990; Konno and Yamazaki 1991; Konno and Koshizuka 2005). For this application, MAD is based on different scenarios of variability on volume, stiffness and resin defects. The portfolio model is as follows.

$$\text{Max:} \quad \frac{1}{S}\sum_{j}^{n}\sum_{i}^{S} R_{ij}\, x_j$$

Subject to:

$$-Dev_i \leq \sum_{j}^{n}\left[R_{ij} - \frac{1}{S}\sum_{i}^{S} R_{ij} \right] x_j \leq Dev_i \quad \forall\ i \text{ in scenario} \tag{6.2}$$

$$\frac{1}{S}\sum_{i}^{S} Dev_i \leq Risk \tag{6.3}$$

$$\sum_{j}^{n} x_j = 1 \tag{6.4}$$

where R_{ij} is the return of the j-th tree in the i-th scenario with $j=1,...,n$ and $i=1,...S$; the variable x_j is the fraction of the portfolio invested in the j-th tree; and, S is the total number of scenarios. Equation (6.2) shows that the mean absolute deviation, represented by the term $\sum_{j}^{n}\left[R_{ij} - \frac{1}{S}\sum_{i}^{S} R_{ij} \right]$ and weighted by x_j, is bounded to the deviations in each scenario. The average of the deviations across scenarios (average MAD) is limited to be the maximum risk that decision makers will want to face (left side Equation (6.3)). Constraint (6.4) shows that a weighted sum of investments in the portfolio must be equal to 1.

The portfolio model was modified to also analyze the selection of silvicultural regimes. In this case, the objective function maximizes the expected weighted return from investing in three silvicultural regimes, while constrains are formulated in terms of the mean absolute deviations of tree returns in each silvicultural regime. The average of deviations across trees and

silvicultural regimes are limited to a maximum level of risk, which is varied to obtain an efficient frontier.

Tree returns were annual equivalent values (NZ $/stem/year) from a cash flow including costs of establishment, silviculture and harvesting with a discount rate of 10%. Silviculture and harvesting costs were provided by New Zealand companies.

The efficient frontier is obtained by varying the level of risk, solving the linear problem, identifying the maximum return portfolio and plotting the return of the portfolios versus risk. All models were run using AMPL with the CPLEX solver. Annual equivalent values changed by varying volume, stiffness and resin defects following several scenarios.

6.4.1   Risk scenarios due to trait variability

In addition to the base condition there were three positive and one negative scenarios generated by changing tree volume, stiffness and resin defects. Changing SED for the first log and extending that change to other logs using a linear regression resulted in updated log volumes, later aggregated to obtain the new tree volume. The effect of changing stiffness on product distribution was obtained by randomly choosing a log with the new required stiffness from our data set and applying that log's outturn. The effect of resin defects was modeled from a Chilean resin study that included 30 radiata pine trees with different levels of resin bleeding (Meneses and Guzmán 2003). Stems and logs were visually assessed for resin and classified in three levels: low, moderate and high resin. Logs were processed and the boards were graded twice for appearance products; the first time using regular commercial grading and the second time ignoring resin defects. The impact of resin was estimated as the board downgrading between the two assessments. These outturn downgrades were predicted using SED and resin levels for our appearance logs.

The first positive scenario increased log SED by 10% with a corresponding increase in tree volume. The second scenario increased STF of the first, second and third logs by 10%. The most optimistic scenario increased both volume and stiffness (first log SED is increased by 25%, and 25% increase of STF for first, second and third). In addition we assumed that stiffness had no effect on the value of appearance grades, and that resin problems did not affect the value of structural products. The pessimistic scenario decreased volume (by reducing first log SED by 25%) and STF by 25%, and introduced resin problems. In summary, we assumed that the most undesirable events for appearance trees were to decrease

volume and to suffer resin defects, while for structural trees the worst conditions were lower volume and stiffness.

6.5   Results and discussion

In the first section we present the economic returns of the three groups of trees, the relationships between returns and tree attributes, as well as the return tradeoffs between volume and stiffness when allocating a tree to produce appearance and structural grades. Later we introduce the tree selection made by the portfolio model, the efficiency frontier and the trends observed when selecting silvicultural regimes.

6.5.1   Economic returns from trees

In the base scenario appearance trees presented a mean value of NZ $ 273/stem and NZ $ 79/m^3, appearance-structural trees had a mean value of NZ $ 394/stem and NZ $ 94/m^3, while structural trees showed a mean value of NZ $ 307/stem and NZ $ 79/m^3.

Table 6.4 Pearson correlation coefficients between tree attributes and tree value

Tree category	Diameter at breast high (DBH)	Stiffness (STF)
Appearance		
NZ $/tree	0.95[*]	
NZ $/m^3 tree	0.78[*]	
Appearance-structural		
NZ $/tree	0.67[*]	0.17
NZ $/m^3 tree	-0.18	0.82[*]
Structural		
NZ $/tree	0.52[*]	0.24
NZ $/m^3 tree	-0.20	0.82[*]

*Significant at 0.05 level.

Table 6.4 shows the correlations between DBH and tree values, and stiffness and tree values for the three types of trees. DBH had the highest correlation with tree value across of all trees; in contrast, the correlations between DBH and value per cubic meter of appearance-structural and structural trees were not significant (p>0.05). Wood stiffness was highly correlated with value per cubic meter of tree; however, the correlation was not significant when using the whole tree value. These results can be explained by i-the negative correlation between

stiffness and volume and, ii- the weight of structural logs in tree value, which have been discussed in other studies (e.g., Lasserre et al. 2004; Xu and Walker 2004).

In both, appearance-structural and structural trees, the structural logs had the highest value per tree which explains the high correlation between STF and the value per cubic meter of tree. However, since STF is negatively correlated with volume, the correlation between DBH and the value per cubic meter of tree was negative, although non-significant. The value contribution of non-structural logs, which are priced by volume, would be precluding the significance of that correlation.

Table 6.5 shows the economic returns for the three groups of trees (NZ $/stem/year) across of five scenarios of variability on volume, stiffness and resin defects. Each scenario has two columns representing average gross return (1) and discounting silviculture and harvesting costs (2). The table also shows the average value of MAD—the absolute value of the difference between the mean tree return—across five scenarios and the tree return in an individual scenario. MAD relates to risk, so a high variability or risk will be reflected in a high MAD.

Table 6.5 Descriptive statistics (in NZ $/stem/year) for average gross tree returns (1) and discounting silviculture and harvesting costs (2) under five scenarios.

Tree groups	Current scenario		Volume increase		STF increase		Bad scenario		Good scenario	
Appearance	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Mean value	1.85	0.59	2.55	1.02	1.85	0.59	0.23	-0.62	3.49	1.59
Maximum value	3.64	1.88	4.87	2.76	3.64	1.88	0.89	0.12	6.64	3.92
Minimum value	0.93	-0.30	1.29	-0.16	0.93	-0.30	-0.55	-1.44	1.81	0.04
MAD	0.14	0.07	0.56	0.39	0.14	0.07	1.77	1.25	1.50	0.95
Appearance-structural	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Mean value	2.87	1.22	3.51	1.66	3.75	2.26	0.63	-0.46	6.67	4.62
Maximum value	4.67	2.58	5.55	3.21	5.44	3.77	1.36	-0.05	10.07	7.67
Minimum value	0.82	-0.15	0.90	-0.17	2.06	0.07	-0.02	-0.71	2.92	1.88
MAD	0.61	0.64	0.25	0.30	0.49	0.57	2.86	2.32	3.18	2.76
Structural	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Mean value	2.23	0.76	2.79	1.06	3.23	1.75	0.53	-0.44	6.72	4.57
Maximum value	4.38	2.94	5.43	3.76	5.54	3.59	1.10	-0.08	10.38	8.31
Minimum value	0.19	-1.76	0.26	-1.97	1.17	-0.07	0.00	-1.18	2.92	0.93
MAD	0.86	0.78	0.34	0.49	0.24	0.27	2.57	1.98	3.62	3.03

In the base scenario, appearance-structural trees had the highest mean gross return whereas appearance trees had the lowest. The mean gross returns of structural trees achieved values between the two previous groups. Return and risk had their lowest value for appearance trees while structural trees had the highest MAD, however appearance-structural trees had the highest returns. Nevertheless, the returns of appearance-structural and structural trees were similar with non-significant differences in the base scenario (p>0.05).

Trends observed in the base scenario were maintained across all scenarios; however, returns from structural trees were slightly superior to those from appearance-structural trees in the optimistic scenario. This was expected because a simultaneous increase of volume and stiffness implied that every log of the structural trees increased its value while for the appearance-structural trees only the first log increased its value due to extra volume. In general, trees that produced appearance lumber had a proportionally higher value increase when increasing volume than when improving stiffness. In contrast, those trees that generated structural grades had their highest value increase when increasing stiffness.

Appearance-structural trees had the highest net return of trees across of all scenarios; in contrast, appearance trees had the lowest returns and risks. Appearance-structural and structural trees had similar gross returns; however, the latter presented the highest variability making them the riskiest assets.

There were value tradeoffs when allocating trees to produce appearance and structural grades. Table 6.6 presents the value increase (%) of logs and trees, when increasing volume or stiffness while maintaining the other traits unchanged.

The PLI of appearance-structural trees increased from 6.7 to 7.0 and the log value increased by 17% when increasing tree volume. The second and third structural logs increased by 22 and 23%, respectively, and the tree value increased by 19%. However, these values are lower than those achieved by trees with a single production goal. Similarly, when increasing stiffness by 10%, structural trees achieved the highest values; however, those logs and tress that produce appearance grades did not change their values. The economic benefits of increasing stiffness have been stressed by Dickson and Walker (1997b; 1997a) when showing the reward of increasing corewood stiffness of radiata pine trees.

Table 6.6 Value increase on logs and trees due to volume and stiffness increase

	Appearance	Appearance-structural	Structural
Volume increase			
Butt log	31%	17%	21%
Second log	32%	22%	22%
Third log	31%	23%	23%
Tree	29%	19%	22%
Stiffness increase			
Butt log	0%	0%	71%
Second log	0%	58%	58%
Third log	0%	81%	81%
Tree	0%	32%	52%

Appearance-structural trees displayed intermediate positions when increasing volume or stiffness, because these trees produce logs for both appearance and structural grades, and have proportionally lower value increases compared to trees with a single production goal. The intermediate position of these trees is also explained by the tradeoff between stiffness and growth (Lasserre et al. 2004; Watt et al. 2005; Waghorn et al. 2007b). Increasing volume decreases average wood stiffness because there is a larger proportion of corewood. The increase of value for unpruned logs is proportionally lower than that for butt logs, because their value is more dependent on stiffness than on volume. On the other hand, this tradeoff would tend to match the values of the butt log for appearance grades and the unpruned logs for structural purposes. This effect could be advantageous from a portfolio perspective, since it favors assets with high return and low variability.

