

**Using Advanced Analysis Techniques to Benchmark  
Forest Harvesting Systems: A Study of the New Zealand  
Forest Industry**

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A thesis submitted in partial fulfilment of the  
requirements for the Degree of  
Doctor of Philosophy in Forest Engineering  
by  
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University of Canterbury

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*To My Lovely and Blessed Family*



## **Abstract**

The concept of benchmarking is applied to businesses and industries for the continuous measurement and improvement of production systems and organizational performance. This makes it important to continuously measure and improve the operational performance in order for any industry to maintain its local and global competitiveness in the ever-changing global business environment. Data analysis techniques has continued to develop allowing a greater level of in-depth analysis of operational data, an example being data envelopment analysis (DEA), a frontier analysis method established in non-parametric framework.

New Zealand has a large forest industry with about 1.7 million net stocked plantation forest area, 30.7 million m<sup>3</sup> of harvested timber and \$5.47 billion in value of export forest products. The New Zealand forest harvesting sector has an existing benchmarking system containing cost and productivity data with over 1000 unique entries on contracted forest harvesting operations in New Zealand from 2009-2015. This thesis shows that advanced operations techniques can be used to analyse the forest harvesting sector by measuring the relative harvesting efficiency of independent logging contractors; identifying external factors that influence the technical efficiency of forest harvesting operations; and including the operating environment factors in the evaluation process of harvesting operations performance. DEA, a non-parametric frontier benchmarking technique is applied in the analyses.

Using DEA on the existing benchmarking database, the relative operational efficiency of independent logging contractors was estimated. Five inputs, which accounted for about 77% variation in the harvesting productivity (output), were used to develop the DEA production models. Output-orientation under the assumption of constant and variable returns to scale were used to estimate the relative aggregate, pure technical and scale efficiencies, and the measure of excessive use of inputs by the contractors. Optimal input usage and output targets were estimated under variable returns to scale for the inefficient contractors to move to the efficient frontier. The results indicate that the majority of logging contractors operated at or near scale efficient level while the main source of inefficiency in the industry is both technical and managerial. Analysis shows that if all inefficient contractors operate at the optimal input and output levels, and were provided with stand and terrain conditions that best suited their operations, on average, system productivity could increase by 45% from 28.7 to 52.2

tons/SMH. The DEA suggests that investment in technology and human capital could improve the overall efficiency of the logging industry.

Although inputs usage are key to the productivity of harvesting operations, factors external to the managerial control of contractors could influence their performance. A two-stage approach that incorporates DEA and regression analysis was used to determine the influence of external factors on the technical efficiency of harvesting operations based on the New Zealand benchmarking dataset. The external factors considered include the size of operation, forest terrain, log sorts, piece size and the forest region. The results indicate that the size of operation, forest terrain, log sorts and piece size, all significantly ( $p < 0.01$ ) influence the technical efficiency of forest harvesting operations. The effect of forest region on the technical efficiency however, was not significant ( $p > 0.01$ ). The result shows that the ability of a harvesting crew to utilize its inputs to achieve desired output level is not only influenced by discretionary factors but also by the operating environment.

Using a forest company-specific database, a multi-step DEA procedure is applied to 67 forest harvesting contractors to estimate their managerial efficiency while taking into account the influence of the operating environment. The performance of the contractors is evaluated using seven inputs, one output and three operating environment factors. The result shows a significant difference between the mean managerial efficiency of the crews before and after controlling for the influence of the operating environment, the latter being higher by 12%. This study provides evidence that without accounting for the influence of the operating environment, the resulting DEA efficiency estimates will be biased; overestimating the performance of crews in favourable environment and underestimating that of those in more difficult environment.

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## Achievements and Experiences

### ***Journal Publications***

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### ***Conferences and Workshops attended, and Presentations***

**Obi, O.F.** and Visser, R. (2018). Using data envelopment analysis to measure logging contractor performance. A paper presented at the 6<sup>th</sup> International Forest Engineering Conference (FEC), Holiday Inn, Rotorua, New Zealand, 16 - 19 April 2018.

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**Obi, O. F.** (2016). Benchmarking the Logging Sub-Sector of New Zealand Forest Industry. A report presented at the School of Forestry, University of Canterbury, Christchurch, New Zealand.

HarvestTECH2017. Improving safety and productivity in harvesting. Steep slope logging – mechanisation and automation – harvest planning, 20 – 21 June 2017, Rotorua, New Zealand.

Professional Development Courses in Forest Engineering, a four consecutive one-day courses, School of Forestry, University of Canterbury, Christchurch New Zealand, 28 – 31<sup>st</sup> August 2017.

Rayonier Matariki Supply Chain Contractors Conference 2017. Building Success Together Towards New Dimensions of Performance, 19 June 2017, Millennium Hotel, Rotorua, New Zealand.

Forest Industry Workshops on Winch-Assist and Cable Harvesting Systems across New Zealand, 2017.

### ***Published Reports***

**Obi, O.F.** and Visser, R. (2017). Harvesting Performance of Ground-Based and Cable-Based Operations by Rayonier Harvesting Contractors. A report prepared for Brendan Slui, Operations Director, Rayonier Matariki Forests.

**Obi, O.F.** and Visser, R. (2017). A Guide to Benchmarking the Performance of Harvesting Contractors Using Data Envelopment Analysis. A report prepared for Rayonier Matariki Forests.

**Obi, O.F.** and Visser, R. (2017). Using the Rayonier Harvesting Benchmarking Database (HARB) to Benchmark Harvesting Contractors using DEA: A First Attempt. A report prepared for Brendan Slui, Operations Director, Rayonier Matariki Forests.

Visser, R. (2018). Next Generation Timber Harvesting Systems: Opportunities for Remote Controlled and Autonomous Machinery. A report prepared for Forest and Wood Products Australia. Project number: PRC437-1718. (I contributed to the report and is duly acknowledged). <[http://www.fwpa.com.au/images/Next\\_Generation\\_Timber\\_Harvesting\\_-\\_PRC437-1718.pdf](http://www.fwpa.com.au/images/Next_Generation_Timber_Harvesting_-_PRC437-1718.pdf)>

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- College of Engineering PhD Scholarship, University of Canterbury 2016–2018
- Owen Browning Scholarships in Forestry, University of Canterbury 2016–2017
- 2<sup>nd</sup> Best Poster Presentation Award, New Zealand Institute of Forestry 2017



## **Structure of the Thesis**

The studies within this thesis are presented as a set of discrete chapters (2, 3 and 4), each addressing one of the research questions in the thesis with the aim of contributing to the literature in the field of benchmarking studies. Each of the chapters consists of an introductory section with a review of relevant literature, detailed methodology, results and discussion section, and conclusions. Chapter 1 provides the introduction and background to the research questions addressed in the thesis, and an overview of the operations technique applied in the thesis. Chapter 2 illustrates the application of DEA to the forest harvesting sector in estimating the relative performance of independent harvesting contractors by utilizing data on their inputs usage and outputs. Chapter 3 examines the potential influence of differences in the working environment of harvesting crews on their estimated technical efficiency, hence on the overall performance of harvesting crews. Chapter 4 applies DEA in a multi-step procedure to account for the operating environment factors outside the management control of the crews capable of influencing their estimated harvesting performance. Chapter 5 presents a summary of the thesis as well as the main conclusions and opportunities for future research.

# **Chapter 1**

## **Introduction**

### **1.1 Forest Harvesting Sector**

Forests are a key component of the ecosystem providing diverse products and production materials for energy, economic, social, and environmental development (Chen *et al.*, 2015). Within the forest products value chain, forest harvesting (or “logging”) is typically the first step at the head of the product line being pivotal in the supply of timber for onward conversion into consumable wood products (Doolittle, 1990). That is, they supply the logs required for the functioning of all other sub-sectors of the industry. An increase or decrease in logging cost will lead to an increase or decrease in the price of wood logs, affecting all other wood-based industries in the value chain. This reflects the critical role of logging contractors in the forestry sector thus deserving much attention (McConnell, 2013; Kant and Nautiyal, 1997). Drolet and LeBel (2010) in their study observe that the activities of forest harvesting operators account for about 47% of the total cost of wood logs before further processing. Hence, the operational performance of forest harvesting contractors is critical to the sustainability of other sub-sectors of the forest industry (Drolet and LeBel, 2010; D’Amours *et al.*, 2004). All strategic policy and management measures for competitiveness must begin at the forest harvesting stage for the forest sector to be able to respond and adapt to environmental, economic, political, technological, and social challenges (Nanang and Ghebremichael, 2006).

The New Zealand forestry sector, for example, is one of its most important sectors in the socio-economic and environmental landscape and is the country’s third highest export earner. Measuring the performance and relative efficiency of New Zealand logging contractors is therefore important in encouraging and maintaining local and global competitiveness. To achieve and maintain competitiveness, many industries have applied the concept of benchmarking for continuous measurement and improvement of organizational performance.

## **1.2 The Benchmarking Concept**

Business owners, managers, entrepreneurs and decision makers are constantly looking for techniques to measure and improve their organization's performance. Benchmarking is one of such techniques that is widely accepted as an effective tool for process improvement, quality assurance, performance evaluation and enhancement, and to measure competitiveness (Lai *et al.*, 2011; Dattakumar and Jagadeesh, 2003). Benchmarking is simply the search for the best practices that will lead to superior performance in an industry, organization or business unit; or striving to be the best among the best (Lai *et al.*, 2011; Prašnikar *et al.*, 2005; Camp, 1989). Lema and Price (1995) defined benchmarking as a positive, structured, continuous, and proactive process that ensures that business units follow the best practices in an ever-changing business environment to achieve superior performance. It involves measuring trends, comparing any part of an organization's operation, product, or service against the best that leads to improved performance. In addition, it helps business units to adopt proven successful practices from elsewhere instead of depending on evolving from within. The essence of benchmarking is to identify the optimum mix of inputs to attain the highest standards of excellence for products, services, or processes. Benchmarking is widely accepted as a performance and productivity improvement tool that can be used to make significant improvements to industry performance (Moriarty and Smallman, 2009; Barber, 2004; Kyrö, 2003; Jackson *et al.*, 1994).

The implementation of benchmarking could take different forms or types including (Lema and Price, 1995):

- i. internal benchmarking - performed within one organization by comparing the performance of similar business units or business processes;
- ii. competitive benchmarking - a measure of an organization's performance compared with competing organizations targeting product designs, processes, or administrative methods;
- iii. functional benchmarking - application of process benchmarking that compares a particular business function in two or more organizations); and
- iv. generic benchmarking - application of functional benchmarking that compares a particular business function in two or more organizations irrespective of industry.

The underlying characteristics of the benchmarking types include gathering business information, examination of internal, external and global business practices, creating new business knowledge by analysing and comparing specific business information, and making better business decisions for efficient and improved performance (Metri, 2005; Prašnikar *et al.*, 2005). In assessing the performance of an industry, the application of functional benchmarking will present performance information of business units within the industry, identifying best performers from which the poor performing units may learn from. This is an accepted means of identifying performance shortfalls by comparing performance of all units to that of the best performing ones (Omid *et al.*, 2011). In view of the complexity of benchmarking, it is often implemented using qualitative and quantitative methods as there is no one method guiding its advancement and implementation (Lai *et al.*, 2011; Peng Wong and Yew Wong, 2008; Bhutta and Huq, 1999).

### **1.3 Benchmarking Techniques**

The performance of production units is measured to obtain estimates of operational inefficiency and to explain variation in inefficiency across units and through time. That is, to describe how well business units are performing in utilizing inputs to generate outputs. Data for such measurements may be obtained through the observation of a number of units in a specific time period (cross-sectional data), observation of one unit over a number of time periods (time series), or observation of a number of units over a number of time periods (panel data) (Salehirad and Sowlati, 2006; Coelli *et al.*, 2005). The efficiency or inefficiency of production units is increasingly being measured by means of frontier production function estimation. Frontier production function provides estimates of production or cost efficiency frontiers of entities with similar production technologies based on their individual use of production factors. The efficient production frontier for a group of homogenous production entities in the input-output space is defined as the maximal attainable level of outputs corresponding to given levels of inputs, or in terms of cost of inputs, cost frontier is defined in the output-cost space as the minimal cost of producing various levels of output (Simar and Wilson, 2015). The technical efficiency of a unit is estimated by an appropriate measure of its position in the input–output or cost-output space relative to the efficient frontier. The estimations are based on observed input-output production data of units under observation.

Frontier estimation technique may be divided into two groups: parametric (e.g. regression based methods, stochastic frontier analysis, etc.) and non-parametric (e.g. data envelopment analysis, free disposal hull, etc.). Both parametric and nonparametric methods offer different tradeoffs depending on the purpose of the benchmark study. In non-parametric methods, there are no restrictive assumptions or specifications about the production technology or function. However, all variation in estimated efficiency resulting from input-output relationship among production units is interpreted as inefficiency (Hjalmarsson *et al.*, 1996). Parametric model however is able to distinguish inefficiency from statistical noise. In addition, parametric frontier method offers the possibility of functional specification allowing for statistical significance testing of hypotheses and estimation of confidence interval. However, in most production technologies, this is difficult to establish.

Among several frontier estimation methods, the nonparametric data envelopment analysis model (DEA) and the parametric stochastic frontier approach (SFA) have both become increasingly popular in the analysis of productive efficiency of business entities in different countries across several sectors of the economy. The empirical approach to measuring efficiency based on production function preferred by most economists is the parametric SFA (Sowlati, 2005; Shiba, 1997). SFA being a parametric model requires the specification of a mathematical production function. Such a function requires price or cost data relating inputs and outputs, which in many situations are difficult to obtain for applied analysis, or the function is difficult to estimate (Salehirad and Sowlati, 2007; Sowlati, 2005). Although SFA approach provides a robust framework for performing hypothesis testing following known functional forms, in many cases, there is no known functional form for the production function (Gadanakis *et al.*, 2015; Shiba, 1997). Performance measurements with the parametric approach are quite demanding in terms of accessing production cost and price data, which often decrease the practicality of this approach, especially when evaluating multiple inputs and outputs. The non-parametric DEA exhibits its methodological strength in the weaknesses of the parametric SFA method – no restrictive assumption about the production function neither is it dependent on cost data. This provides an incentive to lean towards the nonparametric DEA method for advanced benchmarking purpose due to the restrictive nature of SFA. As Hjalmarsson *et al.* (1996) rightly noted, the choice between different approaches – parametric and non-parametric - must be based on tradeoffs

concerning the purpose of analysis, type and available input-output data, and production characteristics of the entities under evaluation.