6.5.2   Portfolio analysis

6.5.2.1   Portfolio selection of trees

There were eleven trees in the general solution for the five scenarios of gross tree returns described in Table 5: 55% appearance, 27% appearance-structural and 18% structural. Under high levels of risk (MAD >2.9) the model selected only structural trees. As risk decreased so did the mean gross return, and the model selected an increasing number of appearance-structural trees. The solution considered only appearance-structural trees for MAD between 1.3-0.95. The model apportioned the investment between appearance and appearance-structural trees for MAD lower than 0.9.

We incorporated extra scenarios, aiming to capture more variability, by assuming that a randomly selected 30% of the trees stayed in the base scenario. This proportion was randomized a hundred times per alternative scenario, resulting in 400 extra scenarios of variability per group of trees. These scenarios were integrated in the portfolio model, resulting in a solution that included six appearance, two appearance-structural and two structural trees. Despite the additional variability, the selections were similar those for only 5 scenarios. The model selected a structural tree for high variability, but as the risk decreased appearance-structural and an additional structural trees were selected. Appearance-structural trees were selected in a small range of risk; in contrast, appearance trees were chosen across of a broad range of risk (MAD between 1 and 0.28).

For returns discounting silvicultural and harvesting costs both 5 and 400 scenarios generated similar trends. There were twelve trees in the solution: 66% appearance (8, 22, 23, 25, 28, 30, 31, 34), 17% appearance-structural (48 and 55) and 17% structural (81 and 86). Figure 6.1 presents the trend for selected trees under changing risk. The model selected only one structural tree (86) for MAD between 5 and 1.8. Further decreasing MAD and returns, the model diversified by including another structural and some appearance-structural trees. The model apportioned the investment into three types of trees as MAD decreasing from 1.5 to 1.0 and selected only appearance trees for MAD lower than 1. This suggests that, under the assumed circumstances, appearance trees would be the best option for risk adverse decision makers.
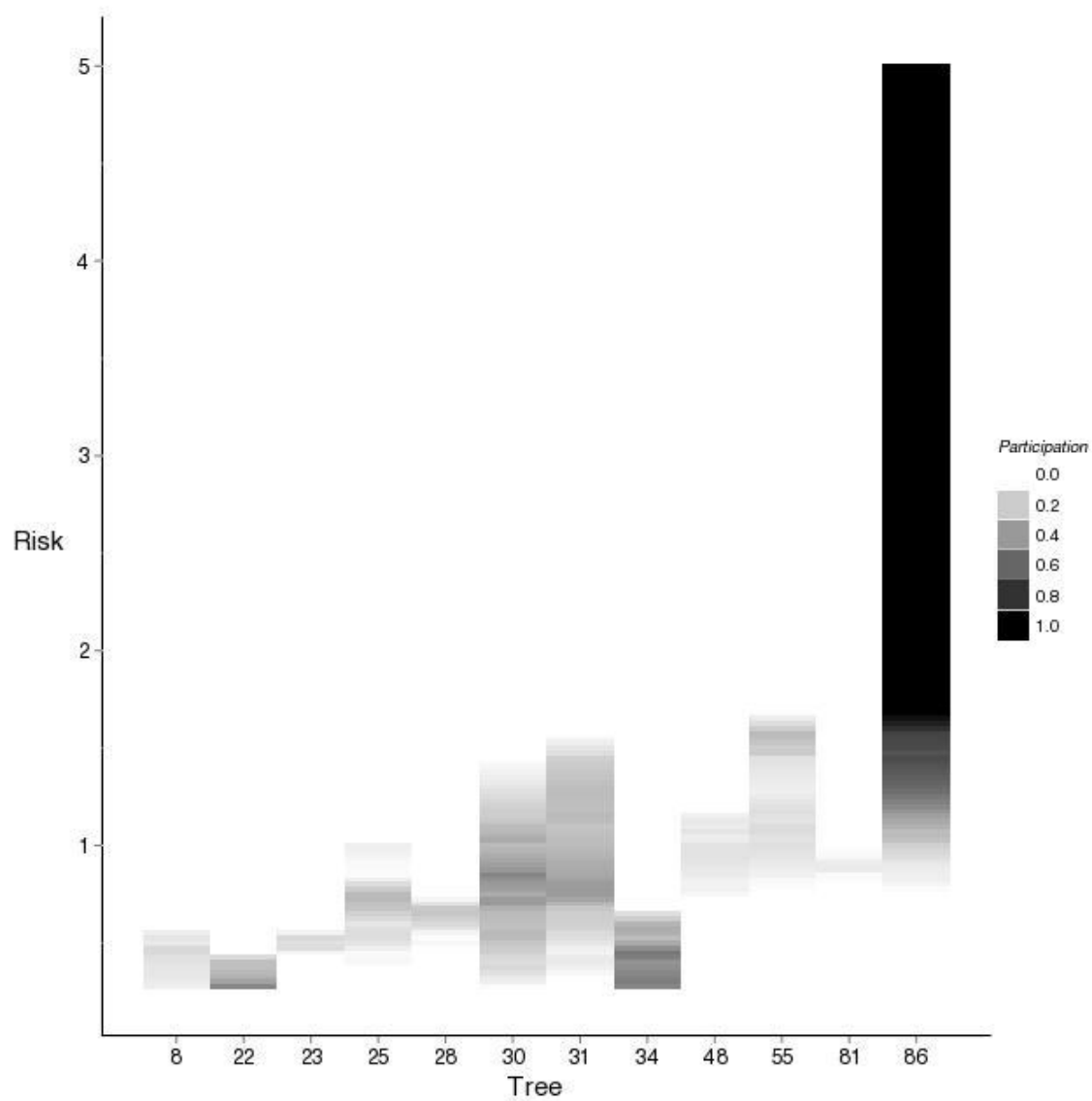
Figure 6.1 Trees selected for different levels of risk. The solutions include appearance (8, 22, 23, 25, 28, 30, 31, 34), appearance-structural (48 and 55) and structural (81 and 86) trees

Table 6.7 presents basic characteristics for five trees included in the solution. There were eight appearance trees in the solution, but we only present the tree with the highest participation in order to simplify the discussion. Structural trees presented the lowest DBH and the highest stiffness. In addition, their second and third logs had the highest ratio between stiffness and small end diameter (higher than 1:4), which would suggest high productive efficiency for structural lumber. Identical results were reported by Alzamora and Apiolaza (2009) when using a non-parametric efficiency analysis to characterize the most efficient logs to produce New Zealand structural grades; furthermore, structural logs from trees 81 and 86 were included in the group of most efficient logs.

Table 6.7 Characteristics of the five trees selected in the portfolio analysis.

Structural trees	Tree DBH (cm)	butt log SED (cm)	2nd log SED (cm)	3rd log SED (cm)	1st log STF (GPa)	2nd log STF (GPa)	3rd log STF (GPa)	2nd log STF/SED	3rd log STF/SED
Tree 86	55.3	44.4	40.8	36.2	9.91	11.6	10.6	0.28	0.29
Tree 81	56.5	41.8	36.4	31.7	7.11	9.5	8.5	0.26	0.28
Appearance-structural trees	Tree DBH (cm)	butt log SED (cm)	2nd log SED (cm)	3rd log SED (cm)	1st log PLI	2nd log STF (GPa)	3rd log STF (GPa)	2nd log STF/SED	3rd log STF/SED
Tree 55	56.7	48.2	43.3	39.8	6.7	9.1	8.9	0.21	0.22
Tree 48	75.9	60.4	56.3	50.6	7.3	7.9	8.0	0.14	0.16
Appearance trees	Tree DBH (cm)	butt log SED (cm)	2nd log SED (cm)	3rd log SED (cm)	1st log PLI	2nd log MIL (cm)	3rd log MIL (cm)	2nd log BIL (cm)	3rd log BIL (cm)
Tree 34	58.0	46.5	43.5	38.9	6.3	189	83	179	112

Appearance-structural trees had high quality butt logs, represented by their SED and PLI; however, their unpruned logs had lower quality, with a low STF:SED ratio by comparison with structural trees. This suggests that those trees were selected mostly due to the quality and value of their butt log. Although most second and third logs had STF greater than 8 GPa, their STF:SED ratios were lower than for structural trees. The strength of appearance-structural would be mainly based on the first pruned log and its traits. Appearance trees had DBH greater that 56 cm, a PLI greater than 5, and a medium internode length (MIL) greater than 35 cm. Internode length is a significant variable to explain the value of unpruned logs to produce appearance grades (Alzamora and Apiolaza 2010).

Figure 6.2 depicts the efficiency frontier derived from the selected trees. The points correspond to the portfolios that have the highest possible expected return for a given level of risk. There was a wide range of risk with constant return, corresponding to a single structural tree (86) selected. This result clearly illustrates the tradeoff between return and risk: the high returns from this tree compensated the variability (MAD 3.64) for a wide-range of risk.

The high expected returns and variability from structural trees suggest that using genetically improved material (such as clones) for stiffness could be a good investment to reduce the risk of variable returns. The advantages of radiata pine clonal forestry has been discussed by Burdon (2001), Sorensson (2002), and Burdon and Aimers-Halliday (2003).
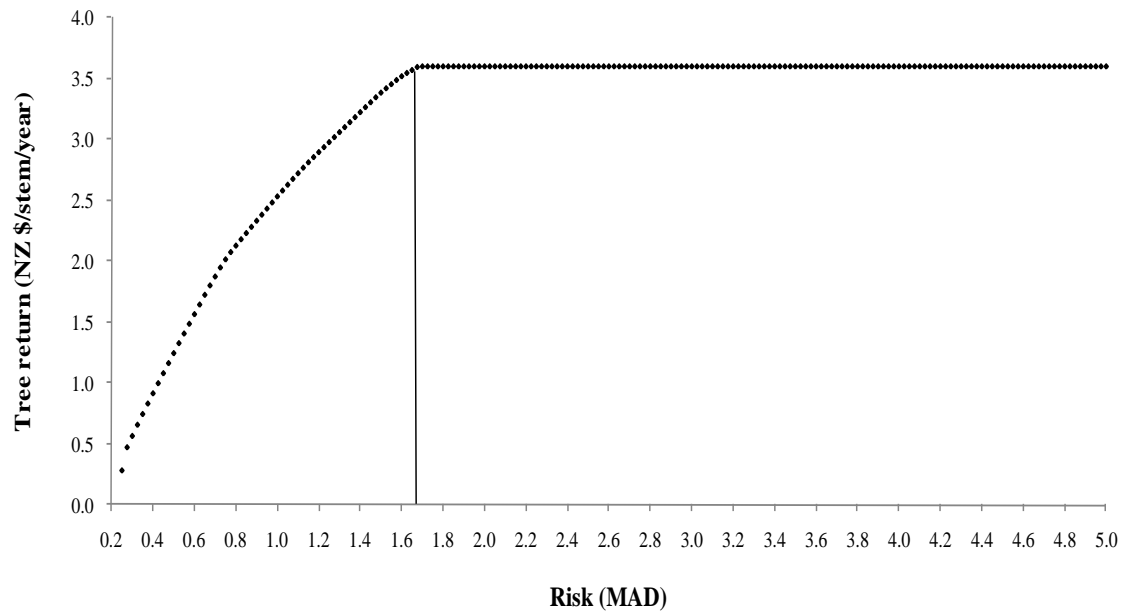
Figure 6.2 Portfolio efficiency frontier for the selected trees

6.5.2.2 Portfolio selection of silvicultural regimes

The portfolio model generated different results for 5 or 405 scenarios of trait variability when analyzing the risk-return tradeoff between groups of trees. Using 405 scenarios and allowing for a high variability of returns (MAD>1.5), the model selected the regime to produce both appearance and structural lumber. As the risk declined the model also selected the structural regime but in a very narrow range of risk (MAD: 1.38-1.3). The model apportioned between appearance-structural and appearance regimes for MAD lower than 1.3; however, only the appearance regime was selected for risk aversion criteria (MAD<0.7). The portfolio model did not select the structural regime when using only the first five variability scenarios. Instead, the model selected an appearance and structural grades regime for high risk and an appearance regime for low risk (MAD<1).

6.6 Conclusions

Trees from three silvicultural regimes were approached as an invest problem with a tradeoff between returns and risk. This analysis permitted selecting and characterizing the most robust trees from an investment point of view.

Producing appearance and structural grades from one tree had a stabilizing effect on returns, as there are phenotypic tradeoffs between stiffness and volume under optimistic and

pessimistic growing scenarios. These trees had a lower variability than structural trees; although both groups of trees had similar returns.

The regime for appearance-structural trees was selected across a wide range of risk when modeling a portfolio to select silvicultural regimes. This showed the benefits of product diversification at the tree level.

Trees to produce appearance grades had the lowest values for return and risk; as a result they were selected under high risk aversion.

The high returns and variability displayed by structural trees suggests an opportunity for narrowing genetic variability (via clonal or family forestry) to make the returns from radiata pine structural grades lumber less risky.

This risk approach could be improved by adding information of product prices, discount rates and production costs to better represent the risk involved in the forestry business.

7 General Discussion

7.1 Introduction

This thesis focuses on the problem of valuing wood traits and showing their role defining wood quality of radiata pine to produce appearance and structural lumber. The discussion firstly addresses the plausibility of the economic weights derived from the hedonic, partial regression and stochastic frontier models introduced in chapters 3, 4 and 5. These approaches were based on log conversion return which is derived from the residual-value appraisal to obtain the purchaser willingness to pay for stumpage (Davis and Johnson 1987).

Log conversion return can be also applied to integrated bioeconomic models, making possible to analyze the distribution of trait value between industry layers. This proposal is discussed using a hypothetical bioeconomic model. Finally the discussion deals with the role of both, traits and economic weights to assess and select logs and trees for improving structural wood quality. Efficiency analyses based on data envelopment analysis and stochastic frontier allowed characterizing the wood traits profile in efficient logs (chapters 4 and 5). Chapter 6 presents an application of portfolio selection to illustrate that trees and silvicultural regimes for deployment can be approached as investment problems. This approach treated variability of wood traits as a risk that affects the decisions about the trees should be targeted for appearance and structural purposes.

7.2 Economic weights derived from hedonic and production approaches

Hedonic models are commonly used to value the traits of a product (Lancaster 1966; Rosen 1974; Lucas 1975; Espinosa and Goodwin 1991; Ekeland et al. 2002). The approach requires that every trait is observable, measurable and directly related to the quality and price of the product. The main impediment to use hedonic models to value log traits is that published radiata pine log prices do not consistently reflect the value of wood traits (Treolar 2005; Alzamora and Apiolaza 2010). Nevertheless, the hedonic approach performed in chapter 3 demonstrated the plausibility of using conversion return as a surrogate log price to value pruned and unpruned log traits for appearance lumber grades. Economic weights for log small end diameter, form, and internode length were statistically significant and plausible. Branch size was non-significant (p>0.05) as the size of knots has a smaller effect on value than their

distribution (considered by internode index). In fact, the requirements for radiata pine appearance lumber relate only to the length of the clear piece (Kretschmann and Hernandez 2006). Results from chapter 3 suggest using mean internode length (MIL) in tandem with base internode length (BIL) when selecting for internode length, as these indices produce complementary information for the production of Shop grades (Meneses and Guzmán 2003).

Economic weights can be obtained as coefficients of a partial regression that links logs wood traits with the value of lumber obtained at the mill (e.g., Cotterill and Jackson 1985; Ernst and Fahey 1986; Aubry et al. 1998). Applying this method to value structural traits resulted in a well behaved linear model. Economic weights for small end diameter, stiffness and largest branch were statistically and economically plausible as well as comparable with other studies (e.g., Cotterill and Jackson 1985; Beauregard et al. 2002; Ivković et al. 2006). Small end diameter and stiffness were the most valuable traits, accounting for 73% of the log value variation. The value of the largest branch was negative (-0.4 NZ \$/mm) as branch size has a negative effect on the recovery of structural grades (Grant et al. 1984; Xu 2002).

Economic values for structural traits were also estimated by using a stochastic frontier. The advantages of deriving log traits values with this approach were i- its economic plausibility, since traits were valued as the value of the marginal product, and ii- that allowed characterizing logs by their technical efficiency to produce structural lumber. Stochastic frontier involved modeling the technical relationship between lumber volume with stiffness of 8 GPa or higher and small end diameter, stiffness and largest branch. This choice assumes that, in making decisions, growers and processors plan their production in terms of a minimum quality threshold rather than of particular mix of grades. In this thesis stochastic frontiers emerged as plausible options to estimate economic weights of wood traits by modeling production functions, and to obtain measures of technical efficiency.

The Cobb-Douglas frontier met the assumption of monotonicity and coefficients associated with small end diameter and stiffness were significant ($p<0.05$). However, the effect of largest branch was non-significant, and the model did not meet the assumption of concavity, presenting increasing returns to scale.

The economic value for small end diameter was similar to that obtained from the partial regression; however, the value of stiffness was lower which could be due to the stochastic frontier being based on a single product (Aigner et al. 1977; Meeusen and van den Broeck 1977; Coelli et al. 2005). In contrast, the partial regression considered the volume and value of three lumber grades whose prices are defined by stiffness.

Previous analyses showed that the relative value of log traits changes depending on end products. The value for small end diameter was greater in unpruned logs for appearance lumber than in logs for structural lumber. In addition, largest branch was not significant to value unpruned logs for appearance purposes, while it was negative and significant to explain the value of structural logs. These divergences are explained by the different requirements for appearance and structural lumber. A large log diameter is an advantage for appearance purposes due to its direct relationship with the recovery of appearance grades; in contrast, for structural lumber that trait has shown a negative phenotypic correlation with stiffness (Chuang and Wang 2001; Lasserre et al. 2004; Ivković et al. 2006; Waghorn et al. 2007b) which has been supported by this study. There are no particular stiffness requisites for appearance lumber, although the trait influences dimensional stability and dry lumber recovery, which were not considered in this thesis. Stiffness is the most important trait for solid lumber applications (Dickson and Walker 1997b; Evans and Ilic 2001; Kumar 2004; Chauhan and Walker 2006)

7.3 Distribution of economic value between forest and mill: bioeconomic models as stumpage transactions

Chapters 3, 4 and 5 showed the convenience of using concepts derived from the stumpage residual-value appraisal, such as the conversion return, to value log traits. These concepts can also be used in integrated bioeconomic models, with the advantage of obtaining the distribution of economic value between forest and mill.

Bioeconomic models have been usually approached at the integrated firm level, which does not necessarily represent the production systems targeted by a breeding program. For instance, most forest growers in New Zealand are independent producers (MAF 2009b), making important to show the distribution of economic value between forest and mill. However, most reported bioeconomic models do not analyze this issue (Greaves et al. 1997b; Apiolaza and Garrick 2001; Berlin et al. 2009), although there are some examples of economic weights for structural traits at the forest, mill and integrated company levels (Ivković et al. 2006). Despite the apparent plausibility of the model, there was not equivalence between the values at the forest and mill levels, and the corresponding value for the integrated system.

Since an bioeconomic model mimics the stumpage transaction between grower and processor, we can apply residual-value appraisal to value wood traits and to analyze their distribution

between forest and mill (Davis and Johnson 1987). This approach implies using extra information to better represent the forest buyer perspective.

Table 1 illustrates the distribution of the value of volume in a hypothetical bioeconomic model described in Table 2. It is assumed that the mean annual increment (MAI) is increased by 1% from a baseline of 25 m^3/ha/year. Values in Table 1 are discounted and display sawlogs priced by logs prices and conversion return. As a result, the value of volume for the integrated company obtained by either prices or conversion return is 18.8 US $/m^3$; in addition, the sum of value at the forest and at the mill in both cases is also 18.8 US$/m^3$. Nevertheless, the distribution of value between forest and mill changes depending on the log valuation scenario. When using log prices the distribution of the value of volume between forest and mill is ~1:2 (6.2 versus 12.6 US$/m^3$) whereas using conversion return the distribution turns out to be ~3:1 (14.6 versus 4.2 US$/m^3$).