#### **1.4 Data Envelopment Analysis**

The core method in non-parametric frontier approach is Data Envelopment Analysis (DEA) (Diaz-Balteiro *et al.*, 2006). Data envelopment analysis (DEA) is a linear programming, non-parametric frontier analysis technique that measures the relative efficiency of comparable organizational units in a production system, usually referred to as decision-making units (DMUs), with homogeneous sets of inputs and outputs (Carrillo and Jorge, 2016; Limaei, 2013; Cooper *et al.*, 2007). It is a decisional tool widely applied in public and private sectors for performance evaluation purposes; and has become an established frontier approach in estimating performance of business units in different industries (Ye *et al.*, 2016; Blomberg *et al.*, 2012; Lai *et al.*, 2011; Cook and Seiford, 2009; Sueyoshi and Aoki, 2001; Lewin *et al.*, 1982). DMUs represent any production or non-production unit that essentially perform the same tasks by transforming certain inputs into outputs (Šporčić and Landekić, 2014). DEA is capable of incorporating and simultaneously analysing multiple inputs and outputs to estimate relative efficiency with no requirement for *a priori* knowledge of the explicit links or functional form relating the inputs and outputs; in addition, the unit of the inputs and outputs need not be congruent (El-Mashaleh *et al.*, 2010). Thus, DEA is a suitable technique where other approaches do not provide satisfactory results due to complex multiple inputs and outputs relationships (Šporčić and Landekić, 2014). Efficiency in the context of DEA represents a measure of how economically a DMU's resources are utilized when providing a given level of customer satisfaction or output (Mohammadi *et al.*, 2011). The DEA method was introduced by Charnes, Cooper, and Rhodes (Charnes *et al.*, 1978) based on the earlier work of Farrell (Farrell, 1957), the foundation for non-parametric performance measurements. DEA is comprised of two main mathematical models: Charnes–Cooper–Rhodes (CCR) and Banker–Charnes–Cooper (BCC) models.

##### **1.4.1 CCR model**

In the DEA model introduced by Charnes *et al.* (1978) (otherwise known as the Charnes–Cooper–Rhodes (CCR) model), the authors proposed that the efficiency of a DMU can be obtained as the maximum of a ratio of weighted outputs to weighted inputs. This is subject

to the condition that the same ratio for all DMUs must be less than or equal to one. It incorporates multiple inputs and outputs in a single efficiency measure, and assigns a relative efficiency score to each DMU. Each DMU is either found to perform efficiently or below the efficient frontier, in which case DEA can find a corresponding set of efficient units to be used as benchmarks in improving the less efficient DMUs (Carrillo and Jorge, 2016). The efficient units receive an efficiency score of 1, meaning that they best use their inputs to obtain outputs. Less efficient units receive a score between 0 and 1 reflecting their level of inefficiency in relationship to the efficient DMUs (efficient target) with similar input–output structure; the inefficiency score is the distance between the inefficient DMU and the efficient frontier (Marinescu *et al.*, 2005; Farrell, 1957). The efficient target units or benchmarks otherwise called reference set are either one of the actual DMUs on the frontier or a linear combination of them. The CCR model is based on a constant returns to scale (CRS) frontier implying that a proportional increase in inputs of a DMU would result in a proportionate increase in outputs (Hof *et al.*, 2004; Farrell, 1957). The efficiency score resulting from CCR model is called the aggregate efficiency of a unit and it is defined as the ratio of weighted sum of outputs to weighted sum of inputs.

#### **1.4.2 BCC model**

Banker et al. (1984) developed the Banker–Charnes–Cooper (BCC) model, which evaluates the technical efficiency of a DMU based on variable returns to scale frontier. Technical efficiency refers to the ability of a unit to utilize its limited inputs to produce the desired outputs and it is influenced by the use of technology and equipment (Coelli *et al.*, 2005). It is a measure of a DMU's operations relative to the industry's production (technical) frontier; a unit that operates on the industry's production frontier is said to be technically efficient while a unit that operates beneath the industry's production frontier is said to operate with some degree of technical inefficiency (Helvoigt and Adams, 2009). BCC model is able to indicate whether a DMU is performing under decreasing, increasing, or constant returns to scale. Increasing returns to scale (IRS) (or decreasing returns to scale - DRS) is when an increase in inputs results in a greater (less) than proportionate increase in outputs. DRS occurs when a unit grows larger than a certain scale and its ability to manage and utilize its inputs decreases; therefore, it becomes scale inefficient while IRS occurs when the unit can still improve its efficiency by using more resources and increasing its size (Salehirad and Sowlati, 2006).

However, a unit in CRS should be kept within that region as an attempt to change its scale of operation can reduce its scale efficiency by moving the unit into either DRS or IRS. Information on the state of returns to scale of a DMU is helpful in indicating the potential redistribution of resources (Omid *et al.*, 2011).

#### **1.4.3 Scale efficiency and model orientation**

The ratio of a DMU's aggregate and technical efficiencies resulting from the CCR and BCC models gives the scale efficiency of the DMU. It reflects the inefficiency of a DMU which is merely due to its scale of operations and size (Salehirad and Sowlati, 2007) or potential productivity gain from achieving optimal size (Coelli *et al.*, 2005). A scale efficiency of 1 indicates the most productive scale size which represents the maximum productivity for a given mix of inputs and outputs (Omid *et al.*, 2011). Scale inefficiency occurs when a unit is not operating at the scale of operations reflective of long-term competitiveness or the unit's operation is inconsistent with constant returns to scale (Lee, 2005). A DMU with scale efficiency less than one suggests that the aggregate efficiency may be improved by changing the scale of operation (Vahid and Sowlati, 2007).

In both the CCR and BCC models, the orientation, that is the projection of the DMUs to the frontier could either be output oriented (producing maximum output using available inputs) or input oriented (minimizing the use of inputs to achieve a given output level). In other words, input-oriented model strives to minimize inputs while maintaining the same level of outputs, whereas output-oriented models focus on increasing outputs with the same level of inputs (Omid *et al.*, 2011). The combination of CCR and BCC DEA models in either output or input orientation provides business performance information on a DMU in terms of its aggregate, technical and scale efficiency scores, its state of returns to scale, as well as its benchmark peers.

### **1.5 Application of DEA in Forestry Research**

DEA is well-deployed to a wide variety of industries in different countries with about 2000 papers published during the period 2010 to 2014, (Liu *et al.*, 2016; Liu *et al.*, 2013). Amidst such a large amount of literature in DEA, its application in forestry research is limited. The application of efficiency measurement techniques using DEA in the forest industry has been

focused mainly on forest management (Li *et al.*, 2016; Boosari *et al.*, 2015; Şafak *et al.*, 2014; Limaei, 2013; Shiba, 1997; Kao and Yang, 1991), and wood-product manufacturing sectors (Zadmirzaei *et al.*, 2015; Helvoigt and Adams, 2008; Vahid and Sowlati, 2007; Salehirad and Sowlati, 2007; Lee, 2005; Nyrud and Baardsen, 2003; Nyrud and Bergseng, 2002). Hailu and Veeman (2003) and LeBel and Stuart (1998) are the only published studies on the application of DEA in forest harvesting industry (to our knowledge). This reflects the concern raised by Doolittle (1990) that in spite of the pivotal role of timber harvesting, little attention is being given to it in terms of research resources compared to other forestry subject areas such as timber management and wood processing. The timber industry is globally competitive thus making it important for the forest harvesting sector to remain competitive both locally and internationally in order to better seize trade opportunities.

LeBel and Stuart (1998) used CCR and BCC DEA models to measure the technical efficiency of 23 logging contractors in the southern United States during the period 1988 – 1994, providing insights on factors that affect technical efficiency and performance. Aggregate, technical, and scale efficiencies of loggers were evaluated based on DEA models with capital, consumables, and labour as the inputs and tons of wood as the output of the DEA models. They reported that many smaller operations were inefficient and were likely to be in a precarious financial position with investment in capital equipment. Hailu and Veeman (2003) using panel data covering the period 1977 to 1995 analysed the technical efficiency of the logging industries for six boreal provinces in Canada using DEA and reported a generally substantial level of technical inefficiency in the provinces.

Salehirad and Sowlati (2005) estimated the performance of primary wood producers in British Columbia using DEA to capture their technical, scale, and aggregate efficiencies. Nyrud and Baardsen (2003) using both DEA and Malmquist productivity index on a panel data set, including about 200 sawmills during the period 1974 to 1991, assessed the productivity growth of the sawmills throughout the period. Yin (2000) analysed the productive efficiency of global producers of bleached softwood pulp using both stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The author concluded that an inappropriate input mix in the production process caused most of the cost inefficiency. Nanang and Ghebremichael (2006) used annual data of log output and four inputs: labour, capital, energy, and materials

from 1961 to 1999 to analyse and compare the production technologies in timber harvesting industries of three provinces in Canada. Using DEA, Vahid and Sowlati (2007) evaluated the performance of six wood-product manufacturing subsectors in Canada from 1993 to 2003.

Diaz-Balteiro *et al.* (2006) in their study investigated the relationship between research and development, and other innovation activities and the production efficiency of Spanish wood-based industry, using DEA and logistic regression, while Nyrud and Bergseng (2002) investigated the production efficiency in the Norwegian sawmilling sector by means of DEA using individual mill observations from the period 1974 – 1991. Limaei (2013) assessed the efficiency of 14 Iranian forest companies and management units. A very recent study is by Li *et al.* (2017) who evaluated the efficiency of China's forestry resources using DEA, and concluded that the limiting factor to China's forestry resource efficiency is technology, suggesting increased investment in science and technology.

### **1.5.1 Benchmarking Logging Operations**

Performance of forest harvesting operations is often measured with the aim of improving productivity, reducing costs, and improving overall operational efficiency, which are important business components of interest to forest harvesting managers or entrepreneurs (Drolet and LeBel, 2010; LeBel and Stuart, 1998; Carter and Cubbage, 1995). Among a number of indicators that can be used in assessing the performance of forest harvesting operations, operational performance defined by measures of efficiency, productivity and cost management (Marchand and Raymond, 2008) remain the preferred performance measurement indicator (Drolet and LeBel, 2010; LeBel and Stuart, 1998). The estimation of performance is however generally relative to a given level of a variable and will continue to change as the level changes. There is no ideal variable for the measurement of business performance as it is multi-dimensional (Drolet and LeBel, 2010; Kaplan and Norton, 2007; Garengo *et al.*, 2005; Cameron, 1986). However, the choice of variables for the performance measurement of any business is often tied to those that are significantly influenced by the business finances, human resources, machines/equipment, innovations and consumables, and that define the peculiar characteristics of the business. The operations and decisions of logging contractors, for example, is often greatly influenced by a number of factors including the equipment type, number of machines, location, harvest area and extraction distance,

duration of contracts, logging rates, available crews, etc. (Visser, 2012; Mäkinen, 1997). Performance assessment in the logging industry have been limited by technical constraints, and where operational data are available, they are often used for short-term targets rather than for long term operational improvement (Drolet and LeBel, 2010; Nanang and Ghebremichael, 2006). This trend needs to change if the logging industry is to remain competitive in both local and global markets, as performance measurement will help evaluate the operational efficiency of the industry and identify areas of improvement.

### **1.5.2 Benchmarking: The Case of the New Zealand Logging Industry**

The New Zealand logging industry over the last two decades has experienced a number of changes in its business environment concerning availability of labour, management approach, technological advancement, and increasing cost and difficulty in accessing steep forest terrain, which are believed to have some effect on the efficiency and productivity of the harvesting operations. However, the effect of these changes on its production efficiency and productivity growth has not been investigated in spite of the importance of this sector to the New Zealand forest economy. One of the unique characteristics of the New Zealand logging industry is the rapid shift from manual chainsaw harvesting system to mechanized operations resulting from the use of mechanized ground and cable-based harvesting systems. The shift has been inspired mainly by the goal of keeping workers safe during logging operations. However, technological advancement in harvesting operations is usually accompanied by fundamental changes in the logging enterprise in terms of capital investment, logging rate and productivity (Rickenbach and Steele, 2005). In addition, LeBel and Stuart (1998) note that the complex business environment of harvesting operations necessitates the continuous measurement of operational performance of the industry especially as technological improvements are achieved at an increasing operational cost. Hence, without careful management, the risk in the logging business may shift from threat of loss of life to bankruptcy. The shift in the direction of mechanized harvesting operation has raised concerns about its future impact on productivity and logging rate. Some studies have reported increased production efficiency following adoption of mechanized operation (Rickenbach and Steele, 2005; Carter and Cubbage, 1995), but the impact of the operating environment - terrain characteristics and forest stand parameters (e.g. terrain slope, harvest area, extraction distance, number of landings, etc.) - are yet to be investigated. Much of the information

regarding production growth in the New Zealand logging industry has been anecdotal with very few empirical studies to validate this especially with the use of established benchmarking techniques.

### **1.6 Research Questions**

Given the limited information on benchmarking in the logging industry, this research aims to contribute to the literature by expanding the scope of knowledge in the application of DEA to the forest harvesting industry. In addition, the study aims to provide some insight into the interaction between the operating environment of harvesting crews and their operational performance. This thesis covers three main research questions including:

- i. How can the forest industry and its stakeholders effectively expand their existing capacity to benchmark the relative performance of independent forest harvesting contractors based on their input-output relationship?
- ii. How much influence do exogenously fixed production factors have on the estimated technical efficiency of forest harvesting operations?
- iii. How can the operating environment variables be accounted for in benchmark studies?

### **1.7 Research Data**

Data used in this PhD thesis were retrieved from the Future Forest Research cost and productivity benchmarking database managed under contract by the University of Canterbury, and from the harvesting benchmarking database of a large forest management company in New Zealand. The databases contain comprehensive information on harvesting crews, logging cost and harvesting output, harvesting systems, stand and terrain factors. The information in the database are considered sensitive to the operations of the forest companies that supply the data, hence a confidentiality agreement is currently binding on the data. This places a restriction on the level of details on the data that can be reported in this thesis. Although mean data are reported in the thesis, where appropriate, some contractor-specific data are provided.