Table 7.1 Value of volume for a generic integrated company using log pricing by log prices and conversion return.

Integrated Company	Log prices		Conversion return	
				+1 % MAI 25.25
	Base	+1 % MAI	Base	
Discounted incomes [US$/ha]	25 m^3/ha/year	25.25 m^3/ha/year	25 m^3/ha/year	m^3/ha/year
Pulp logs	421.2	425.4	421.2	425.4
Sawlogs	2682.0	2724.5	2932.6	3045.3
Moulding & better	2541.7	2591.2	2541.7	2591.2
Shop 1	1347.7	1376.9	1347.7	1376.9
Shop 2	1415.8	1449.0	1415.8	1449.0
Shop 3	1790.8	1824.8	1790.8	1824.8
Finger-joint	1787.2	1830.1	1787.2	1830.1
Others	206.3	208.4	206.3	208.4
TOTAL	12192.8	12430.4	12443.4	12751.3
Discounted costs [US$/ha]				
Establishment	950.0	950.0	950.0	950.0
Annual	350.0	350.0	350.0	350.0
Silviculture	200.0	200.0	200.0	200.0
Harvest	694.6	694.6	694.6	694.6
Transport	390.7	398.5	390.7	398.5
Sawlogs	2682.0	2724.5	2932.6	3045.3
Sawing costs	4642.0	4688.4	4642.0	4688.4
TOTAL	9909.3	10006.0	10159.9	10326.8
Net Present Value (NPV)	2283.5	2424.4	2283.5	2424.4
NPV difference	140.9	US$/ha	140.9	US$/ha
Attribute difference	7.5	m^3/ha	7.5	m^3/ha
Attribute value	18.8	US$/m^3$	18.8	US$/m^3$

Forest	Log prices		Return of Conversion	
Discounted incomes [US$/ha]	Base	+1 % MAI	Base	+1 % MAI
Pulp logs	421.2	425.4	421.2	425.4
Sawlogs	2682.0	2724.5	1847.3	1952.2
Total	3103.3	3149.9	2268.6	2377.7
Discounted costs [US$/ha]				
Establishment	950.0	950.0	950.0	950.0
Annual	350.0	350.0	350.0	350.0
Silviculture	200.0	200.0	200.0	200.0
TOTAL	1500.0	1500.0	1500.0	1500.0
Net Present Value (NPV)	1603.3	1649.9	768.6	877.7
NPV difference	46.7	US$/ha	109.1	US$/ha
Attribute difference	7.5	m^3/ha	7.5	m^3/ha
Attribute value	6.2	US$/m^3	14.6	US$/m^3

Sawmill	Log prices		Return of Conversion	
Discounted incomes [US$/ha]	Base	+1 % MAI	Base	+1 % MAI
Moulding & better	2541.7	2591.2	2541.7	2591.2
Shop 1	1347.7	1376.9	1347.7	1376.9
Shop 2	1415.8	1449.0	1415.8	1449.0
Shop 3	1790.8	1824.8	1790.8	1824.8
Finger-joint	1787.2	1830.1	1787.2	1830.1
Others	206.3	208.4	206.3	208.4
TOTAL	9089.5	9280.5	9089.5	9280.5
Discounted costs [US$/ha]				
Saw logs	2682.0	2724.5	7574.6	7733.7
Harvest	694.6	694.6	694.6	694.6
Transport	390.7	398.5	390.7	398.5
Sawing	4642.0	4688.4	4642.0	4688.4
TOTAL	8409.3	8506.0	5727.3	5781.5
Conversion return (CR)			3362.3	3499.0
Margin for profit and risk			1514.9	1546.7
Profit ratio			20%	20%
Net Present Value (NPV)	680.2	774.5	1514.9	1546.7
NPV difference	94.3	US$/ha	31.8	US$/ha
Attribute difference	7.50	m^3/ha	7.5	m^3/ha
Attribute value	12.6	US/$m^3	4.2	US$/m^3

Table 7.2 Assumptions and economic information for the distribution of trait value between forest and mill when using a bioeconomic model.

Assumptions		
Mean Annual Increment (MAI)	25	m^3/ha/year
MAI+1%	25.25	m^3/ha/year
Rotation	30	years
Total volume (MAI+1%)	757.5	m^3/ha
Sawn volume (proportion total volume)	60	%
Prices		
Moulding & better	616	US$/$m^3$
Shop 1	402	US$/$m^3$
Shop 2	366	US$/$m^3$
Shop 3	248	US$/$m^3$
Finger-joint	385	US$/$m^3$
Others sawn products	80	US$/$m^3$
Pulp logs	49	US$/$m^3$
Pruned logs	140	US$/$m^3$
Un-pruned logs	80	US$/$m^3$
Rate discount	10	%
Processing & Shipping	180	US$/$m^3$

The exercise includes a margin for profit and risk for the buyer, which is a common practice at mills. This value represents the return that the log buyer obtains as a compensation for non-profitable sales, or as a reward for the time and effort involved in the transaction. In estimating that margin there was a profit ratio of 20%. This ratio depends on log market conditions and as the market becomes more competitive both profit ratio and margin decrease. In United States the profit ratio used to range between 11 to 13% (Davis and Johnson 1987).

This example showed that we can better represent the business structure of the sawmill in a bioeconomic model by including the conversion return and the margin for profit and risk. In turn this makes possible to analyze the distribution of economic value between industry layers, as well as of the factors influencing it.

7.4 Efficiency and economic weights to support wood quality improvement

Structural traits and their economic weights were used to assess the technical and economic efficiencies of logs. Multi-product efficiency analysis was performed in chapter 4 using data envelopment analysis (DEA). This analysis included small end diameter, stiffness and basic density.

As a result, a set of fully efficient logs to produce lumber with stiffness of 8, 10 and 12 GPa were shown to have common features such as the highest stiffness and the largest conversion.

Those logs were also characterized by a ratio of 1:4 or higher, between stiffness (GPa) and small end diameter (cm). Technical efficiency was significantly correlated with stiffness (0.46, p<0.05) and total efficiency with log conversion return (0.85, p<0.05); however, there was a poor correlation between log prices and efficiency. Chapter 3 already mentioned the limitations of log prices to reflect the value of wood traits, which is a common problem with commodities' traits (e.g., Lambert and Wilson 2003; Treolar 2005; Baker and Babcock 2008).

DEA offered a suitable framework to assess the efficiency of logs. This analysis could be improved by including logs processing options, as done by Todoroki and Carson (2003) using DEA and log sawing optimization to identify the best attributes for appearance lumber grades.

The stochastic frontier fitted in chapter 5 also generated the technical efficiency of logs to produce lumber with stiffness of 8 GPa or higher. In general, the results were comparable to those obtained by using a multi-product DEA; however, the most technically efficient logs derived from the stochastic frontier showed a lower wood quality standard than those selected by DEA. The most efficient logs derived from DEA were characterized by presenting a 1:4 ratio between stiffness and small end diameter; whereas with the stochastic frontier that ratio was 1:5. Therefore, when considering one aggregate product both the quality standards and the technical efficiency were lower. Running DEA with the same aggregate product resulted on efficiency results that were comparables to those from the stochastic frontier. DEA and the stochastic frontier are expected to give equivalent results when the systems have a high inefficiency, which was supported by the composite error of the stochastic frontier (Coelli et al. 2005).

These analyses have a much larger component of inefficiency, associated to natural log variability, than when studying classical production systems such as firms. Nevertheless, this would not invalidate the contribution of efficiency approaches in selecting logs for wood quality purposes. Both tree breeding and efficiency analyses offer the possibility of selecting in alternative contexts of variability: one grounded on genetics and the other one based on economic fundamentals of production.

This thesis approached the economic value of wood traits and the production efficiency from the demand side; however, it would be interesting to apply these methods from the supply side to analyse growers' production costs when improving wood attributes. Bioeconomic models have valued wood traits from the growers' side; nevertheless, those models have not been based on classical production functions but mainly on assumptions and expert opinions. In estimating a wood production function that represents the growers' technology, time should

be introduced as an input due its influence on volume, wood quality traits and opportunity costs. Accordingly, this approach would allow estimating a plausible measure of the marginal cost that growers have to face when producing an extra unit of wood attributes.

7.5 Deploying genetically superior material

Chapter 6 explored the situation when forest growers have access to a clonal or family portfolio of material bred for specific end-uses (appearance, structural or intermediate), and face the choice of what to deploy under variable environmental and management scenarios. A portfolio selection model approached trees, from three silvicultural regimes, as investment problems with a tradeoff between returns and risk. This analysis permitted selecting and characterizing the most robust trees from an investment point of view.

Commonly, portfolio selection theory has approached risk in terms of prices due to their high influence on return. However, since this thesis focussed on wood traits, the portfolio model assessed the influence of traits variability in tree selection, maintaining product prices and production costs.

The portfolio model maximized tree return subject to a risk constrain, which was formulated in terms of the variability of volume, stiffness and resin defects. The risk was linearity approached using the mean absolute value (MAD) of the returns, which has been shown to be as efficient as the variance with the advantage of being readily solved using linear programming algorithms (Konno and Yamazaki 1991; Byrne and Lee 1997; Konno and Koshizuka 2005).

Producing appearance and structural grades from one tree had a stabilizing effect on returns, as there were phenotypic tradeoffs between stiffness and volume under optimistic and pessimistic growing scenarios. The financial robustness of these trees showed the benefits of product diversification at the tree level. In addition, when running a portfolio model for silvicultural regimes, the regime for appearance-structural trees was selected in a wide range of risk which supported the financial advantage of forming trees with two production goals.

Trees for structural lumber had similar returns to those producing both appearance and structural grades; however, the former presented higher variability of returns. The financial performance displayed by structural trees suggested an opportunity for narrowing genetic variability (via clonal or family forestry) to make the returns from radiata pine structural

grades lumber less risky. Trees to produce appearance grades had the lowest return and risk; as a result they were selected for high risk aversion.

The characteristics of the selected trees supported the results from previous chapters. Volume was the most important trait when producing appearance grades, whereas stiffness had the highest influence on the returns from structural trees.

While silviculture would be able to generate better trees for appearance lumber; clonal forestry would be a better option to increase return and reduce variability from trees targeting structural wood quality.

The portfolio model could be improved by adding risk constrains that reflected the variability of economic variables such as lumber prices, discount rates and production costs with a view to better representing the risk involved in the forestry business.