## **Chapter 2**

### **Estimating the Harvesting Efficiency of Independent Logging Contractors Using Data Envelopment Analysis**

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#### **2.1 Introduction**

While New Zealand is a small player in the international forest market (1.1% of world's total supply of industrial wood and 1.3% of world's trade in forest products), it is entering an expansion phase as forests planted in recent decades reach maturity accompanied by expected increase in production volume (MPI, 2016). Historical data indicate that global production and trade of forest products have been on the increase over the last 53 years (FAOSTAT, 2015). This trend is expected to continue (Hashiramotois *et al.*, 2004) with competition for a larger share of global market among wood exporting countries intensifying due to the emergence of new exporting countries and increasing production volume by existing ones. Consequently, the future competitiveness and sustainability of the industry will be determined by how well logging contractors can adapt to the changing business environment. This will depend on improving their operational performance (Vahid and Sowlati, 2007). Carter and Cubbage (1995) note that in business sectors that deviate from pure competition, inefficiency may persist for a long period with trivial consequence. This is the opposite of the logging industry where global competition is on the increase and inefficient units are expected to exit its international markets. It is therefore very important to continuously measure and improve the operational efficiency of the forest harvesting industry if it is to remain competitive both in the local and international markets. To evaluate, monitor and improve the efficiency of forest harvesting sector, organizational and industry performance assessment techniques can be used. Salehirad and Sowlati (2006) note that such

performance assessments can help in developing and improving policies that are appropriate to the business environment of the organization or industry under observation.

This study is thus focused on evaluating the performance and competitiveness of New Zealand forest harvesting industry by measuring the operational efficiency of logging contractors operating in the industry, and investigating opportunities for improvement using data envelopment analysis (DEA). This study provides the first attempt to investigate the operational efficiency of New Zealand logging contractors using data envelopment analysis.

## **2.2 DEA Models**

The DEA technique was introduced by Charnes *et al.* (1978) based on the earlier work of Farrell (1957). DEA is comprised of two main mathematical models: CCR (Charnes, Cooper and Rhodes) and BCC (Banker, Charnes and Cooper) models. The CCR model is built on the assumption of constant returns to scale (CRS) of production function while the BCC model is built on the assumption of variable returns to scale (VRS). The CCR and BCC models are classified as radial models, relying on equiproportional increases or reductions of inputs or outputs, or both, and thus require the selection of an orientation which can be input- or output-oriented (Mariano *et al.*, 2015). There have been numerous subsequent developments in literature extending the CCR and BCC models in different forms (Liu *et al.*, 2016; Olesen and Petersen, 2016; Mariano *et al.*, 2015; Liu *et al.*, 2013; Odeck, 2009; Cook and Seiford, 2009; Fried *et al.*, 2002). The performance of a decision making unit (DMU) which represents a production entity is measured with DEA models using three efficiency measurements: aggregate/overall, pure technical, and scale efficiencies.

### **2.2.1 Aggregate efficiency**

The Charnes–Cooper–Rhodes model otherwise known as the CCR model (Charnes *et al.*, 1978) is used to estimate the aggregate efficiency of a production unit. CCR model separates the DMUs into efficient and inefficient units by assigning to each DMU a relative efficiency score. A relatively efficient unit receives a score of 1 while an inefficient unit relative to the efficient ones a score less than 1. For every inefficient unit, a corresponding set of efficient targets (reference set) are located to be used as benchmark for improving the inefficient DMU (Carrillo and Jorge, 2016; Marinescu *et al.*, 2005; Farrell, 1957). The aggregate or overall

efficiency (AE) resulting from the CCR model takes no account of the effect of scale of operation on the efficiency of the DMUs. AE is represented mathematically as in equation 2.1 (Heidari *et al.*, 2012; Cooper *et al.*, 2007):

$$AE = \frac{\sum_{p=1}^P u_p y_{p,j}}{\sum_{q=1}^Q v_q x_{q,j}} \quad (2.1)$$

where 'x' and 'y' are inputs and outputs, 'v' and 'u' are input and output weights, respectively, 'q' is the number of inputs ( $q = 1, 2, \dots, Q$ ), 'p' is the number of outputs ( $p = 1, 2, \dots, P$ ), and 'j' represents  $j$ th DMU. The output-oriented CCR model (Charnes *et al.*, 1978) is indicated in equation 2.2:

$$\text{Max}\theta = \emptyset + \varepsilon \left( \sum_{r=1}^s s_r^+ + \sum_{i=1}^m s_i^- \right)$$

Subject to

$$\begin{aligned} \sum_{j=1}^n \lambda_j X_{ij} + s_{i0}^- &= X_{i0} & (2.2) \\ \sum_{j=1}^n \lambda_j y_{rj} - s_{r0}^+ &= \emptyset y_{r0} \\ \lambda_j, s_i^-, s_r^+ &\geq 0, i = 1, 2, \dots, m; r = 1, 2, \dots, s \end{aligned}$$

Where  $m$  and  $s$  represent inputs and outputs respectively for  $n$  DMUs to be evaluated.  $X_{ij}$  ( $i = 1, 2, \dots, m$ ) and  $y_{rj}$  ( $r = 1, 2, \dots, s$ ) represent the input and output values of  $DMU_j$  ( $j = 1, 2, \dots, n$ ), respectively.  $\theta$  is efficiency index,  $\varepsilon$  is a non-Archimedean infinitesimal,  $\lambda_j$  is the scalar vector associated with  $DMU_j$  in defining the efficient target,  $s_{r0}^+$  and  $s_{i0}^-$  indicate non-radial increase in output and decrease in inputs (slack), respectively;  $DMU_0$  is efficient if and only if  $\emptyset = 1$  and all slacks are equal to zero.

### 2.2.2 Pure technical efficiency

Banker *et al.* (1984) developed the Banker–Charnes–Cooper (BCC) model, which evaluates pure technical efficiency (PTE) of a DMU based on variable returns to scale (VRS) frontier. Pure technical efficiency refers to the ability of a unit to utilize its limited inputs to produce

the desired outputs and it is influenced by the use of technology and equipment (Coelli *et al.*, 2005). It is a measure of a DMU's operations relative to the industry's production (technical) frontier; a unit that operates on the industry's production frontier is said to be technically efficient while a unit beneath the frontier is said to operate at some degree of technical inefficiency (Helvoigt and Adams, 2009). The BCC model accounts for the effect of scale of operation or size in the DEA model by adding a convexity constraint ( $\sum_{j=1}^n \lambda_j = 1$ ) to the CCR model which compares each DMU with units in its own scale size as shown in equation 2.3 (Örkcü *et al.*, 2016; Vahid and Sowlati, 2007; Charnes *et al.*, 1978):

$$Max\theta = \emptyset + \varepsilon \left( \sum_{r=1}^s s_r^+ + \sum_{i=1}^m s_i^- \right)$$

Subject to

$$\begin{aligned} \sum_{j=1}^n \lambda_j X_{ij} + s_{i0}^- &= X_{i0} \\ \sum_{j=1}^n \lambda_j y_{rj} - s_{r0}^+ &= \emptyset y_{r0} \\ \sum_{j=1}^n \lambda_j &= 1 \quad j = 1, 2, \dots, n \\ \lambda_j, s_i^-, s_r^+ &\geq 0, i = 1, 2, \dots, m; r = 1, 2, \dots, s \end{aligned} \tag{2.3}$$

### 2.2.3 Scale efficiency

The ratio of a DMU's aggregate and pure technical efficiencies resulting from CCR and BCC models gives a measure of its scale efficiency (SE) (Equation 2.4) which reflects the inefficiency due to its scale of operations and size (Salehirad and Sowlati, 2007) or potential productivity gain from achieving optimal size (Mohammadi *et al.*, 2011; Coelli *et al.*, 2005). The overall or aggregate efficiency of a DMU at a particular level of technologies (inputs) can be improved by increasing its scale efficiency or moving toward its best size of operation.

$$SE = \frac{AE}{TE} \tag{2.4}$$

The combination of CCR and BCC DEA models in either output or input orientation provides business performance information of a DMU or an industry in terms of its aggregate efficiency, technical efficiency and scale efficiency, its state of returns to scale, target units or

reference sets if inefficient, and the slacks of an inefficient unit required to make it efficient (i.e., input and output targets). Input and output targets for relatively inefficient DMUs can be determined as follows (Singh, 2016):

$$\dot{y}_{kr} = \rho_k y_{kr} + S_{kr}^+ \text{ (output target); } \dot{x}_{ik} = x_{ik} - S_{ik}^- \text{ (input target) on output orientation} \quad (2.5)$$

$$\dot{y}_{kr} = y_{kr} + S_{kr}^+ \text{ (output target); } \dot{x}_{ik} = \theta_k x_{ik} - S_{ik}^- \text{ (input target) on input orientation} \quad (2.6)$$

Where  $\frac{1}{\rho_k}$  and  $\theta_k$  are the output and input oriented efficiency scores respectively for the  $k^{th}$  DMU,  $\dot{x}_{ik}$  and  $\dot{y}_{kr}$  ( $i = 1, 2, \dots, m; r = 1, 2, \dots, s$ ) are the  $i^{th}$  input and  $r^{th}$  output target respectively for the  $k^{th}$  DMU,  $x_{ik}$  and  $y_{kr}$  are the actual input and output values respectively for the  $k^{th}$  DMU,  $S_{ik}^-$  and  $S_{kr}^+$  are optimal input and output slacks respectively for the  $k^{th}$  DMU. Slacks here represent additional improvement in the production factors of  $k^{th}$  DMU (reduction in inputs or increase in output) needed for it to become efficient.

## 2.3 Methodology

### 2.3.1 Data source

Data on the production factors of New Zealand logging contractors for the period 2009 - 2015 retrieved from the University of Canterbury (UC)/Future Forest Research, FFR (now Forest Growers Research, FGR) benchmark database system is used in this study. The UC/FFR benchmark database system is a comprehensive and detailed database that provides information for the monitoring and understanding of relationships between logging inputs and outputs over time in New Zealand (Visser, 2009). The database contains information on logging production factors cutting across forest companies and logging contractors, harvesting systems, terrain and forest stands. It is the only existing logging contractor-level database in the country. Using contractor-specific data for the study offers a number of benefits as they present higher variability unlike aggregated (summed across forest management companies) data with reduced variability and potentially lower efficient frontier (Helvoigt and Adams, 2009). For detailed information on the UC/FFR benchmark database system, readers may refer to Visser (2009), Visser (2011) and Visser (2012).

### 2.3.2 Selection of production factors

To measure the performance of the logging contractors, otherwise referred to as DMUs in this study, a DEA production model is developed comprising of the forest harvesting production factors (inputs and outputs) of the units. The production factors considered were limited by availability within the UC/FFR benchmark database. For performance measurements in the forest industry, Bonds and Hughes (2007) and Vahid and Sowlati (2007) suggest the use of physical factors covering the resources used by DMUs to produce outputs since the factors are not constant but vary over the course of harvest cycle. Based on the literature review and available data, eight inputs and one output were considered in this study for the DEA models. The inputs are harvest days ( $x_1$ ), number of machines ( $x_2$ ), harvest area size ( $x_3$ ), log sorts ( $x_4$ ), timber production ( $x_5$ ), number of workers ( $x_6$ ), piece size ( $x_7$ ), and the extraction distance ( $x_8$ ). While the output is system productivity ( $y_1$ ). The production factors were selected to reflect the business activities of the logging contractors. Table 2.1 shows the definition of the production factors.

**Table 2.1** Definition of production factors

Production factors	Description
<b>Inputs</b>	
Harvest days	Number of work days used to complete a harvest area
Machines	Total number of machines on site including primary and secondary harvest machines.
Harvest area size	This is defined as a single contiguous harvest area in ha.
Log sorts	Average number of log sorts made at the landing(s) during the harvest in the harvest area.
Timber	Total merchantable timber harvested from the harvest area in tonnes.
Workers	Average number of crew members in the harvest team for the duration of the harvest
Piece size	Average piece size from the harvest area in ton/stem
Extraction distance	Average extraction distance from the harvest area in metres
<b>Output</b>	
System productivity	Total volume of timber harvested divided by the total harvest time in tonnes per system machine hour (tons/SMH)

In a preliminary analysis to select appropriate factors for the DEA, correlation and regression tests were performed to identify highly correlated inputs, the relationship between the inputs

and the output, and the direction of the relationship, i.e. whether positive or negative. Positive correlation is desirable between the input and output factors, and weak correlation desirable among the input factors, otherwise redundant factors may be deleted (Dong *et al.*, 2015; Šporčić *et al.*, 2009; Kao *et al.*, 1993; Lewin *et al.*, 1982). Regression test aims to show a plausible production relationship between the input and output factors (Schumock *et al.*, 2009; Sun, 2002). Table 2.2 shows correlation (Pearson's correlation) coefficients among the inputs and output considered. Some inter-correlations worthy of note include the relationship between:

- a. 'Number of harvest days' and 'Harvest area size' ( $R = 0.79$ )
- b. 'Number of harvest days' and 'Total timber' ( $R = 0.76$ )
- c. 'Harvest area size' and 'Total timber' ( $R = 0.82$ )

**Table 2.2** Pearson's correlation coefficients of input and output factors

	Inputs								Output
	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$	$y_1$
$x_1$	1								
$x_2$	0.051	1							
$x_3$	0.792	0.209	1						
$x_4$	0.143	0.083	0.199	1					
$x_5$	0.759	0.226	0.822	0.225	1				
$x_6$	0.074	0.240	0.138	0.213	0.140	1			
$x_7$	0.002	-0.009	-0.038	0.158	0.050	0.208	1		
$x_8$	0.117	0.158	0.156	-0.021	0.144	0.141	-0.004	1	
$y_1$	0.026	0.328	0.257	0.196	0.582	0.135	0.095	0.092	1

Harvest days (days) -  $x_1$ , number of machines -  $x_2$ , harvest area size (ha) -  $x_3$ , log sorts -  $x_4$ , timber production (tonnes) -  $x_5$ , number of workers -  $x_6$ , piece size (tons/stem) -  $x_7$ , extraction distance (metres) -  $x_8$ , system productivity (tons/SMH) -  $y_1$ .