8   General Conclusions

The main conclusions from this thesis were:

- The conversion return was a suitable measure to value logs and derive economic weights of wood traits. Conversion return, in combination with the margin for profit and risk, permitted the analysis of the distribution of economic value between forest and mill when using an integrated bioeconomic model.

- Log small end diameter and form were the traits with the highest economic value for the production of appearance lumber, followed by the value of internode length in unpruned logs destined to Shop grades. Branch sizes did not have a significant effect on value.

- Log small end diameter, stiffness and largest branch were the most valuable traits to produce structural lumber. Wood stiffness and small end diameter explained more than 70% of the variation of log conversion return.

- This thesis supported the relevance of stiffness to value structural logs with an economic value of 29 NZ \$/Gpa and a high correlation between stiffness and log conversion return (0.85, $p < 0.05$).

- Efficient logs to produce structural lumber with stiffness of 8, 10 and 12 GPa were characterized by a 1:4 ratio between stiffness (GPa) and small end diameter (cm).

- The efficiency of logs to produce structural lumber grades was significantly correlated with stiffness and with conversion return; in contrast, the correlation between efficiency and log small end diameter was non-significant ($p < 0.05$).

- On average radiata pine trees to produce structural lumber were very profitable; however, their returns were also highly variable due to the high variability of stiffness. This suggested an opportunity for narrowing genetic variability (via clonal or family forestry) to make the returns from radiata pine structural grades lumber less risky.

- Radiata pine trees that produced both appearance and structural lumber had a stabilizing effect on returns, as there were phenotypic tradeoffs between stiffness and volume under optimistic and pessimistic growing scenarios. These trees were preferred when selecting individuals that optimized the tradeoff between return and risk.

9 References

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

Adamowicz, W.L., and T. Graham-Tomasi. 1991. Revealed preference tests of nonmarket goods valuation methods. J. Environ. Econ. Manag. 20(1):29-45.

Aigner, D., C.A.K. Lovell, and P. Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. J. Econometrics 6:21-37.

Alzamora, R.M., and L.A. Apiolaza. 2009. Economic weights for structural wood attributes and characterization of efficient logs using DEA analysis. Radiata Pine Breeding Company (RPBC), Tech. Rep. 18 p.

Alzamora, R.M., and L.A. Apiolaza. 2010. A hedonic approach to value *Pinus radiata* log traits for appearance-grade lumber production. Forest Sci. 53(6):283-291.

Amer, P., G. Emmans, and G. Simm. 1997. Economic values for carcass traits in UK commercial beef cattle. Livest. Prod. Sci. 51:267- 281.

Amer, P.R., and G.C. Fox. 1992. Estimation of economic weights in genetic improvement using neoclassical production theory: an alternative to rescaling. Anim. Prod. 54:341-350.

Amer, P.R., R. Kemp, J. Buchanan-Smith, G. Fox, and C. Smith. 1994. A bioeconomic model for comparing beef cattle genotypes at their optimal economic slaughter end point. J. Anim. Sci. 72:38- 50.

Amer, P.R., B.G. Lowman, and G. Simm. 1996. Economic values for reproduction traits in beef suckler herds based on calving distribution. Livest. Prod. Sci. 46:85-96.

Angel, C., S. Beare, and A.C. Zwart. 1990. Product characteristics and arbitrage in the Australian and New Zealand wool markets. Aust. J. Agr. Econ. 34:67-79.

Apiolaza, L.A. 2000. Multiple trait improvement of radiata pine, Massey University, Palmesrton North. 143p p.

Apiolaza, L.A. 2009. Very early selection for solid wood quality: screening for early winners. Ann. Forest Sci. 66 601-611.

Apiolaza, L.A., and D.J. Garrick. 2001. Breeding objectives for three silvicultural regimes of radiata pine. Can. J. Forest Res. 31:654-662.

Apiolaza, L.A., and B.L. Greaves. 2001. Why are most breeders not using economic breeding objectives? *in* IUFRO Symposium Developing the Eucalypt for the Future, Valdivia, Chile.

Armstrong, S., J. Wilton, L. Schaeffer, and W. Pfeiffer. 1990. Feed intake, weaning weight and net returns comparisons for four breeding systems. *J. Anim. Sci.* 68:1848-1856.

Atkinson, S.E., and R. Halvorsen. 1984. A new hedonic technique for estimating attributes demand: an application to the demand for automobile fuel efficiency. Rev. Econ. Stat. 66:417-426.

Aubry, C.A., W.T. Adams, and T.D. Fahey. 1998. Determination of relative economic weights for multitrait selection in coastal Douglas-fir. Can. J. Forest Res. 28:1164-1170.

Baker, M.L., and B.A. Babcock. 2008. Value maximization from corn fractionation: feed, greenhouse gas reductions, and cointegration of ethanol and livestock. P. 13 *in* Transition to a bio-economy: integration of agricultural and energy systems Atlanta, Georgia.

Bannister, H.M. 1962. Some variation in the growth pattern of *Pinus radiata* in New Zealand. New Zeal. J. Forest Sci. 5:342-370.

Barkley, A., and H.H. Peterson. 2008. Wheat variety selection: a application of portfolio theory to improve returns. *in* NCCC-134 Confererce on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, Missouri, United States.

Bascuñán, A., J.R. Moore, and C.J.F. Walker. 2006. Variations in the dynamic modulus of elasticity with proximity to the stand edge in radiata pine stands on the Canterbury Plains, New Zealand. NZ Journal of Forestry 51(3):4-8.

Bastian, C.T., D.M. McLeod, M.J. Germino, W.A. Reiners, and B.J. Blasko. 2002. Environmental amenities and agricultural land values: a hedonic model using geographic information systems data. Ecol. Econ. 40(3):337-349

Beattie, B., and R. Taylor. 1985. The economics of production. John Wiley & Sons. 258 p.

Beauregard, R.L., R. Gazo, and R.D. Ball. 2002. Grade recovery, value, and return-to-log for the production of NZ visual grades (cutting and framing) and Australian machine stress grades. Wood Fiber Sci. 34(3):485-505.

Beckman, J.S., and J.A.M. van Arendonk. 1993. Derivation of economic values for veal, beef and milk production traits using profit equations. Livest. Prod. Sci. 34:35-56.

Berlin, M., G. Jansson, O.J.E. Danell, and B. Andersson. 2009. Economic weight of tree survival relative to volume production in tree breeding: A case study with Pinus sylvestris in northern Sweden. Scand. J. Forest Res. 24(4):288-297.

Bloomberg, M. 2001. Regional variation in radiata pine sawlog prices in New Zealand. M.A.Sc. thesis, Lincoln University, Christchurch. 124 p.

Bloomberg, M., H. Bigsby, and R. Sedcole. 2002. Regional variation in radiata pine sawlog prices in New Zealand. New Zeal. J. Forest Sci. 47(1):25-27.

Borralho, N.M.G., P.P. Cotterill, and P.J. Kanowski. 1993. Breeding objectives for pulp production of *Eucalyptus globulus* under different industrial cost structures. Can. J. Forest Res. 23:648-656.

Bowman, K., and D. Ethridge. 1992. Characteristic supplies and demands in a hedonic framework: U.S. Market for cotton fiber attributes. Am. J. Agr. Econ. 74(4):991-1020.

Box, G.E.P., and D.R. Cox. 1964. An analysis of transformations. J. Roy. Stat. Soc. B Stat. Meth. 26:211-246.

Brascamp, E.W., S. C., and D.R. Guy. 1985. Derivation of economic weights from profit equations. Anim. Prod. 40:175-180.

Brasington, D., and D. Hite. 2005. Demand for environmental quality: a spatial hedonic analysis. . Reg. Sci. Urban. Econ. 35(1):57-82.

Bruce, D., R.O. Curtis, and C. Vancoevering. 1968. Development of a system of taper and volume tables for red alder. Forest Sci. 14(3):339-350.

Burdon, R.D. 1990. Implications of non-linear economic weights for breeding. Theor. Appl. Genet. 79:65-71.

Burdon, R.D. 2001. Genetic aspects of risk-species diversification, genetic management and genetic engineering. NZ Journal of Forestry 45:20-24.

Burdon, R.D., and J. Aimers-Halliday. 2003. Risk management for clonal forestry with Pinus radiata-analysis and review. 1: Strategic issues and risk spread. New Zeal. J Forest Sci. 33(2):156-180.

Burdon, R.D., M.H. Bannister, and C.B. Low. 1992. Genetic survey of *Pinus radiata*. 5: between-trait and age-age correlations for growth rate, morphology, and disease resistance. New Zeal. J. Forest Sci. 22(2/3):211-227.

Butler, R.V. 1982. The specification of hedonic indexes for urban housing. Land Econ. 58(1):96-108.

Byrne, P., and S. Lee. 1997. Real estate portfolio analysis under conditions of non-normality: the case of NCREIF. Journal of Real Estate Portfolio Management 3(1):37-46.

Carew, R. 2000. A hedonic analysis of apple prices and product quality characteristics in British Columbia. Can. J. Agr. Econ. 48(3):2441-2257.

Carson, M.J. 1987. Improving log and wood quality: the role of the radiata pine improvement programme. NZ Journal of Forestry 32:26-30.

Carson, M.J., and C.S. Inglis. 1988. Genotype and location effects on internode length of *Pinus radiata* in New Zealand. New Zeal. J. Forest. Sci. 18 (3):267-279.

Carter, D.R., and F.W. Cubbage. 1994. Technical efficiency and industry evolution in southern U.S. pulpwood harvesting. Can. J. Forest Res. 24:217-224.

Carter, D.R., and F.W. Cubbage. 1995. Stochastic frontier estimation and sources of technical efficiency in southern timber harvesting. Forest Sci. 41(3):576-593.

Chakraborty, K., S. Misra, and P. Johnson. 2002. Cotton farmers' technical efficiency: Stochastic and nonstochastic production function approaches. Agr. Resource Econ. Rev. 31(2):211-220.

Chambers, P., and N. Borralho. 1999. A simple model to examine the impact of changes in wood traits on the costs of thermomechanical pulping and high brightness newsprint production with radiata pine. Can. J. Forest Res. 29:1615-1626.

Chang, S.J. 1998. A generalized Faustmann model for the determination of optimal harvest age. Can. J. Forest Res. 28(5):652–659.

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2(6):429-444.

Chauhan, S.S. 2006a. Wood quality: in context. P. 144-152 in Primary wood processing, principles and practice Walker, J.C.F. (ed.). Springer.