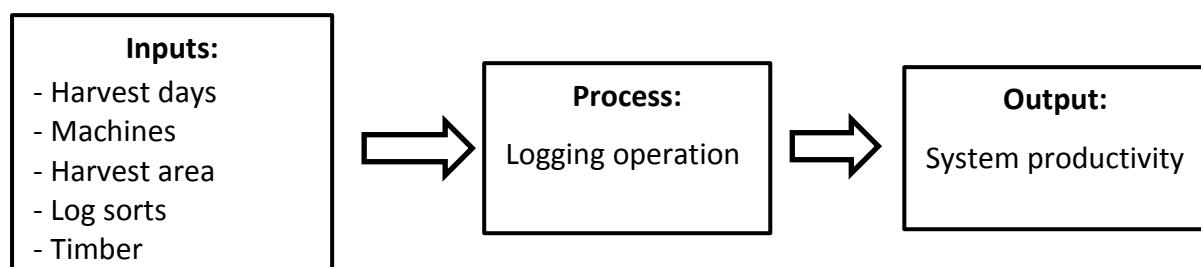
In addition to the correlation test, multiple regression was carried out to determine plausible relationship between the inputs and the output, as well as the significance of the inputs in relation to the output. The regression result of all the factors under consideration (Table 2.3) shows a plausible relationship between the inputs and outputs however, number of workers ( $x_6$ ), average piece size ( $x_7$ ), extraction distance ( $x_8$ ) show no significant effect on the output. The non-significant effect of extraction distance is not surprising as it has earlier been reported to have a weak relationship with productivity (Visser, 2009; Visser, 2011). Although extraction distance may play a significant role in extraction output, a possibly more significant

factor in overall system productivity could be the average volume extracted per cycle. Further multiple regression test without the insignificant factors resulted in a reduction in  $R^2$  by 0.03% (Table 2.3). The discriminating power of DEA (differentiating efficient and inefficient DMUs) is increased by reducing the number of factors relative to the DMUs (Toloo and Tichý, 2015; Adler *et al.*, 2002). Being a good incentive to have limited factors, the insignificant factors were dropped. Highly correlated inputs were retained because of their significant influence on productivity. This is in line with the findings by Dyson *et al.* (2001) who reported that although it might be tempting to omit highly correlated variables, this however could lead to significant changes in efficiency estimates. The variance inflation factor shows that the inputs are moderately correlated ( $1 < \text{VIF} < 5$ ). Figure 2.1 shows the production system used in the DEA models.

**Table 2.3** Regression results of inputs and output factors of logging contractors

Inputs	All factors			Without insignificant factors		
	Coefficients	P-value	VIF	Coefficients	P-value	VIF
$x_1$	-0.45 <sup>a</sup>	0.00	3.15	-0.45	0.00	3.15
$x_2$	1.39 <sup>a</sup>	0.00	1.18	1.41	0.00	1.12
$x_3$	-0.25 <sup>a</sup>	0.00	4.08	-0.26	0.00	3.99
$x_4$	0.23 <sup>a</sup>	0.00	1.12	0.23	0.00	1.06
$x_5$	0.0024 <sup>a</sup>	0.00	3.62	0.0024	0.00	3.57
$x_6$	-0.01	0.95	1.17			
$x_7$	0.19	0.47	1.09			
$x_8$	0.0032	0.41	1.06			
Constant	19.05			19.87		
$R^2$	<b>77.15%</b>			<b>77.12%</b>		

Harvest days (days) -  $x_1$ , number of machines -  $x_2$ , harvest area size (ha) -  $x_3$ , log sorts -  $x_4$ , timber production (tonnes) -  $x_5$ , number of workers -  $x_6$ , piece size (tons/stem) -  $x_7$ , extraction distance (metres) -  $x_8$ , system productivity (tons/SMH) -  $y_1$ . <sup>a</sup>Statistically significant at 0.05 level; VIF – Variance inflation factor



**Figure 2.1** Production model for the forest harvesting operations

As it is in many cases of decision making studies, all the factors influencing work processes are never available due to difficulty in quantifying some factors, high cost and complexity in obtaining data, as well as some unidentified factors (Sun, 2002; Sundberg and Silversides, 1988). Hence, the goal in decision-making process is to use the knowledge available to arrive at the best decision. The productive factors considered in this study were not exhaustive and were limited by availability of data, however, they accounted for 77.12 % variation in the production output.

### **2.3.3 Data analysis**

This study makes use of the well-established DEA models of constant and variable returns to scale widely used in applied analysis (Ye *et al.*, 2016; Mohammadi *et al.*, 2011). To estimate the operational efficiency of New Zealand logging contractors based on CCR and BCC DEA models, DEA software (DEAP version 2.1) developed by Coelli (1996) was used. DEAP was used to calculate the efficiencies of the DMUs, returns to scale and slack values for determining input and output targets. Multi-stage DEA methodology was selected in calculating input and output slacks as it identifies more representative efficient projection points, and it is invariant to units of measurement (Coelli, 1998). The output-oriented DEA model was used in this study considering that it is appropriate to assume that logging contractors will be more interested in maximizing their production output using available inputs. However, it is acknowledged that from a different perspective, input orientation may well be suited for efficiency measurement of logging contractors considering that profitability of businesses lies in the ability to attain desired outputs with minimum level of inputs/resources (Chauhan *et al.*, 2006). An important suggestion in DEA models is that the number of DMUs compared should be greater than three times the total sum of productive factors used in the analysis to ensure reliability and validity of result (Šporčić and Landekić, 2014; Cooper *et al.*, 2007; Banker *et al.*, 1984). Thus, the DMUs used in this study should be more than 18, a requirement that is met in this study.

## **2.4 Results and Discussion**

A total of 423 DMUs were identified in the UC/FFR database and utilized to estimate the operational efficiency of New Zealand logging contractors for the period 2009 - 2015 after discarding missing and erroneous entries. The contractors were represented using identifiers

for confidentiality purpose. Five inputs and one output were used in the DEA, and the descriptive statistics of the production factors over the study period is shown in Table 2.4. The statistics suggest large variations among the logging contractors in terms of their input and output levels.

#### **2.4.1 Efficiency measures**

To provide a picture of the efficiency of New Zealand logging contractors over the study period 2009 - 2015, an output-oriented CCR DEA model (Equation 2.2) was used to measure the aggregate efficiency while output-oriented BCC DEA models (Equations 2.3 and 2.4) were applied to estimate the technical and scale efficiency of the contractors. The results in Table 2.5 show that the mean aggregate, pure technical and scale efficiencies of the logging contractors over the study period are 0.53, 0.55 and 0.97, respectively. The relatively high average scale efficiency score of the contractors indicates that efficiency loss due to the DMUs scale of operation is small (3 %). A scale efficiency score of 1.00 indicates that the size and volume of activities are well balanced (Šporčić *et al.*, 2009). Although the scale efficiency score for the contractors is highest over the study period, only 9.2 % of the 423 contractors were scale efficient, while 3.8 and 5.7 % were aggregate and pure technical efficient, respectively. Majority of the contractors operate at near scale efficient level. A scale efficient DMU indicates that it is operating at the most productive scale size while a scale inefficient DMU is an indication of potential gain in productivity by achieving optimal scale or size of operation. Scale inefficient DMUs can improve their performance by better allocation and utilization of production resources.

The aggregate inefficiency of DMUs can be due to the pure technical inefficiency, scale inefficiency or both. As presented in Table 2.5, the average relative scale efficiency score of the logging contractors is high, however the aggregate efficiency which is a measure of the overall efficiency of the DMUs, including both pure technical and scale efficiencies is low across the years. A scale efficient DMU might have a low aggregate efficiency score if it poorly transforms its available resources into the desired output. This is the case for New Zealand logging contractors; although they have high average scale efficiency score over the whole study period, the reported average aggregate efficiency is low due to the low pure technical efficiency of the contractors. This means that the production technology and management

**Table 2.4** Summary statistics of input and output data of the DMUs for the period 2009-2015

Year	Statistics	Inputs					Output
		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	
<b>2009</b>	Mean	29.8	3.8	14.9	11.3	6671	30
	Std. Dev.	24.1	0.9	13.9	4.1	4583.6	13.2
	Min	8	2	1.66	1	892	7.83
	Max	133	6	91.7	18	23067.3	71.6
<b>2010</b>	Mean	38.3	4.5	17.5	10	8330.2	27
	Std. Dev.	32.5	1.4	15.6	3.1	7594.8	12.3
	Min	6.7	2	2	5	1009	5.4
	Max	176	10	93.2	17	43920	65.3
<b>2011</b>	Mean	34.6	4.6	15.9	10.3	8166.2	27.2
	Std. Dev.	29.9	1.1	16.5	3.5	9290.2	10.4
	Min	2.5	2	1.1	2	378.3	5.3
	Max	173	7	114.8	20	71281.5	68.3
<b>2012</b>	Mean	35	4.4	14.7	10.8	7074.2	24.6
	Std. Dev.	26.8	1.3	11.6	3.4	5336.9	9.6
	Min	7	1	2	2	1393.5	7.6
	Max	243	11	62.1	21	45846	69.4
<b>2013</b>	Mean	41.8	4.4	20.3	10.7	9995.3	27.8
	Std. Dev.	38.5	1.2	20.4	3	11253.4	13
	Min	4	2	1	4	632	5.2
	Max	240	8.5	119.4	18	79089	93.5
<b>2014</b>	Mean	42.2	4.9	19.9	10.1	10714.9	29.7
	Std. Dev.	34.8	1.1	18.6	2.4	10408.1	11.6
	Min	5	2	2.1	5	1134.8	10.0
	Max	210.5	9	90.5	17	50095	83.1
<b>2015</b>	Mean	37.7	5.2	18.2	9.0	11491.7	34.9
	Std. Dev.	37.2	1.6	20.9	3.7	15817.1	33.6
	Min	2	3	0.2	4	164	10.1
	Max	210.5	10	138.4	15	137782	437.4

Harvest days (days) -  $x_1$ , number of machines -  $x_2$ , harvest area size (ha) -  $x_3$ , log sorts -  $x_4$ , timber production (tonnes) -  $x_5$ , system productivity (tons/SMH) -  $y_1$ .

**Table 2.5:** Summary of efficiency scores of logging contractors from 2009 - 2015

Year	Statistics	Efficiency			Returns to Scale (% DMU)		
		Aggregate	Pure	Scale	CRS	IRS	DRS
		Technical					
2009	Mean	0.68	0.75	0.93			
	Standard dev.	0.22	0.23	0.12	17.95	51.3	30.8
	Min.	0.26	0.26	0.47			
	Max	1	1	1			
	% Inefficient DMUs	84.6	71.8	84.6			
2010	Mean	0.64	0.72	0.91			
	Standard dev.	0.20	0.23	0.12	14.8	68.5	16.7
	Min.	0.34	0.35	0.52			
	Max	1	1	1			
	% Inefficient DMUs	90.7	72.2	85.2			
2011	Mean	0.63	0.68	0.92			
	Standard dev.	0.20	0.20	0.09	19.7	17.1	63.2
	Min.	0.17	0.17	0.62			
	Max	1	1	1			
	% Inefficient DMUs	88.2	84.2	81.6			
2012	Mean	0.57	0.61	0.93			
	Standard dev.	0.22	0.21	0.07	17.4	24.6	57.97
	Min.	0.23	0.24	0.68			
	Max	1	1	1			
	% Inefficient DMUs	89.9	88.4	82.6			
2013	Mean	0.64	0.71	0.91			
	Standard dev.	0.20	0.21	0.11	10.5	60.5	29.1
	Min.	0.29	0.31	0.42			
	Max	1	1	1			
	% Inefficient DMUs	90.7	80.2	90.7			
2014	Mean	0.77	0.81	0.96			
	Standard dev.	0.19	0.18	0.09	33.3	33.3	33.3
	Min.	0.42	0.48	0.52			
	Max	1	1	1			
	% Inefficient DMUs	75	64.6	68.8			
2015	Mean	0.68	0.74	0.93			
	Standard dev.	0.20	0.21	0.10	17.7	58.8	23.5
	Min.	0.24	0.24	0.50			
	Max	1	1	1			
	% Inefficient DMUs	90.2	76.5	84.3			
2009-2015*	Mean	0.53	0.55	0.97			
	Standard dev.	0.19	0.19	0.05	13.0	36.4	50.6
	Min.	0.15	0.15	0.58			
	Max	1	1	1			
	% Inefficient DMUs	96.2	94.3	90.8			

\*Intertemporal analysis; CRS – Constant returns to scale; IRS – Increasing returns to scale; DRS – Decreasing returns to scale; Number of DMUs in each year in brackets: 2009 (39), 2010 (54), 2011 (76), 2012 (69), 2013 (86), 2014 (48), and 2015 (51).

skills of the DMUs are relatively poor (Li *et al.*, 2016). Hence, the focus of the forest harvesting industry in New Zealand should be to improve the pure technical efficiency of the logging contractors through capacity building for improved inputs utilization, training, knowledge sharing, efficient use of technology, and improving harvesting systems and managerial capability.

The average efficiency measures of the DMUs across the years and over the entire study period is a reflection of the competitiveness of the New Zealand forest harvesting industry. Changes in the performance of the contractors through the years is expected as changes in technology, machineries, input flows, management approach, including random events such as machinery failure, etc. can significantly alter their relative efficiency. The average pure technical efficiency of the contractors ranges from 0.61 in 2012 to 0.81 in 2014 with 88.4 and 64.6 % of the DMUs estimated to be inefficient at the two periods, respectively. Whereas, the average aggregate efficiency ranges from 0.57 in 2012 to 0.77 in 2014 with 89.9 and 75% of the DMUs being inefficient at the two time periods, respectively. The highest average aggregate efficiency score of the logging contractors in 2014 (0.77) indicates that they had the highest relative performance in that year in terms of system productivity. Although no defined trend was observed in the average efficiency measurements across the years, caution must be applied in attempting to compare the yearly reported average efficiency scores since they were calculated based on frontiers which are unique to each year. As earlier explained, the efficient units within a group of comparable DMUs create an envelopment frontier and the performance of every other DMU within that group is measured against it.

As shown in Table 2.5, the average aggregate and pure technical efficiency scores over the entire study period (2009-2015) was lower compared to the efficiency scores for individual years. This is expected since each DMU was compared to a larger sample of DMUs over the entire study period thus raising the production frontier (Kao and Yang, 1991). Also, the average efficiency score estimated from the CCR model across the years was less than the average efficiency score estimated from the BCC model for the logging contractors. This is mainly due to the fact that under variable returns to scale, logging contractors are compared only to efficient contractors of similar size, hence the higher efficiency score. The high scale efficiency of the DMUs over the entire study period supports the relatively high scale

efficiency estimated for the DMUs across the years. Similar results were reported by Salehirad and Sowlati (2007) for sawmills in British Columbia.

It should be noted that the efficiency results reported are based on the production factors used in the DEA models (Figure 2.1) reflecting how efficiently New Zealand logging contractors transformed available input resources to the desired output. From the reported results (Table 2.5), a high percentage of logging contractors (greater than 90%) were identified as having some level of inefficiency across the entire study period. This is based on the low average aggregate efficiency (0.53), pure technical efficiency (0.55), and the very high percentage of inefficient logging contractors (greater than 90%) across the entire study period. This is also reflected in the high standard deviation reported for system productivity in Table 2.4 indicating high variation in the productivity of the contractors which could be attributed to wide variance in optimum utilization of input resources. Poor industry competitiveness which is often associated with high technical inefficiency can only lead to long term economic losses. Thus, increasing performance through the efficient use of inputs for increased productivity appears to be a reasonable immediate management objective for New Zealand forest harvesting industry.

#### **2.4.2 Returns to scale**

One recurring theme in forest economics literature has been on returns to scale; determining an appropriate scale of operation is crucial for the long term competitiveness of logging businesses (Stuart *et al.*, 2010). The results of the returns to scale of the New Zealand logging contractors obtained from BCC DEA model over the study period is shown in Table 2.5. The results indicate that 36.4 % of the logging contractors operated under increasing returns to scale, 50.5 % operated under decreasing returns to scale, while 13 % performed under constant returns to scale over the entire study period (2009-2015). This implies that majority (87 %) of New Zealand logging contractors are performing under variable returns to scale. The high percentage of the DMUs operating under decreasing returns to scale (increase in inputs produces less than proportionate increase in output) is a reflection of the reported poor pure technical efficiency of the DMUs. The result indicates that about 50 % of the contractors operate in a scale larger or smaller than their most productive size. The results of this study

is in line with the previous findings of Stuart *et al.* (2010), and LeBel and Stuart (1998) suggesting that the logging industry is characterized mainly by decreasing returns to scale.

To maximize economies of scale, mergers and acquisition of DMUs under increasing returns to scale is a viable option as they have opportunities to expand and utilize more resources to produce greater than proportionate output and become efficient; creating larger and more competitive firms. However, merger and acquisition is not a common trend among forest harvesting entrepreneurs as they often favour maintaining status quo, selling or closing the business with very few expanding or diversifying the activities of the business (Drolet and LeBel, 2010). The strong desire for independence by harvesting contractors which is often the primary motivation for going into business, and the lack of formal training in business management (Drolet and LeBel, 2010) could be some contributing factors. A more realistic option would be for the clients (forest companies) of the logging contractors operating under increasing returns to scale to allocate more forest resources to them, and for the firms to invest in promoting growth in order to increase average productivity.

On the other hand, logging firms operating under decreasing returns to scale are already operating in super-optimal scale with less than proportionate increase in output following an increase in inputs. Input resources available to these DMUs could be redistributed or reallocated to contractors operating under increasing returns to scale unless they are willing to improve their production capacity through capital investment in equipment and machinery, human capital, and technology in order to increase average productivity. DMUs under constant returns to scale are operating at their optimal scale and thus, do not need a change in their size or scale of operation as far as efficiency improvement is concerned (Singh, 2016). A change in their size could move them into sub-optimal or super-optimal scale thus reducing their scale efficiency.

It is not uncommon for firms that have been in operation for a long time to operate under constant or decreasing returns to scale, while newer firms operate under increasing returns to scale, with opportunities for growth (Vahid and Sowlati, 2007). This is mainly because older firms are often very large, with more complex decision making process to effectively oversee each unit of the production process as opposed to start-ups which are often smaller in size

(Odeck, 2009; Lee, 2005). Nyrud and Bergseng (2002) in their study on the production efficiency of Norwegian saw mills is of the opinion that investments in technology is often not fully utilized to enhance production efficiency until the business unit had gained sufficient experience with the technology and knowledge of the production structure. Although lacking in the data source for this study, average age of the management team, years of operation of the firm (experience), and education level of the crews could be some excellent factors to assess the influence of age of business on the returns to scale of logging contractors.

From 2009 to 2015, lower percentage of the contractors operated under constant returns to scale in comparison to those that operated under increasing and decreasing returns to scale (Table 2.5). The values range from 10.5% in 2013 to 33.3% in 2014. New Zealand logging contractors should aim to move from the position of sub-optimal or super-optimal scale to constant returns to scale, and remain in that position to efficiently transform available resources for optimal productivity, and for long term competitiveness. With the near maturity of forests planted in recent decades (MPI, 2016), this might be the right time for the New Zealand logging contractors operating under DRS to focus more on improving their technical efficiency which could move them to operate under constant returns to scale. While those under increasing returns to scale explore opportunities for expansion. With most harvesting operations moving on to more difficult and distant terrain in New Zealand, Kant and Nautiyal (1997) are of the opinion that the logging industry must not be complacent about its technology, as it must invest in technological sophistication and training of workers on the efficient use of such technologies to counteract the negative effect of this movement.

#### **2.4.3 Optimal input and output targets for inefficient DMUs**

One of the major objectives for measuring the efficiency of a production unit is to evaluate its relative productivity, and to identify opportunities for improving production efficiency based on its current available resources and performance of its efficient peers. The relative technical efficiency scores reported for the DMUs over the years (Table 2.5) is an indication of their ability to efficiently transform available resources into desired output. Relatively inefficient contractors can operate at the output levels of their efficient peers by increasing production capacity, investing in new technologies, and optimizing harvesting processes. To buttress this point, Table 2.6a and b shows the original input and output level of some

contractors and the projected input-output targets that will allow the DMUs to operate at the efficient frontier based on BCC model. The projection targets were calculated using the value of slacks determined for the DMUs (Equation 2.5). The slacks are related to allocative efficiency, that is, the capacity of a DMU to utilize its inputs in optimal proportions (Coelli, 1996) and are estimated based on empirical observations and comparative calculations (Lewin *et al.*, 1982). Low performing DMUs have to reduce their inputs by their respective value of slacks in order to become allocative efficient (Omid *et al.*, 2011). Zero value of slacks for an input of a DMU shows that it has been efficiently allocated and utilized in the right proportion.

**Table 2.6a** Production factor levels of some contractors

S/No.	DMU Identifier	Original value					
		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$y_1$
1	246	31	5	29	14	22185	67
2	171	18	2	5	7	3063	21
3	205	12	4	3	11	1986	20
4	125	10	4	5	11	2700	30
5	6	13	3	7	11	4118	40

Harvest days -  $x_1$ , number of machines -  $x_2$ , harvest area size (ha) -  $x_3$ , number of log sorts -  $x_4$ , Timber (tonnes) -  $x_5$ , Productivity (tons/SMH) -  $y_1$

**Table 2.6b** Projected production factor targets based on BCC model

S/No.	DMU Identifier	Projected targets					
		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$y_1$
1	246	29	5	21	13	22185	75
2	171	12	2	3	7	3063	28
3	205	9	4	3	11	1986	26
4	125	8	4	4.	11	2700	36
5	6	11	3	6	11	4118	42

Harvest days -  $x_1$ , number of machines -  $x_2$ , harvest area size (ha) -  $x_3$ , number of log sorts -  $x_4$ , Timber (tonnes) -  $x_5$ , Productivity (tons/SMH) -  $y_1$

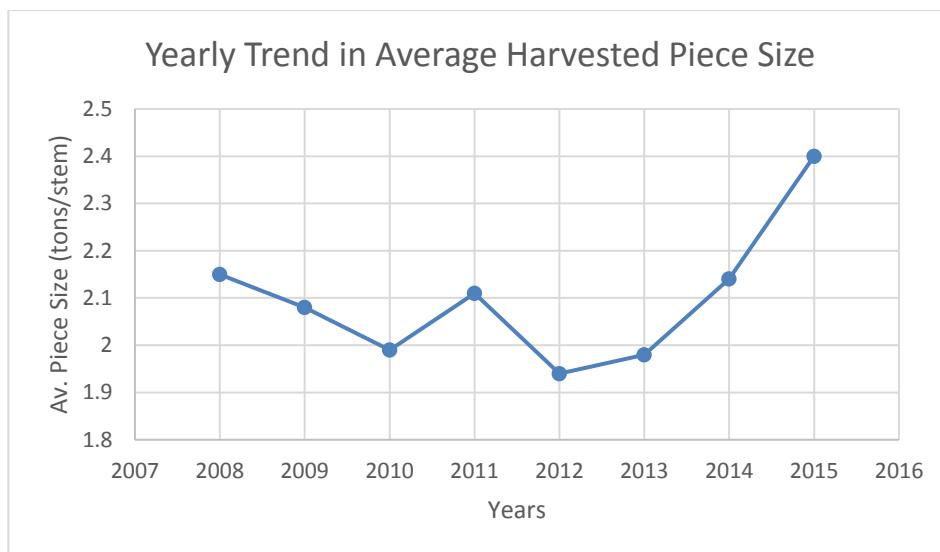
Theoretically, for contractor 246 to operate on the efficient production frontier, it has to be allocated a smaller harvest area of 21 ha from its original value of 29 ha, and reduce its log sorts by 1. The reduction in the allocated harvest area is expected to bring about a reduction in its harvest days by 6% with a resultant increase in productivity by 11% (from 67 to 75 tons/SMH). Similarly, for contractor 171 that operated on a woodlot of about 5ha to attain

the efficient production frontier, it should be allocated a smaller harvest area of about 3ha that would bring about a reduction in its harvesting days as suggested by DEA. This is could increase its productivity by 25% from 21 to 28 tons/SMH. Forest management companies can identify harvesting capacity of crews and effectively allocated resources to them by using information on the input-output targets of DEA. Crews may also use the information to identify the need for investment in technology and in managerial skills for improved harvesting capacity. Although input-output targets are theoretically possible, they must be interpreted with caution as the attainment of the targets may be interfered with by external factors since forest harvesting operations are carried out in complex and unstructured environment.

For the DMUs to reduce harvest area size and maintain the present level of timber harvest ( $x_5$ ), average harvested piece size and forest density (volume of wood per area) is expected to increase thus, requiring the application of sound management practices by forest managers to improve the size and quality of harvested forest trees. However, the average harvested piece size in New Zealand has generally been on the decline from 2008 up until 2014 when it recorded an increase (Figure 2.2). As rightly pointed out in Hailu and Veeman (2003), these factors are positively related to the technical efficiency of forest harvesting operations.

If all the less efficient DMUs identified over the entire study period achieve their individual projected factor targets and operate at the level of efficient DMUs, a reduction in the average input values and an increase in average output for the industry as a whole is expected. An increase of 45 % in system productivity from an average value of 28.7 to 52.2 tons/SMH is achievable. Considerable reduction in inputs per harvest cycle is expected from the average number of harvest days (60 %) and the mean harvest area size (44.5 %). A reduction of 1.8, 1.9, and 4.9 % is expected from the average number of machines, number of log sorts, and total harvest timber per harvest area, respectively for the industry as a whole. The overall reduction in average input levels particularly for the average harvest days, and an increase in the average productivity is expected to positively affect the revenue of the contractors due to the expected significant reduction in operational costs and increased revenue per SMH. However, better explanation of this outcome requires cost data. That notwithstanding, LeBel

and Stuart (1998) note that the level of technical efficiency determines the average production cost for a contractor; for a given scale size, logging contractors with lower efficiency always have higher production costs than the more efficient ones. Projected input and output values should be achievable because some of the logging contractors (efficient ones) involved in the analysis achieved them successfully hence they are benchmarks for the inefficient ones. As earlier stated, these targets may be difficult for some crews to attain due to the influence of external factors.



**Figure 2.2** Trends in average harvested piece size (2008 - 2015)

## 2.5 Conclusions

This paper presents the first performance evaluation of the New Zealand forest harvesting sector. A non-parametric mathematical programming approach, DEA was used to calculate the aggregate or overall efficiency, pure technical efficiency, and scale efficiency of the logging contractors for the period 2009 - 2015. Based on the available data for five inputs and one output, output-oriented CCR and BCC DEA models were used for the performance analysis. The logging industry is characterized mainly by less efficient DMUs, requiring improvement in their technical and resource management skills. In terms of efficient DMUs, the majority of contractors are scale efficient with an average scale efficiency score of 0.97 over the entire study period. The industry can improve its overall efficiency level through technological advancement, training, improved managerial capability, and effective allocation of resources by the forest management companies. However, a more detailed and

extensive data is required for in-depth understanding of the specific reasons for the low performance of some contractors, and understand what the efficient contractors are doing differently. Such reasons could be linked to machinery type – purpose built or modified, harvesting system and its configuration, the nature of the operating environment, experience of the crew, age of the business, weather delays, and operating skill. About 50 % of the contractors operate under decreasing returns to scale thus requiring appropriate redistribution or allocation of input resources to operate at their most productive scale size. To attain efficient level, optimal input and output targets have been calculated for the less efficient DMUs using output-oriented BCC DEA model. The results indicate that, on an average, an increase of 45 % in output (productivity) of the contractors is achievable with considerable reduction in average number of harvest days (60 %) and mean harvest area size (44.5 %). This is expected to have some level of positive effect on the contractors' revenue. It is important to note that the expected increase in productivity is subject to the provision of stand and terrain conditions conducive for efficient harvesting operations since the influence of the operating environment on performance was unaccounted for in the DEA. The potential contribution of the operating environment on harvesting performance is addressed in the subsequent chapters of the thesis.