Chauhan, S.S. 2006b. Wood quality: multifaceted opportunities. P. 170-175 in Primary wood processing, principles and practice Walker, J.C.F. (ed.). Springer.

Chauhan, S.S., and J.C.F. Walker. 2006. Variations in acoustic velocity and density with age, and their interrelationships in radiata pine. Forest Ecol. Manag. 229(1-3):388-394.

Chiang, A.C. 1984. Fundamental methods of mathematical economics. 788 p.

Chuang, S.T., and S.Y. Wang. 2001. Evaluation of standing tree quality of Japanese cedar grown with different spacing using stress-wave and ultrasonic-wave methods. J. Wood Sci. 47(4):245-253.

Clapp, J.M. 2004. A Semiparametric Method for Estimating Local House Price Indices. R. Estate Econ. 32(1):127-161.

Clutter, M., B.C. Mendell, and D.H. Newman. 2005. The Changing Landscape of Timberland Ownership in the South. P. 25-27 in Carolina Forestry Magazine.

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

Conington, J., S. Bishop, A. Waterhouse, and G. Simm. 2000. A bio-economic approach to estimating economic values for UK hill sheep. *in* Proc. Br. Soc. Anim. Sci.

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

Cown, D.J. 1973. Resin pockets: their occurrence and formation in New Zealand forests. NZ Journal of Forestry 18:233-251.

Dalton, T.J. 2003. A hedonic model of rice traits:economic values from farmers in West Africa. P. 18 *in* Annual Meeting of Agricultural Economists, Economists, I.A.o.A. (ed.), Durban, South Africa

Daniels, P.W., U.E. Helms, and F.S. Baker. 1979. Principles of Silviculture Mc-Graw-Hill Book Co. USA, 245 pp.

Davis, L.S., and K.N. Johnson. 1987. Forest Management. McGraw-Hill Book Company, New York. 789 p.

Dekkers, J.C.M. 1991. Estimation of economic values for dairy cattle breeding goals: bias due to sub-optimal management policies. Livest. Prod. Sci. 29(2-3):131-149.

Dickson, R.L., and J.C.F. Walker. 1997a. Growing commodities or designer trees. Com. For. Review 76 (4):273-279.

Dickson, R.L., and J.C.F. Walker. 1997b. Selecting wood quality characteristics for pines. P. 45–52 *in* Timber Management Toward Wood Quality and End-Product Value.

Dunham, R.A., and A.D. Cameron. 2000. Crown, stem and wood properties of wind-damaged and undamaged Sitka spruce. Forest Ecol. Manag. 135(1-3):73-81.

Ekeland, I., J.J. Heckman, and L. Nesheim. 2002. Identifying hedonic models. Am. Econ. Rev. 92(2):304-309.

Ernst, S., and T.D. Fahey. 1986. Changes in product recovery of Douglas-fir from old growth to young growth P. 103-107 *in* Proc. of conf. on Douglas-fir: stand management for the future, Oliver, C.P., Hanley, D.P. and Johnson, J.A. (ed.), Seattle, United States.

Espinosa, J.A., and B.K. Goodwin. 1991. Hedonic price estimation for Kansas wheat characteristics. J. Agr. Resource Econ. 16:72-85.

Ethridge, D.E. 1982. Hedonic price estimation for commodities: an application to cotton. J. Agr. Resource Econ. 7(2):293-300.

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

Färe, R., S. Grosskopf, and C.A.K. Lovell. 1985. The measurement of efficiency of production. Kluwer Academic Publishers, Boston.

Farrell, M.J. 1957. The measurement of productive efficiency. J. Roy. Stat. Soc.:253-290.

Fernandez-Castro, A.S., and P.C. Smith. 2002. Lancaster's characteristics approach revisted: product selection using non-parametric methods. . Manag. Decis. Econ. 23:83-91.

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

Freeman, A.M., III. 2003. The measurement of environmental and resource values, Theory and Methods. Resources for the Future, Washington. .

Fried, H.O., C.A. Lovell, and S.S. Schmidt. 2008. The measurement of productive efficiency and productivity growth Oxford University Press US. 638 p.

Galligan, D.T., C. Ramberg, C. Curtis, J. Ferguson, and J. Fetrow. 1991. Application of portfolio theory in decision tree analysis. J. Dairy Sci. 74(7):2138-2144.

Gapare, W.J., M. Ivković, B.S. Baltunis, A.C. Matheson, and H.X. Wu. 2009. Genetic stability of wood density and diameter in Pinus radiata D. Don plantation estate across Australia Tree Genetics & Genomes 6(.):13-125.

Gazo, R., R. Beauregard, M. Kimberly, and D. McConchie. 2000. Incidence of defects by tree characteristics in radiata pine random-width boards. Forest Prod. J. 50(6):83-89.

Gelman, A., and J. Hill. 2007. Data analysis using regression and multilevel/hierarchical models. Cambridge University Press. 625 p.

Gilley, O.W., and R.K. Pace. 1995. Improving hedonic estimation with an inequality restricted estimator. Rev. Econ. Stat.:609-621.

Goddard, M.E. 1998. Consensus and Debate in the Definition of Breeding Objectives. J. Dairy Sci. 81(2):6-18.

Gordon, A.D. 2005. New Zealand Institute of Forestry Hand Book. P. 133-135, Colley, M. (ed.).

Grace, J.C., and M.J. Carson. 1993. Prediction of internode length in *Pinus radiata* stands. New Zeal. J. Forest Sci. 23(1):10-26.

Grant, D.J., A. Anton, and P. Lind. 1984. Bending strength, stiffness, and stress-grade of structural Pinus radiata: effect of knots and timber density. New Zeal. J. Forest Sci. 14(3):331-348.

Greaves, B.L., N.M. Borralho, and C.A. Raymond. 1997a. Assumptions underlying the use of economic weights: are they valid in breeding for eucalipt kraft pulp? . Forest Genet. 4(1):35-42.

Greaves, B.L., N.M.G. Borralho, and C.A. Raymond. 1997b. Breeding objective for plantation eucalypts grown for production of kraft pulp Forest Sci. 43(4):465-475.

Greene, W.H. 2000. Econometrics Analysis. Prentice-Hall.

Griliches, Z. 1961. Hedonic price indexes for automobiles: An econometric analysis of quality change. in The price statistics of federal government, the National Bureau of Economic Research, New York.

Griliches, Z. 1971. Introduction: Hedonic Price Indexes Revisited. Cambridge, MA:Harvard University Press.

Groen, A. 2003. Poultry genetics, breeding and biotechnology. CABI publishing 706 p.

Haab, T., and K. McConnell. 2003. Valuing enviromental and natural resources. The econometrics of non-market valuation Edward Elgar Publishing Limited, Massachusetts, USA.

Hardie, I.W., and P.J. Parks. 1997. Land use with heterogeneous land quality: an application of an area base model. Am. J. Agr. Econ. 79(2):299-310.

Harris, B.L., and A.E. Freeman. 1993. Economic weights for milk yield traits and herd life under various economic conditions and production quotas. J. Dairy Sci. 76:868-879.

Harris, P., and M. Andrews. 1999. Tools and acoustic techniques for measuring wood stiffness: Proceedings of 3rd Wood Quality Symposium, Emerging. in Wood Quality Symposium.

Hassan, R., R. Scholes, and N. Ash. 2005. Ecosystems and human well-being: current state and trends : findings of the Condition and Trends Working Group of the Millennium Ecosystem Assessment. Island Press, Washington

Hazel, L.N. 1943. The genetic basis for constructing selection indexes. Genetics 28:476-490.

Hazel, L.N., and C.E. Terrill. 1946. Effects of some environmental factors on weanling traits of range Columbia, Corriedale and Targhee lambs. J. Anim. Sci. 5(3):318.

Heikkinen, V.P. 2002. Co-integration of Timber and Financial Markets-Implications for Portfolio Selection. Forest Sci. 48(1):118-128.

Helvoigt, T.L., and D.M. Adams. 2009. A stochastic frontier analysis of technical progress, efficiency change and productivity growth in the Pacific Northwest sawmill industry. Forest Pol. Econ. 11(4):280-287.

Henderson, J., and R. Quandt. 1980. Microeconomic theory -a mathematical approach-. Economics Handbook Series. 420 p.

Henningsen, A., and C. Henning. 2009. Imposing regional monotonicity on translog stochastic production frontiers with a simple three-step procedure. J. Prod. Anal. 32(3):217-229.

Hillier, F.S., and G.J. Lieberman. 2001. Introduction to operations research. Published: Boston, McGraw-Hill. . 1214p. p.

Hunter, I.R., and A.R. Gibson. 1984. Predicting Pinus radiata site index from environmental variables. New Zeal. J. Forest Sci. 14(1):53-64.

Ivković, M., H.X. Wu, T.A. McRae, and M.B. Powell. 2006. Developing breeding objectives for radiata pine structural wood production. I. Bioeconomic model and economic weights. Can. J. Forest Res. 36(11):2920-2931.

Jansen, G.B., and J.W. Wilton. 1984. Linear programming in selection of livestock. J. Dairy Sci. 67(4):897-901.

Jayawickrama, K.J.S. 2001a. Breeding radiata pine for wood stiffness: review and analysis. Aust. Forest. 64(1):51-56.

Jayawickrama, K.J.S. 2001b. Genetic parameter estimates for radiata pine in New Zealand and New South Wales: a synthesis of results. Silvae Genet. 50(2):45-53.

Jayawickrama, K.J.S., and M.J. Carson. 2000. A breeding strategy for the New Zealand radiata pine breeding cooperative. Silvae Genet. 49(2):82-89.

Jayawickrama, K.J.S., C.J.A. Shelbourne, and M.J. Carson. 1997. New Zealand's long internode breed of *Pinus radiata*. New Zeal. J. Forest. Sci. 27 (2):126-141.

Johnson, G.R., and R.D. Burdon. 1990. Family-site interaction in *Pinus radiata*: Implications for progeny testing strategy and regionalised breeding in New Zealand. Silvae Genet 39(2):55-62.

Jones, H., P. Amer, R. Lewis, and G. Emmans. 2004. Economic values for changes in carcass lean and fat weights at a fixed age for terminal sire breeds of sheep in the UK. Livest. Prod. Sci. 89 1 -17.