This research demonstrates the application of DEA within the forest harvesting sector in estimating the performance of harvesting crews using data on their production inputs and outputs. With the collection and the use of right data, the results from DEA can be a useful guide for forest companies, logging entrepreneurs and other stakeholders in identifying sources of inefficiency and improve the allocation of input resources. The study is unique being the first to use firm-level data to measure the performance of logging contractors using DEA, and important considering the scarcity of literature on performance measurement in forest harvesting industry. Beyond providing information on the performance of DMUs, it is important to examine possible variations in technical efficiency of the DMUs attributable to exogenous variables characterising the production environment of harvesting crews.



## **Chapter 3**

### **Influence of External Factors on the Technical Efficiency of Forest Harvesting Operations: A Frontier Approach**

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The contents of this chapter have been published as:

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#### **3.1 Introduction**

The performance of a production entity, that is, its ability to transform inputs into outputs is not only affected by discretionary inputs (i.e. variables controllable by the management), but also by factors exogenous to the production system (otherwise referred to as the operating environment or environmental factors), beyond managerial control (Fried *et al.*, 2002; Ruggiero, 1996). Exogenous factors here refers generally to factors outside the direct managerial influence of the production entity under investigation – they neither can increase nor decrease such factors to favour their output. This is particularly worth considering when the production entities under analysis utilize a complex mix of inputs (Da Cruz and Marques, 2014) as it is in the case of forest harvesting operations. Some researchers have investigated the influence of the operating environment on efficiency within the forest harvesting sector using stochastic frontier analysis (SFA) – a parametric frontier approach. Aalmo and Baardsen (2015) applied SFA to assess selected sources of inefficiency on productivity of steep terrain harvesting crews based on data from 11 harvest crews operating on 22 harvesting sites in Norway. Lien *et al.* (2007) examine how the technical efficiency of forest owners as timber suppliers and forest managers is affected by owner and ownership characteristics using SFA. However, there is no existing study that has assessed variations in estimated technical efficiency of forest harvesting operations due to exogenously fixed or non-discretionary factors using the non-parametric frontier approach of DEA in a two-stage procedure.

With only a few studies on the influence of exogenous factors on forest harvesting sector (i.e. those contributing to the increase or decrease in inefficiency within the sector), there is limited empirical evidence available to stakeholders and policy-makers in understanding performance patterns. Using an existing New Zealand benchmarking dataset (Visser, 2016) at the individual contract level, this study examines some exogenous factors capable of influencing the technical efficiency of forest harvesting operations using a two-stage approach that employs DEA and regression model. Previously, using the same dataset aggregated at the contractor level, Obi and Visser (2017b) estimated the operational efficiency of timber harvesting contractors using DEA. Evaluating the influence of environmental factors on the efficiency of production units is an important aspect of benchmarking analyses as it provides explanations for conditions outside the production units that create inefficiency. This study is expected to help logging entrepreneurs and forest companies identify external factors that warrant careful attention with regard to improving performance in harvesting operations.

### **3.2 Methodology**

#### **3.2.1 Dataset**

An existing cost and productivity benchmarking dataset managed by the University of Canterbury (UC) on contract to Future Forest Research (FFR) is used in this study. Visser (2009) and Visser (2011) provide detailed background information on the UC/FFR benchmark database system, and summary reports are prepared annually to industry participants that include cost and productivity trends. The dataset contains comprehensive and detailed information on system, stand and terrain factors with over 1000 unique entries on forest harvesting operations in New Zealand from 2008-2015 (Visser, 2016). Data is provided by participating forestry management companies based on actual harvesting contracts, and provides opportunities for tracking changes in the terrain, stand and harvest system parameters based on defined harvest areas. The uniqueness of the dataset is that it provides opportunity to analyse data at harvest contract-level thus capturing the unique environmental conditions specific to each contracted harvest operation, which could have been difficult to obtain with operations aggregated at firm- or crew-level. After discarding invalid and missing entries, a total of 1006 entries were utilized for the study.

### **3.2.2 Production and exogenous factors**

In this study, individual harvest operations completed by logging contractors in which certain inputs are utilized to produce an output is considered a production unit. The criteria for the selection of inputs and outputs in this study are primarily based on availability of data in the UC/FFR database and survey of relevant literature. Five inputs and one output that relate to quantifiable production factors in forest harvesting operations were selected. The input includes: number of harvest days used to complete the harvesting of a defined forest area; number of machines on site including primary (felling and extraction) and secondary (processing and loading out) machines; number of workers or crew members for the harvest operation; harvest area size (ha) defined as a contiguous forest area extracted to a single landing; and average system hour per day excluding travel time to and from the harvest area. The output is system productivity (tons/SMH) defined as total volume of timber divided by the total harvest time. The factors provide tangible measureable input resources and output that characterize forest harvesting operation, and are recognised as good indicators for harvesting efficiency measurement (Upadhyay *et al.*, 2012; Šporčić *et al.*, 2009; Lien *et al.*, 2007; Nanang and Ghebremichael, 2006; Siry and Newman, 2001; Kao *et al.*, 1993).

The choice of exogenous factors selected in this study is limited by availability of data in the UC/FFR database and the unique operating environment associated with the harvesting operations. The influence of five exogenous factors (explanatory variables) on the technical efficiency of forest harvesting operations is investigated namely, forest region which could vary in terms of soil characteristics or even level of competition; size of forest harvesting operation defined on the basis of average merchantable harvested timber per day (tons/day) from a defined forest area; terrain slope which defines the average steepness or slope of the forest area; number of log sorts, and average piece size of harvest log from a harvest area. Table 3.1 presents the summary statistics of the inputs, output and exogenous factors (explanatory variables).

**Table 3.1** Summary statistics of the production and explanatory factors

Factors	Statistics			
	Mean	Std. Dev.	Minimum	Maximum
<b>Inputs</b>				
Harvest days	38	33.3	2	243
Number of machines	4.5	1.3	1	11
Number of workers	8	2.1	2	17
Harvest area size (ha)	17.8	17.6	0.2	138.4
System hour/day (hr)	8.4	0.5	7	10
<b>Output</b>				
System productivity (tons/SMH)	28.2	11.9	5.2	72.9
<b>Exogenous</b>				
Size of operation (tons/day)	238.9	127.6	43	2884
Terrain slope (%)	32.5	21.1	0	100
Number of log sorts	10.3	3.4	1	21
Piece size (ton/stem)	2.1	0.7	0.3	6.2
*Region	South Island = 1 East Coast and Hawke's Bay = 2 Rest of North Island = 3			

\*Dummy variables are used to represent the three different regions. '1' represents SI, '2' represents ECHB, and '3' represents RNI

### 3.2.3 A two-stage approach

To evaluate the effect of exogenous factors, that is the operating environment, on the technical efficiency of forest harvesting operations, a two-stage procedure is employed. In the two-stage approach, technical efficiency of the production entities (forest harvesting operations) is determined in the first stage using DEA based on inputs and outputs of the entities, and in the second stage the efficiency is regressed against a set of exogenous factors (Liu *et al.*, 2016). The two-stage approach is the most widely used approach in the literature in investigating the effect of external factors on efficiency measures using DEA (Cordero *et al.*, 2015; He and Weng, 2012). It is considered logical, easy to communicate, and intuitively appealing for policy analysis and decision making by industry practitioners since it relates the exogenous variables directly to the estimated efficiencies of the production entities (Da Cruz and Marques, 2014; Yang and Pollitt, 2009; Yu, 1998).

The two-stage approach has been applied by a number of researchers in different context or production sectors (Fragoudaki and Giokas, 2016; Zhang *et al.*, 2016; Benito *et al.*, 2014; Wu *et al.*, 2013; Bädin *et al.*, 2012; Cordero *et al.*, 2009; Barros, 2008; Simar and Wilson, 2007;

Ray, 1991) including the timber processing mills. He and Weng (2012) applied the two-stage procedure to examine the technical efficiency of forest product processing mills, and the relationship between external factors (ownership type, autonomy, lucrative incentive schemes, and other manager and mill characteristics) and the estimated efficiency index of forest product processing mills. Similarly, Diaz-Balteiro *et al.* (2006) applied the same procedure to analyse the relationship between productive efficiency and innovation activity in Spain's wood-based Industry. Nyrud and Bergseng (2002) investigated the production efficiency in the Norwegian sawmilling sector by means of data envelopment analysis, and the effect of size on the efficiency score evaluated using censored regression analysis. The literature findings suggest that there are no available studies assessing the effect of external environment on the technical efficiency of forest harvesting sector using the two-stage approach hence, the relevance of this study.

### ***3.2.3.1 DEA specification: first-stage***

Performance in this study, which measures the ability of production units to maximize output (defined as system productivity) with a given set of inputs, is explained in terms of technical efficiency based on the production frontier of the units. The frontier defines the most efficient relationship between inputs and output of the units. The technical efficiency of the harvest operations is estimated based on the standard DEA approach of variable returns to scale (Banker *et al.*, 1984) in output orientation using the specialized DEA software package (DEAP version 2.1) (Coelli, 1996). The choice of an assumption about the returns-to-scale (either constant or variable) is not neutral as it conditions the representation of the DMUs on the envelopment frontier (Botti *et al.*, 2009). The VRS model (technical efficiency) is considered most appropriate for practical DEA study when analysing DMUs of varying sizes as it is in the case of forest harvesting operations (Metters *et al.*, 1999). However, the overall efficiency (CRS model) which is composed of a non-additive combination of pure technical and scale efficiencies is also presented. By considering performance in terms of output orientations, the study in effect investigated the impact of exogenous factors on profit maximization. The linear programming equations of CRS and VRS DEA models are well established in the literature (Coelli *et al.*, 2005; Banker *et al.*, 1984; Charnes *et al.*, 1978) and have been described in Chapter 2 of this thesis.

### **3.2.3.2 Kruskal-Wallis Test**

Prior to regressing the efficiency scores against the set of external variables, Kruskal-Wallis rank test, a non-parametric rank test is applied to the efficiency estimates to provide statistical rationale regarding what level of an environmental factor contributes more to the increase or decrease of technical efficiency of forest harvesting operations (Goncalves, 2013; Salehirad and Sowlati, 2005; Sueyoshi and Aoki, 2001; Kruskal and Wallis, 1952). That is, to determine whether one group of DEA efficiency scores based on its unique operating environment is statistically different (or more efficient) from another group. The non-parametric rank test is applied since the theoretical distribution of DEA efficiency scores is unknown and a simple comparison based on average efficiency scores would have no statistical validity (Lee *et al.*, 2009).

To apply the test, the external factors are grouped into different categories or levels based on the prevailing situation in New Zealand logging sector. Three regions, as earlier stated are identified for the purpose of this study: SI, ECHB, and RNI. Size of operation is a variable of extensive interest in studies on enterprise performance (He and Weng, 2012) and it is categorized into three levels: large, medium and small. With most New Zealand's production forests on steep terrain (Bayne and Parker, 2012), terrain slope makes an important consideration in forest harvesting performance. Three categorizes are identified, steep, rolling and flat terrain. The number of log sorts in logging operations in New Zealand range from 8 – 22, sorts less than 8 is considered small while sorts more than 12 is considered large. The piece size is categorized into three groups: large ( $>2.5$  tons), medium ( $2.5 \leq$  piece size  $\geq 1.7$  tons), and small ( $<1.7$  tons).

The Kruskal-Wallis test ( $H$ ), which has been applied in previous DEA performance studies (Goncalves, 2013; Pulina *et al.*, 2010; Lee *et al.*, 2009; Salehirad and Sowlati, 2005; Nyrud and Bergseng, 2002; Sueyoshi and Aoki, 2001) is defined by (Goncalves, 2013; Sueyoshi and Aoki, 2001):

$$H = \frac{12}{n(n+1)} \sum_{i=1}^k \frac{R_i^2}{n_i} - 3(n+1) \quad (3.1)$$

Where  $k$  is the number of categories or size level of the variables,  $n$  is the total number of observations, that is, the number of harvest operations,  $n_i$  is the number of observations in category  $i$  ( $i = 1, \dots, k$ ) and  $R_i$  is the sum of rank for category  $i$ . When using the Kruskal–Wallis test, what is tested is the validity of hypothesis. To test for the null hypothesis  $H_0$  assuming that the harvest operations in different groups of operating environment are from the same population.  $H_0$ : There is no statistically significant difference in the mean of efficiency estimates across the environmental factor levels or categories. The alternate hypothesis  $H_1$ : There is statistically significant difference in the mean of efficiency estimates across the groups.

### **3.2.3.3 Regression analysis: second-stage**

In the second stage of the two-stage approach, the efficiency scores ( $\theta_j$ ) estimated in the first stage DEA are regressed against a set of exogenous factors ( $X_j$ ) being the dependent and explanatory variables, respectively. The regression model can be formulated as follows (Seifert and Nieswand, 2014):

$$\theta_j = \beta_o + \beta X_j + \varepsilon_j \quad j = 1, 2, 3, 4 \dots, n \quad (3.2)$$

with  $\theta_j$  representing the efficiency score of the  $j$ th observation bounded between zero and unity,  $\beta_o$  denotes the intercept (a constant term),  $X_j$  is a vector of environmental factor for  $j$ th unit,  $\beta$  is the coefficient which needs to be estimated and  $\varepsilon_j$  is error term. The second stage uses regression techniques to relate the efficiency index to the operating environment factors with the aim of identifying the factors whose impact are statistically significant and to determine the size of their marginal effects (Benito *et al.*, 2014). Tobit regression, which is widely used in the literature in determining the effect of exogenous factors on efficiency estimates, is applied in this study. Influential factors, their signs (positive or negative) and the size effect of each factor on the estimated efficiency score can be identified from the value of the estimated coefficients estimates (Aristovnik *et al.*, 2014; Ancarani *et al.*, 2009; Hoff, 2007). In Tobit regression, DEA efficiency scores are selected as right-censored (i.e. upper limit of 1).