Jones, L.E. 1988. The characteristics model, hedonic prices, and the clientele effect. J. Polit. Econ. 96(3):551-567.

Knowles, R.L., G.G. West, and A.R. Koehler. 1987. Predicting diameter-over-stubs in pruned stands of radiata pine. Rotorua. P. 1-25 in Bulletin 12. Forest Research Institute.

Konno, H. 1990. Piecewise linear risk function and portfolio optimization. J. Oper. Res. Soc. Jpn. 33(2):139-156.

Konno, H., and T. Koshizuka. 2005. Mean-absolute deviation model. IIE Transactions 37(10):893-900.

Konno, H., and H. Yamazaki. 1991. Mean-absolute deviation portfolio optimization model and its applications to Tokyo stock market. Manag. Sci. 37(5):519-531.

Koots, K.R., and J.P. Gibson. 1998. Economic values for beef production traits from a herd level bioeconomic model. Can. J. Anim. Sci. 78(1):29-45.

Korol, R.L., M.U.F. Kirschbaum, G.D. Farquhar, and M. Jeffreys. 1999. Effects of water status and soil fertility on the C-isotope signature in Pinus radiata. Tree Physiology 19(9):551.

Kretschmann, D.E., and R. Hernandez. 2006. Grading of timber. P. 339-346 in Primary wood processing, principles and practice Walker, J.C.F. (ed.). Springer.

Krupova, Z., M. Oravcova, E. Krupa, and D. Peskovicova. 2008. Methods for calculating economic weights of inportant traits in sheep. Slovak J. Anim. Sci. 1:24-29.

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

Kumar, S., K.J.S. Jayawickrama, J. Lee, and M. Lausberg. 2002. Direct and indirect measures of stiffness and strength show high heredability in a wind-pollinated radiata pine progeny test in New Zealand. Silvae Genet. 51:256-261.

Ladd, G.W., and C. Gibson. 1978. Microeconomics of technical change: what's a better animal worth. Am. J. Agr. Econ. 61:236-240.

Ladd, G.W., and M.B. Martin. 1976. Prices and demands for input characteristics. Am. J. Agr. Econ. 58:21-30.

Ladd, G.W., and V. Suvannunt. 1976. A model of consumer goods characteristics. Am. J. Agr. Econ. 58:504-510.

Lambert, D.K. 2009. The expected utility of genetic information in beef cattle production. Agr. Syst. 99:44-52.

Lambert, D.K., and W.W. Wilson. 2003. Valuing varieties with imperfect output quality measurement. Am. J. Agr. Econ. 85(1):95-107.

Lancaster, K.J. 1966. A new approach to consumer theory. J. Polit. Econ. 74:132-157.

Lancaster, K.J. 1971. Consumer Demand: A New Approach. Columbia University Press, New York.

Lancaster, K.J. 1991. Modern Consumer Theory. Edward Elgar Publishing Limited, USA. 242 p.

Lasserre, J.P., E.G. Mason, and M.S. Watt. 2004. The influence of initial stocking on corewood stiffness in a clonal experiment of 11 year-old *Pinus radiata* D. Don. NZ Journal of Forestry 49 (2):18-23.

Lasserre, J.P., E.G. Mason, and M.S. Watt. 2005. Effects of genotype and spacing on *Pinus radiata* corewood stiffness in an 11 year-old experiments. Forest Ecol. Manag. 205:375-383.

Lasserre, J.P., E.G. Mason, and M.S. Watt. 2007. Assessing corewood acoustic velocity and modulus of elasticity with two impact based instruments in 11-year-old trees from a clonal-spacing experiment of *Pinus radiata* D.Don. Forest Ecol. Manag. 239:217-221.

Lindstrom, H., R. Evans, and M. Reale. 2005. Implications of selecting tree clones with high modulus of elasticity. New Zeal. J. Forest. Sci. 35(1):50.

Lindström, H., P. Harris, and R. Nakada. 2002. Methods for measuring stiffness of young trees. Holz Roh. Werkst. 60:165-174.

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

Lucas, R. 1975. Hedonic price functions. Econ. Inq. 13:157-178.

Maclaren, P. 1993. Radiata Pine Growers' Manual. P. 140

MAF. 2009a. Indicative New Zealand Radiata Pine Log Prices. The Ministry of Agriculture and Forestry Wellington, New Zealand.

MAF. 2009b. A forestry sector study. The Ministry of Agriculture and Forestry Wellington, New Zealand.

Manley, B. 2005. New Zealand Institute of Forestry Hand Book. P. 268-269 Colley, M. (ed.).

Markowitz, H. 1952. Portfolio selection. J. Finance 7(1):77-91.

Matheson, A.C., R.L. Dickson, D.J. Spencer, B. Joe, and J. Illic. 2002. Acoustic segregation of *Pinus radiata* logs according to stiffness. Ann. Forest Sci. 59:471-477.

Matheson, A.C., W.J. Gapare, J. Ilic, and H.X. Wu. 2008. Inheritance and Genetic Gain in Wood Stiffness in Radiata Pine Assessed Acoustically in Young Standing Trees. Silvae Genet. 57(2):56-64.

Matheson, A.C., and H.X. Wu. 2005. Genotype by environment interactions in an Australia-wide radiata pine diallel mating experiment: implications for regionalized breeding. Forest Sci. 51(1):29-40.

McConchie, D., and D. Cown. 2008. Field guide: resin and other features in logs and lumber. WQI Limited. 25 p.

McConchie, D.L. 2002. Field guide to assist recognition and classification of resinous defects on the bark of radiata pine. Wood Qualiy Inititive 35.

McConchie, D.L., and J. Turner. 2002. How external resin on radiata pine logs relates to clearwood quality and value. Wood Quality Iinitiative 5p.

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

Melton, B.E., W.A. Colette, and R.L. Willham. 1994. Imputing input characteristic values from optimal commercial breed or variety choice decisions. Am. J. Agr. Econ. 76(3):478-491.

Meneses, M.O., and S. Guzmán. 2003. Clasificación de rollizos y rodales. Informe N° 5 Proposición de un sistema de clasificación de trozas podadas y no podadas. Universidad Austral de Chile. 164-178.

Mills Jr, W.L., and W.L. Hoover. 1982. Investment in forest land: Aspects of risk and diversification. Land Econ. 58(1):33-51.

Mitchell, H.L. 1961. A concept of intrinsic wood quality, and nondestructive methods for determining quality in standing timber. Forest products laboratory

Moore, J., and C.P. Quine. 2000. A comparison of the relative risk of wind damage to planted forests in Border Forest Park, Great Britain, and the Central North Island, New Zealand. Forest Ecology and Management 135(1-3):345-353.

Munn, I.A., and R.B. Palmquist. 1997. Estimating hedonic price equations for a timber stumpage market using stochastic frontier estimation procedures. Can. J. Forest Res. 27:1276-1280.

Munn, I.A., and R.R. Rucker. 1994. The Value of Information Services in a Market for Factors of Production with Multiple Attributes: The Role of Consultants in Private Timber Sales. Forest Sci. 40:474-496.

Nalley, L., A. Barkley, W. Brad, and J. Hignight. 2009. Enhancing Farm Profitability through Portfolio Analysis: The Case of Spatial Rice Variety Selection. Southern Agricultural Economics Association.

Nambiar, E.K.S. 1995. Relationships between water, nutrients and productivity in Australian forests: Application to wood production and quality. Plant and Soil 168(1):427-435.

Nash, D.L., and G.W. Rogers. 1996. Risk management in herd sire portfolio selection: a comparision of rounded quadratic and separable convex programming. J. Dairy Sci. 79(2).

Nerlove, M. 1995. Hedonic price functions and the measurement of preferences: The case of Swedish wine consumers. Eur. Econ. Rev. 39:1697-1716.

Niquidet, K., and H. Nelson. 2010. Sawmill production in the interior of British Columbia: A stochastic ray frontier approach. J. Forest Econ. 16:257-267.

Núñez, D., L. Nahuelhual, and C. Oyarzún. 2006. Forests and water: The value of native temperate forests in supplying water for human consumption. Ecological Economics 58(3):606-616.

Palmquist, R.B. 1984. Estimating the demand for the characteristics of housing. Rev. Econ. Stat. 66:394-404.

Palmquist, R.B. 1989. Land as a differentiated factor of production: a hedonic model and its implications for welfare measurement. . Land Econ. 65(1):23-28.

Palmquist, R.B., and K. Smith. 2001. The Use of Hedonic Property Value Techniques for Policy and Litigation. in International Yearbook of Environmental and Resource Economics. Volume VI.

Park, J.C. 1989. Pruned log index. New Zeal. J. Forest. Sci. 19(1):41-53.

Parker, D.D., and D. Zilberman. 1993. Hedonic estimation of quality factors affecting the farm-retail margin. Am. J. Agr. Econ. 75(2):458-466.

Ponzoni, R. 1986. A profit function for the definition of the breeding objective of Australian merino sheep. Journal of animal breeding and genetics 103:342-357.

Ponzoni, R.W., and S. Newman. 1989. Developing breeding objectives for Australian beef cattle production. Anim. Product. 49:35-47.

Pruyn, M.L., B.J. Ewers Iii, and F.W. Telewski. 2000. Thigmomorphogenesis: changes in the morphology and mechanical properties of two Populus hybrids in response to mechanical perturbation. Tree Physiology 20(8):535.

Puttock, G.D., D.M. Prescott, and K.D. Meilke. 1990. Stumpage prices in southwestern Ontario: a hedonic function approach. Forest Sci. 36(4):119-1132.

Quinn, G.P., and M.J. Keough. 2002. Experimental design and data analysis for biologists. Cambridge Univ Pr.

Rawlings, J.O., S.G. Pantula, and D.A. Dickey. 1998. Applied regression analysis: a research tool. Springer New York.

Raymond, C.A., and L.R. Schimleck. 2002. Development of near infrared reflectance analysis calibrations for estimating genetic parameters for cellulose content in Eucalyptus globulus. Can. J. For. Res. 32:170–176.

Ready, R., and C. Abdalla. 2005. The Amenity and Disamenity Impacts of Agriculture: Estimates from a Hedonic Pricing Model. Am. J Agr Econ. 87:314-320.

Ridoutt, B.G., D.L. McConchie, and R.D. Ball. 1999. Predicting resin pockets in radiata pine logs from blemishes on log ends. Wood Fiber Sci. 31(4):434-440.