### **3.3 Results and Discussion**

#### **3.3.1 Harvest operation efficiency estimates**

Table 3.2 presents the average estimated efficiency scores for 1006 forest harvesting operations under output-oriented DEA from 2008–2015. The average aggregate, technical and scale efficiency scores are 0.473, 0.483, and 0.965, respectively. The forest harvest operations appear to operate at high level of scale efficiency with about 90 % of the total DMUs at or above 90 % scale efficiency score (Table 3.3). This suggests that there are little unexploited scale economies by the harvesting operations. For aggregate and technical efficiency only about 3 and 4 % of the units operate at above 90 % score, respectively. More than 50 % of the operations are below 50 % efficiency score for both aggregate and technical efficiencies (Table 3.3). In terms of the returns to scale, some of the DMUs (39 %) operate under constant returns to scale while 28 and 33 % operate at increasing and decreasing returns to scale, respectively. Harvesting operations with increasing returns to scale suggest unexploited capacity to increase production while those with decreasing returns to scale handle more inputs than their capacity allow thus producing less than proportionate output with increase in inputs. Units with constant returns to scale are operating at their optimal scale or size. The source of inefficiency among the units could be related to technology and managerial skills, as they are often associated with technical efficiency of production units. This result is consistent with the findings previously reported in Chapter 2 of this thesis on the performance of New Zealand independent forest harvesting contractors.

**Table 3.2** Average efficiency score of the forest harvesting operations

Efficiency	Mean	Std. Dev.	Min	Max	Returns to scale (% of DMU)
Aggregate	0.473	0.178	0.114	1	CRS 39
Pure technical	0.493	0.190	0.116	1	IRS 28
Scale	0.965	0.064	0.36	1	DRS 33

CRS – constant returns to scale; IRS – increasing returns to scale; DRS – decreasing returns to scale;  
Total number of DMUs = 1006

**Table 3.3** Breakdown of harvest operation efficiency scores

Efficiency Range (%)	% of harvest operations		
	Aggregate	Technical	Scale
Equals 100	1.3	2.6	35.7
≥ 90 and < 100	1.7	1.8	57
≥ 70 and < 90	8.9	10.8	6.3
≥ 50 and < 70	23.7	25.2	0.5
< 50	64.4	59.6	0.5

### 3.3.2 Statistical comparison of different categories of exogenous factors

A comparison of technical efficiency (TE) of the forest harvesting operations across the different categories or levels of the exogenous factors - forest region, size of operation, terrain slope, log sorts and piece size, is presented in Table 3.4. Table 3.5 shows a breakdown of average input usage and output of the operations based on the operating environmental factor levels. The result in Table 3.4 shows that for each of the exogenous factors, the mean technical efficiency score for at least one of the categories of each of the operating environment factors is significantly different from the others ( $p < 0.01$ ) indicating some level of influence of the factors on forest harvesting performance.

Among the three different regions, ECHB has the lowest mean TE score of 0.423 (or 42.3 %) with 33 % of the harvest operations carried out in that region. None of the operations in that region is estimated as efficient indicating some level of inefficiency exhibited by the harvest operations in that region. Production units in RNI region (45 % of total units) has the highest mean technical efficiency score of 0.532 (or 53.2 %) with 19 of the operations estimated as efficient, that is, operating on the efficient frontier. The highest mean TE score of units in RNI region is reflected in its relatively high mean system productivity of 30.1 ton/SMH (Table 3.5). The high mean technical efficiency score and number of operations recorded in RNI suggest high competition among independent harvesting contractors in that region. For size of operation, large operations producing more than 300 tons/day of merchantable timber have the highest mean TE score of 0.728 (Table 3.4) and mean system productivity of 47.2 tons/SMH (Table 3.5). This is followed by medium size operations (mean TE = 0.491; mean system productivity = 28.1 tons/SMH) and then small operations with a TE score of 0.378 and system productivity of 18.2 tons/SMH, producing less than 200 tons/per day. As shown in Table 3.4, only 20 % of the total harvest operations are categorized as large operation while

**Table 3.4** Assessment of the mean efficiency estimates across different categories of the exogenous factors

Factors	Category	Scale	% of Units	Technical Efficient DMUs	Mean Technical Efficiency	*p value of Kruskal–Wallis test
Region	SI	1	22	7	0.515	0.000***
	ECHB	2	33	0	0.423	
	RNI	3	45	19	0.532	
Size of operation (tons/day)	Large	>300 tons/day	20	11	0.728	0.000***
	Medium	300≤ size ≥200 tons/day	39	4	0.491	
	Small	<200 tons/day	41	11	0.378	
Terrain slope (%)	Steep	>50%	21.7	0	0.399	0.000***
	Rolling	50 ≤ slope ≥ 20%	45.4	11	0.476	
	Flat	<20%	32.9	15	0.577	
Number of Log sorts	Large	>12 sorts	23	6	0.583	0.000***
	Medium	12≤ sorts ≥8	59.4	8	0.442	
	Small	<8 sorts	17.6	12	0.545	
Piece size (tons)	Large	>2.5 tons	24	6	0.547	0.000***
	Medium	2.5≤ piece size ≥1.7 tons	47	12	0.488	
	Small	<1.7 tons	29	8	0.456	

SI – South Island; ECHB – East Coast/Hawke's Bay; RNI – Rest of North Island. Dummy variables are used for to represent the three different regions under the scale column. '\*\*\*' indicate significance at  $\alpha = 1\%$ .

**Table 3.5** Breakdown of mean inputs and output across different categories of the exogenous factors influencing forest harvesting performance

Factors	Category	Scale		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$y_1$
Region	SI	1		39.9	5.3	6.8	20.8	8.5	29.1
	ECHB	2		32.6	4.3	8.7	12.5	8.5	24.8
	RNI	3		40.9	4.3	8.0	20.1	8.3	30.1
Size of operation (tons/day)	Large	>300 tons/day		41.4	5.3	8.5	28.6	8.3	47.2
	Medium	300 ≤ size ≥ 200 tons/day		36.0	4.7	8.1	16.8	8.5	28.7
	Small	<200 tons/day		38.1	4.0	7.6	13.3	8.5	18.2
Terrain slope (%)	Steep	>50%		33.5	4.5	8.8	13.3	8.5	24.0
	Rolling	50 ≤ slope ≥ 20%		37.3	4.7	8.0	16.8	8.5	27.0
	Flat	<20%		41.8	4.4	7.3	22.0	8.4	32.5
Number of Log sorts	Large	>12 sorts		45.8	4.9	8.7	24.8	8.4	36.9
	Medium	12 ≤ sorts ≥ 8		37.5	4.4	7.9	16.1	8.5	25.0
	Small	<8 sorts		29.2	4.5	7.1	14.1	8.3	27.3
Piece size (tons)	Large	>2.5 tons		33.9	4.5	8.8	16.4	8.4	32.9
	Medium	2.5 ≤ piece size ≥ 1.7 tons		38.6	4.5	8.1	17.8	8.4	27.7
	Small	<1.7 tons		40.3	4.6	7.1	18.8	8.5	25.0

SI – South Island; ECHB – East Coast/Hawke's Bay; RNI – Rest of North Island. Dummy variables are used for to represent the three different regions under the scale column;  $x_1$ - Harvest days;  $x_2$ - Number of machines;  $x_3$ - Number of workers;  $x_4$ - Harvest area size (ha);  $x_5$ - System hour per day (hr);  $y_1$ - System productivity (ton/SMH)

41% of the operations are categorized as small in terms of size. The high percentage of small operations could be attributed to the capacity of independent harvesting contractors, and the increasing trend in ownership of small forest blocks. As shown in Table 3.2, 28 % of the DMUs operate under IRS with capacity to expand their production capacity. Mean harvest area size for small operations is 13.3 ha while that of large size operations is 28.6 ha (Table 3.5).

Forest harvesting on steep terrain (slope greater than 50 %) is often difficult, and as expected recorded the lowest mean TE score of 0.399 (39.9 %). The mean system productivity for operations on steep terrains is also lowest with a value of 24 ton/SMH as opposed to 27 and 32.5 tons/SMH calculated for rolling and flat forest terrains, respectively (Table 3.5). None of the operations on steep terrain is estimated to operate on the efficient frontier. Harvest operations on flat terrain (slope less than 20 %) are estimated to have the highest mean TE of 0.577 followed by operations on rolling terrain (mean TE = 0.476). The lowest mean TE estimated for operations on steep forest terrain suggests that the technology as well as the required management practices for steep terrain harvesting is still in its developmental stages in New Zealand compared to flat or rolling terrain harvesting. With most of production forest areas to be harvested in near future in New Zealand situated on steep terrain (Bayne and Parker, 2012), this calls for concerted effort by industry stakeholders to invest in and develop appropriate technologies for steep terrain harvesting in order to improve harvesting performance.

Interestingly, operations with large number of sorts are estimated to have the highest mean TE score among the categories under the exogenous factor, number of log sorts. This is understandable in that operations with large log sorts are often carried out in large forest areas (mean harvest area ( $x_4$ ) is 24.8 ha higher than 16.1 and 14.1 ha for medium and small log sorts operations as shown in Table 3.5) producing large quantity of logs. Moreover, as earlier discussed, large operations producing more than 300 tons of timber per day are estimated to have the highest mean TE score among the different categories of size of forest harvesting operation. In terms of piece size, operations with large piece size (>2.5tons/stem) is estimated to operate at a mean TE of 0.547 followed by those with medium piece size from 1.7 to 2.5 tons/stem (mean TE = 0.488). Increasing piece size has been reported to significantly favour forest harvesting productivity (Strandgard *et al.*, 2014; Nakagawa *et al.*, 2010). The

production output that is, the system productivity presented in Table 3.5, appears in a pattern that supports conclusions drawn from the mean TE estimated for each category of the exogenous factors in Table 3.4.

### **3.3.3 Regression analysis of determinants of harvesting efficiency**

To identify the non-discretionary or exogenous factors that influence the performance of forest harvesting operations, and determine the direction and magnitude of the effects, the technical efficiency score is regressed against the set of exogenous factors using Tobit regression. The regression model is specified as:

$$\theta_j = \beta_0 + \beta_1 Region_j + \beta_2 Size_j + \beta_3 Slope_j + \beta_4 Log\ sorts_j + \beta_5 Piece\ size_j + \varepsilon_j \quad (3.3)$$

where  $\theta_j$  is the VRS DEA technical efficiency score,  $\beta_0$  is the intercept (a constant term),  $\beta$  are coefficients of associated factor that needs to be estimated, and  $\varepsilon_j$  is the error term. A positive (negative) sign of the second-stage estimation coefficient indicates a positive (negative) impact of the exogenous factor on the technical efficiency of forest harvesting operations.

Table 3.6 presents the results of the regression analysis using Tobit regression. The estimated coefficients for the explanatory variables generally conform to *a priori* expectations. As presented in Table 3.6, all the exogenous factors have significant influence ( $p < 0.01$ ) on the technical efficiency of the forest harvesting operations except the forest region where the operation is carried out. Although the region of operation influences technical efficiency, the effect is not statistically significant ( $p > 0.01$ ). Among the exogenous factors, piece size has the largest significant ( $p < 0.01$ ) positive effect on the technical efficiency. This agrees with the finding by Nakagawa *et al.* (2010) who reported that about 68 % of total time for tree processing work components is influenced by piece size, which could vary depending on the work combination. Nakagawa *et al.* (2010) and Puttock *et al.* (2005) further report a significant increase in harvesting productivity as diameter at breast height (DBH), and piece volume increased. The region, size of operation and piece size all have positive effects on the technical efficiency of harvest operations whereas terrain slope and log sorts have negative effects.

Increasing terrain slope significantly ( $p < 0.01$ ) reduces technical efficiency of harvesting operation. Earlier published studies report a negative significant influence of terrain slope on forest harvesting machine productivity (Aalmo and Baardsen, 2015; Spinelli *et al.*, 2010). Increasing the size or scale of forest harvesting operation significantly ( $p < 0.01$ ) impacts positively on technical efficiency of the operation. The negative influence of increased log sorts on technical efficiency is supported by earlier studies. Tolan and Visser (2015) in their study on the effect of number of log sorts on log processing productivity and value recovery report that harvesting operations with 15 log sorts decrease processor productivity by around 10 %, but cutting 9 log sorts gave the optimum cutting scenario in terms of the value produced per productive machine hour.

**Table 3.6** Regression result of the effect of exogenous factors on harvesting efficiency

Factors	Coefficient	Std. Error	z-statistic	p-value
<b>Tobit estimation</b>				
Constant	0.2989	0.0215	13.9333	0.0000
Region	0.0037	0.0052	0.7018	0.4828
Size of operation	0.0014	0.0000	31.0578	0.0000
Terrain slope	-0.0022	0.0002	-10.5253	0.0000
Log sorts	-0.0114	0.0013	-9.0068	0.0000
Piece size	0.0225	0.0066	3.4134	0.0006
Likelihood ratio	891.09			0.0000

Probability level,  $\alpha = 1\%$

### 3.4 Implications for Industry Stakeholders

This study sheds light on factors outside the control of independent logging contractors that can affect the performance of forest harvesting operations. Size of operation, terrain slope, number of log sorts and piece size all have statistically significant impact on the estimated technical efficiency of forest harvesting operations whereas the effect forest region is not significant. This suggests that the technical efficiency of harvest operations by independent logging contractors could change from high to low and from low to high as the operating environment changes. The findings from this study have implications beyond simply providing a better understanding of the technical efficiency of forest harvesting operations as influenced by the operating environment. The positive impact of size of operation on harvesting efficiency suggests the need for small independent logging contractors to increase their capacity to handle large scale harvest operations. To achieve this, capital investment in

equipment and human development could be explored as well as mergers or collaborative operations among small contractors to benefit from economies of scale of operation. It is a common knowledge that the number of small forest owners in New Zealand is on the increase, and the small volume involved in small forest areas as well as the associated high costs of moving equipment to isolated small areas make most woodlots uneconomical to harvest. As a result, tract consolidation in the form of aggregation of woodlots in close proximity represents an important pre-requisite for improved operational performance by the contractors through capacity expansion since size of operation has been linked to tract size as shown in Table 3.5.

As expected, increased forest terrain slope offers increasing negative impact on technical efficiency due to the difficult nature of efficiently using forest machines on steep slopes. Aalmo and Baardsen (2015) add that steep terrain harvesting remains one of the most physically demanding forest harvesting operation in spite of increased mechanization. Specialization is generally believed to improve efficiency and as such, investing in the development and optimization of specialized technologies for steep terrain harvesting (e.g. the cable-assisted ground-based harvesting system), could help reduce technical inefficiency associated with steep forest harvesting. Robotics, for example, may aid harvesting of logs from difficult terrain to improve productivity and effectively manage the cost of safety regulatory compliance of having crews on such terrain (Bayne and Parker, 2012). Providing targeted training to equip harvesting crew members for such challenging environment could also be a plausible strategy (Aalmo and Baardsen, 2015). These strategies have potentials to increase harvesting performance on steep terrain since technological product and process innovation are some key determinants of competitiveness (Orfila-Sintes and Mattsson, 2009).