Roos, A. 1995. The price for forest land on combined forest estates. Scand. J. Forest Res. 10(204-208.).

Roos, A. 1996. A hedonic price function for forest land in Sweden. Can. J. Forest Res. 26:740-746.

Rosen, S. 1974. Hedonic prices and implicit markets: product differentiation in pure competition. J. Polit. Econ. 82(1):34-55.

Ruszczy ski, A., and R.J. Vanderbei. 2003. Frontiers of stochastically nondominated portfolios. Econometrica 71(4):1287-1297.

Sakia, R.M. 1992. The Box-Cox transformation technique: a review Journal of the Royal Statistical Society - Series D: The Statistician 4(2):169-178.

Samuelson, P.A. 1948. Consumption Theory in Terms of Revealed Preference Economica 15(60):243-253.

Samuelson, P.A. 1953. Prices of Factors and Goods in General Equilibrium. Rev. Econ. Studies 21 (1):1-20

Schimleck, L.R., R. Evans, J. Ilic, and A.C. Matheson. 2002. Estimation of wood stiffness of increment cores by near-infrared spectroscopy. Can. J. Forest Res. 32(1):129-135.

Shapcott, J. 1992. Index tracking: genetic algorithms for investment portfolio selection. Edinburgh Parallel Computing Centre.

Sharpe, W.F. 1971. A linear programming approximation for the general portfolio analysis problem. J. Financ. Quant. Anal. 6(5):1263-1275.

Shelboume, C.J.A., L.A. Apiolaza, K.J.S. Jayawickrama, and C.T. Sorensson. 1997. Developing breeding objectives for radiata pine in New Zealand. IUFRO Conference. P. 160-168 *in* Developing breeding objectives for Radiata Pine in New Zealand, Burdon, R.D.a.M., J.M. (ed.), Rotorua.

Shelbourne, C.J.A. 1997. Genetic of adding value to the end products of radiata pine P. 129-141 *in* Developing breeding objectives for radiata pine in New Zealand. IUFRO Conference, Burdon, R.D.a.M., J.M. (ed.), Rotorua.

Shelbourne, C.J.A., M.J. Carson, and M.D. Wilcox. 1989. New techniques in the genetic improvement of radiata pine. Commonw For Rev 68(3):191-201.

Shirley, J.W. 1974. Pruning radiata pine in New Zealand to produce clearwood. M.Sc. thesis, University of Canterbury, Christchurch, New Zealand. 154 p.

Siry, J.P., and D.H. Newman. 2001. A stochastic production frontier analysis of polish state forests. Forest Sci. 47(4):526-533.

Sivarajasingam, S., E.B. Burnside, J.W. Wilton, W.C. Pfeiffer, and D.G. Grieve. 1984. Ranking dairy sires by a linear programming dairy farm model. J. Dairy Sci. 67:3015–3024.

Smith, S.P., and K. Hammond. 1987. Portfolio theory, utility theory and mate selection. Genet. Sel. Evol. 19(3):321-336.

Smith, V.K., R.B. Palmquist, and P. Jakus. 1991. Combining Farrell frontier and hedonic travel cost models for valuing estuarine quality. Rev. Econ. Stat. 73(4):694-699.

Snyder, S.A., M.A. Kilgore, R. Hudson, and J. Donnay. 2007. Determinants of forest land prices in Northern Minnesota: A hedonic pricing approach. Forest Sci. 53 (1):25-36.

Somerville, A. 1997. Resin Pockets: Their description, methods of assessment and measures of incidence. P. 38-44 *in* FFPM Cooperative proceedings

Sorensson, C. 2002. Reflections on radiata pine genetic improvement by a clonal forester. NZ Journal of Forestry 47:29-31.

Spence, A.M. 1973. Job Market Signaling. Q. J. Econ. 87(3):355–374.

Stewart, T.S., D.L. Bache, D. Harris, M.E. Einstein, D.L. Lofgren, and A.P. Schinckel. 1990. A Bioeconomic profit function for swine production: application to developing optimal multitrait selection indexes. J. Anim. Breed. Genet. 107:340-350.

Stiglitz, J.E. 1975. The Theory of Screening, Education and the Distribution of Income. Am. Econ. Rev. 65(3):283-300.

Stone, B.K. 2009. A linear programming formulation of the general portfolio selection problem. J. Financ. Quant. Anal. 8(04):621-636.

Talbert, C.B. 1984. An analysis of several approaches to multiple-trait index selection in loblolly pine (*Pinus Taeda* L.*)*. Ph.D. thesis, North Carolina State University, Raleigh, United States.

Telewski, F.W., and M.J. Jaffe. 1986. Thigmomorphogenesis: field and laboratory studies of Abies fraseri in response to wind or mechanical perturbation. Physiol. Plantarum 66(2):211-218.

Todoroki, C.L., and S.D. Carson. 2003. Managing the future forest resource through designer trees. Int. Trans. Oper. Res. 10:449-460.

Tombleson, J.D., J.C. Grace, and C.S. Inglis. 1990. Response of radiata pine branch characteristics to site and stocking. P. 229-231 *in* IUFRO Symposium: New approaches to spacing and thinning in plantation forestry, James, R.N., Tarlton, G.L. (ed.). FRI Bulletin No.151.

Treolar, C. 2005. Log grade revision: structural log grades NZ Journal of Forestry 49(4):33.

Tsehaye, A. 1985. Within- and between-tree variations in the wood quality of radiata pine, University of Canterbury Christchurch, New Zealand.

Tsehaye, A., A.H. Buchanan, and J.C.F. Walker. 2000a. Selecting trees for structural timber. Holz Roh. Werkst. 58(3):162-167.

Tsehaye, A., A.H. Buchanan, and J.C.F. Walker. 2000b. Sorting of logs using acoustics. Wood Sci. Tech. 34(4):1432-5225.

Tsuchikawa, S. 2007. A review of recent near infrared research for wood and paper. Appl. Spectros. Rev. 42(1):43-71.

Turner, J., M.J. Lambert, P. Hopmans, and J. McGrath. 2001. Site variation in Pinus radiata plantations and implications for site specific management. New Forests 21(3):249-282.

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

Varian, H.R. 1992. Microeconomic Analysis. W. W. Norton & Company. 563 p.

W.W.P.A. 1989. Western wood species book Vol.3: Factory lumber. Western Wood Products Association, Oregon. 48 p.

Waghorn, M.J., E.G. Mason, and M.S. Watt. 2007a. Influence of initial stand density and genotype on longitudinal variation in modulus of elasticity for 17-year-old Pinus radiata. Forest Ecol. Manag. 252(1-3):67-72.

Waghorn, M.J., M.S. Watt, and E.G. Mason. 2007b. Influence of tree morphology, genetics, and initial stand density on outerwood modulus of elasticity of 17-year-old Pinus radiata. Forest Ecol. Manag. 244(1-3):86-92.

Walburger, A.M. 2002. Estimating the implicit prices of beef cattle attributes: a case from Alberta. Can. J. Agr. Econ. 50:135-149.

Walford, G.B. 1985. The mechanical properties of New Zealand-grown radiata pine for export to Australia. FRI Bulletin 93.

Walker, J.C.F., and R. Nakada. 1999. Understanding corewood in some softwoods: a selective review on stiffness and acoustics. Int. Forest Rev. 1(4):251-259.

Watt, M.S., G.M. Downes, T. Jones, M. Ottenschlaeger, A.C. Leckie, S.J. Smaill, M.O. Kimberley, and R. Brownlie. 2009. Effect of stem guying on the incidence of resin pockets. Forest Ecol. Manag. 258(9):1913-1917.

Watt, M.S., G.M. Downes, D. Whitehead, E.G. Mason, B. Richardson, J.C. Grace, and J.R. Moore. 2005. Wood properties of juvenile Pinus radiata growing in the presence and absence of competing understorey vegetation at a dryland site. Trees Struct. Funct. 19(5):580-586.

Watt, M.S., J.A. Turner, and E.G. Mason. 2000. Genetic influence on second-log branching in *Pinus radiata*. New Zeal. J. Forest. Sci. 30 (3):315-331.

Waugh, F.V. 1929. Quality as a determinant of vegetable prices. Columbia Univ.

Weaver, R.D. 1983. Multiple input, multiple output production choices and technology in the U.S wheat region Am. J. Agr. Econ. 65:45-56.

Weller, J. 1994. Economics aspects of animal breeding. TJ Press Ltd, Padstow, Cornwall. 244 p.

Woollons, R., B. Manley, and J. Park. 2008. Factors influencing the formation of resin pockets in pruned radiata pine butt logs in New Zealand. New Zeal J. Forest. Sci. 38(2/3):323-333.

Woollons, R.C., A. Haywood, and D.C. McNickle. 2002. Modeling internode length and branch characteristics for *Pinus radiata* in New Zealand. Forest Ecol. Manag. 160:243-261.

WWPA. 1995. Western wood species book Vol.3: Factory lumber. Western Wood Products Association, Oregon. 48 p.

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

Xu, P., and J.C.F. Walker. 2004. Stiffness gradients in radiata pine trees. Wood Sci. Tech. 38(1):1-9.

Xue, M., and P.T. Harker. 1999. Overcoming the inherent dependency of DEA efficiency scores: a bootstrap approach. Unpublished Working Paper, Wharton Financial Institutions Center, University of Pennsylvania.

Yin, R.S. 2000. Alternative measurements of productive efficiency in the global bleached softwood pulp sector. Forest Sci. 46(4):558-569.

Young, G., T. Ltd, and L. Grading. 2004. Profitable wood processing-sawn timber needs. NZ Journal of Forestry 49:18-20.

Zhang, S.Y. 1997. Wood quality, its definition, impact and implications for value-added timber management and end uses. P. 17-39 *in* International Wood Quality Workshop: timber management toward wood quality and end-product value Gosselin, T., R., and G. Chauret (eds.), Canada, Quebec.

Zhang, S.Y., G. Chauret, H.Q. Ren, and R. Desjardins. 2002. Impact of initial spacing on plantation black spruce lumber grade yield, bending properties, and MSR yield. Wood Fiber Sci. 34(3):460-475.

Zinkhan, F.C. 1988. Forestry projects, modern portfolio theory, and discount rate selection. South. J. Appl. Forest. 12(2):132-135.

Zobel, B.J., and J.P. Van Buijtenen. 1989. Wood variation: its causes and control. Springer, Berlin (Germany, F.R.). 363 p.