Based on the regression analysis, increasing number of log sorts negatively affects technical efficiency of harvesting operations. However, increased log sorts favour technical efficiency of large-scale due to the capacity of large number of machinery to handle large volumes. In small-scale operations, fewer numbers of stems are often obtained, as such small number of log sorts is recommended. Piece size measured in ton/stem arguably is the most influential exogenous factor on technical efficiency of forest harvesting based on its positive marginal effect. Previous studies have shown that piece size is the most influential factor affecting

harvesting productivity, with productivity increasing as tree size increases (Strandgard *et al.*, 2014; Ghaffariyan *et al.*, 2012; Nakagawa *et al.*, 2010; Spinelli *et al.*, 2010). Tolan and Visser (2015) report a strong positive influence of piece size on harvesting productivity that is in agreement with the findings of this study. The positive impact of piece size on technical efficiency suggests that the ongoing campaign among forest industry stakeholders to encourage the harvesting of older trees with larger piece size as opposed to younger ones needs to be intensified. Although the upstream sector benefits from this campaign through improved harvesting efficiency, this benefit trickles to the downstream sector in the form of improved quality of forest products. Based on the existing production technology in New Zealand, the change in forest plantation silviculture regimes from pruning (clears) to structural (framing) (Mason, 2012) could negatively impact harvesting efficiency due to the small piece size. Further study is suggested to better understand the influence of piece size on efficiency as it could have some interplay with machine type, size, as well as the operator skill. In practical application, this study provides information useful in identifying important external factors that need to be considered in the assessment and improvement of harvesting performance.

### **3.5 Conclusions**

This paper employs a two-stage procedure to determine the influence of the operating environment factors on the technical efficiency of forest harvesting operations. The study shows that DEA in addition with Tobit estimation can be successfully applied to measure the determinants of efficiency in forest harvesting operations. DEA is used to estimate the technical efficiency of the operations, and the efficiency index regressed against a set of selected exogenous factors. Majority of the harvesting operations are highly scale efficient but the source of inefficiency among the units is technical. The study shows that the technical efficiency of forest harvesting operations can be significantly influenced by the unique operating environmental characteristics of the harvesting sites exogenous to managerial control. The environmental factors include size of the operation, terrain slope, number of log sorts and piece size. These exogenous factors can contribute (increase or decrease) inefficiency and, must be taken into consideration by industry stakeholders when assessing performance and evaluating potential operational improvement strategies or policies. An important aspect of the operating environment not covered in this study are factors

endogenous to independent logging contractors such as years of experience, age and educational background, age of the business, system configurations, etc.; the influence of such factors on harvesting performance could form a future line of study.



## **Chapter 4**

### **Accounting for the Operating Environment Factors in the Performance Estimates of Harvesting Operations**

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The contents of this chapter have been presented as a poster and has been accepted for publication:

*Obi, O.F. and Visser, R. (2017). Measuring the harvesting efficiency of logging crews and the effect of external factors. A poster presented at the 2017 New Zealand Institute of Forestry Conference, 4 – 6<sup>th</sup> September, 2017, Novotel Rotorua Lakeside, Rotorua, New Zealand.*

*Obi, O.F. and Visser, R. (2017). Including Exogenous Factors in the Evaluation of Harvesting Crew Technical Efficiency using a Multi-Step Data Envelopment Analysis Procedure. Croatian Journal of Forest Engineering, Accepted for publication.*

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#### **4.1 Introduction**

Researchers in the field of logging operations have recently began to apply DEA in estimating performance of forest harvesting operations and it is gaining attention (Obi and Visser, 2017b; Hailu and Veeman, 2003; LeBel and Stuart, 1998). The application of DEA in the forest harvesting sector offers opportunities for examining harvesting efficiency owing to its flexibility, without requiring assumptions about the functional relationships among inputs and outputs, and its invariant nature to units of production factors (Macpherson *et al.*, 2013). The effective application of DEA is based on the assumption that the decision making units (DMUs) or production units whose performance is being estimated operate within a homogenous production system or environment (Carrillo and Jorge, 2016). However, this assumption in practice does not hold in forest harvesting operations as the ability of a production entity to transform inputs into outputs is not only affected by discretionary inputs (i.e. controllable by the management) or managerial skills. It is also influenced by exogenous factors such as terrain slope, roughness or tree size (otherwise referred to as the operating environment or environmental variables) that are beyond direct managerial control (Obi and Visser, 2017a;

Aalmo and Baardsen, 2015). An unfavourable operating environment would demand additional inputs from a production unit to produce the same level of output as a unit in a favourable environment in order to overcome the external disadvantage making the unit's efficiency to be underestimated (Hu *et al.*, 2011). This has been identified as a major problem in benchmarking as most performance assessment techniques do not account for differences in the operating environment of production units (Carvalho and Marques, 2011; Fried *et al.*, 2008).

In forest harvesting where operations are carried out in complex and unstructured operating environments (Di Fulvio *et al.*, 2017), factors exogenous to harvesting crews' control are likely to either positively or negatively influence the performance of harvesting operations. For example, steep terrain or terrain hindrance is expected to be more difficult for ground-based harvesting systems in terms of machine trafficability as opposed to flat or rolling terrain. As such, a relatively efficient crew in a harvest operation with high degree of terrain hindrance may be labelled as inefficient when benchmarked against another in an operation with low level of terrain hindrance. Without adequately controlling for exogenous factors, efficiency estimates in DEA will most often be biased as inefficiencies are assumed to be attributable purely to managerial skills (Macpherson *et al.*, 2013). The managerial efficiency of units in adverse or unfavourable operating environments could be underestimated, conversely those in favourable environments could be overestimated (Yang and Pollitt, 2009) and could lead to inefficient allocation of resources (Kontodimopoulos *et al.*, 2010). Accounting for differences in the operating environment of independent forest harvesting contractors is critical for objective and unbiased assessment of performance among harvesting crews.

There is an established four-stage DEA procedure developed by Fried *et al.* (1999) which is able to account for the factors that are not in direct control of the harvesting crews. There are some publications on performance evaluation that accounted for the effects of exogenous factors on the efficiency of production entities in different industries (Zhu *et al.*, 2016; Ferrera *et al.*, 2014; Macpherson *et al.*, 2013). However, there is no literature controlling for the effects of the operating environment on efficiency estimates of forest harvesting operations. Existing studies on the application of DEA in the forest harvesting sector have so far focused on assessing performance without considering non-discretionary inputs. The objective of this

study therefore, is to measure the managerial efficiency of independent forest harvesting contractors in New Zealand taking into account the effect of differences in the operating environment. This removes the environmental bias and the resulting performance estimates are attributable purely to managerial efficiency. The key contributions of the study is its application of the four-stage DEA to the forest harvesting sector considering the complex and unstructured nature of forest harvesting operations, and the direction it provides as to the interaction between exogenous factors and the use of individual inputs.

## 4.2 Methodology

### 4.2.1 The four-stage DEA procedure

Fried *et al.* (1999) developed an empirical technique named the *four-stage DEA approach* to separate managerial inefficiency from other inefficiency components beyond managerial control. The four-stage DEA procedure rests on the premise that DMUs operating in relatively unfavourable environments may be wrongly labelled as inefficient (Hu *et al.*, 2011; Yang and Pollitt, 2009). This procedure is able to control for the exogenous factors by compensating for the effects of the factors, and has been applied in previous literature (Zhu *et al.*, 2016; Ferrera *et al.*, 2014; Kontodimopoulos *et al.*, 2010; Yang and Pollitt, 2009). Data on the original production factors are modified according to the effects of the exogenous factors, and the modified data are used for the final performance evaluation, thus providing a pure measure of managerial efficiency. The procedure is briefly described here so that the reader can follow the process through to the results. For extended description of the four-stage DEA procedure readers are referred to Fried *et al.* (1999).

#### 4.2.1.1 Stage one DEA

In the first stage, following a standard production theory set under variable returns to scale, a DEA production frontier is estimated using selected inputs and outputs for the production units. The DEA estimator is used to estimate the Farrell technical efficiency (Farrell, 1957) defined as a measure of efficiency under the restriction that a linear combination of efficient units produces the same or more of all outputs and that the reduction in inputs is equiproportional. The efficiency scores are estimated without regard to the environment factors. This establishes a best-practice frontier for the DMUs based on the inputs and outputs included in the DEA. However, the efficiency estimates of units operating under “good”

operating environment are overestimated and that of the units under “harsh” or “difficult” operating environments are underestimated. An input-oriented DEA framework with variable returns to scale (Banker *et al.*, 1984) is adopted in the first DEA stage and can be represented by the following expression (Cordero-Ferrera *et al.*, 2011):

$$\text{Min } \theta_0 - \varepsilon \left( \sum_{r=1}^s s_r^+ + \sum_{i=1}^m s_i^- \right)$$

Subject to

$$\begin{aligned} \sum_{j=1}^n \lambda_j x_{ij} + s_i^- &= \theta_0 x_{ij0} & (4.1) \\ \sum_{j=1}^n \lambda_j y_{rj} - s_r^+ &= y_{rj0} \\ \sum_{j=1}^n \lambda_j &= 1 \\ \lambda_j, s_i^-, s_r^+ &\geq 0, i = 1, 2, \dots, m; r = 1, 2, \dots, s; j = 1, 2, \dots, n \end{aligned}$$

where  $x_{ij}$  is the vector of inputs and  $y_{rj}$  the vector of outputs for unit  $j$ ;  $\theta_0$  is the efficiency score,  $\varepsilon$  is an infinitesimal non-Archimedean constant,  $\lambda_j$  are the weightings and  $s_i^-$  and  $s_r^+$  are the inputs slacks and outputs slacks, respectively.

#### **4.2.1.2 Stage two**

The second stage is to estimate  $N$  input equations using an appropriate econometric method such as the Tobit regression. The dependent variables are total input slacks (radial plus non-radial slack) estimated from the first stage DEA, while the independent variables are measures of the external operating environment applicable to the particular input. This quantifies the effect of the external environment as it affects the excessive use of inputs so they can be adjusted accordingly. The slack arise from two distinguishable effects: the technical inefficiency of the units and the influence of the exogenous factors which this approach aims to decompose and make adjustments on the original input values (Cordero *et al.*, 2009). The sign of the coefficients estimated in the regressions provides information about the direction of the effects of the exogenous factors on each total input slack which may vary from one slack to another including in significance. Tobit regression is applied in this study, and has been applied in previous studies (Hung and Shiu, 2014; Macpherson *et al.*, 2013; Hu *et al.*,

2011; Kontodimopoulos *et al.*, 2010; Avkiran, 2009; Fried *et al.*, 1999). The  $N$  input equations are specified as follows:

$$ITS_j^k = f_j(Q_j^k, \beta_j, u_j^k), \quad j = 1, \dots, N \quad (4.2)$$

$$k = 1, \dots, K$$

where  $ITS_j^k$  is unit  $k$ 's total slack for input  $j$  based on the DEA efficiency estimates from the first stage,  $Q_j^k$  is a vector of variables characterizing the external environment for unit  $k$  that may affect the utilization of input  $j$ ,  $\beta_j$  is a vector of coefficients, and  $u_j^k$  is a disturbance term.

#### **4.2.1.3 Stage three**

The third stage uses the estimated parameters from the second stage regression model (Tobit regression) to predict new total input slack for each input and for each production unit based on the external environmental factors applicable to the unit:

$$I\hat{S}_j^k = f_j(Q_j^k, \hat{\beta}_j), \quad j = 1, \dots, N \quad (4.3)$$

$$k = 1, \dots, K$$

The predicted total input slacks are used to adjust the primary input data for each unit according to the difference between maximum predicted slack and the predicted slack for each input:

$$x_j^{k adj} = x_j^k + [Max^k\{I\hat{S}_j^k\} - I\hat{S}_j^k], \quad j = 1, \dots, N \quad (4.4)$$

$$k = 1, \dots, K$$

where  $x_j^{k adj}$  is the value of unit  $k$ 's adjusted  $j$ th input,  $x_j^k$  is the value of unit  $k$ 's primary  $j$ th input,  $Max^k\{I\hat{S}_j^k\}$  is the maximum predicted slack for unit  $k$ . Equation 4.4 creates a new dataset for each production unit wherein the inputs are adjusted for the influence of the operating environment. The maximum predicted slack is used to establish a base equal to the least favourable set of external conditions; thus a unit with external factors generating lower level of predicted slack would have its input adjusted upwards to put it on the same level with

the unit operating in the least favourable environment. By increasing the unit's input and leaving the output unchanged, its performance is purged of any advantage offered by its favourable operating environment.

#### **4.2.1.4 Stage four DEA**

The fourth and final stage re-runs the DEA model (Equation 4.1) under the initial input–output production specification and generates new measure of efficiency by using the adjusted input dataset free from the influence of the operating environment. The new efficiency scores provide a measure of the efficiency that is attributable purely to managerial skills.

#### **4.2.2 Dataset**

This study uses a dataset on individual contracted harvesting operations (involving mechanized felling, extraction, processing of stems and loading out onto trucks) obtained from a large commercial forest company in New Zealand. The dataset contains detailed information on harvesting crews, stand, terrain, cost, harvesting system and productivity factors on contracted harvesting operations from 2016 to 2017. The data was collected at individual-contract level representing the DMUs in order to capture the operating environment specific to each harvesting operation. Thus, it is able to capture the true reflection of the effect of the exogenous factors on inputs requirement for the operations. The data were collated from different regions of New Zealand amounting to a total of 67 entries on harvesting operations executed by 26 independent forest harvesting contractors. Due to the confidentiality agreement binding on the data, information on the identity of the harvesting contractors is not provided; each independent contractor is assigned a unique identifier for ease of reference. All the harvesting operations are clear fell in New Zealand Radiata pine plantations.

#### **4.2.3 Production and exogenous factors**

Previous studies on performance evaluation in the forest harvesting sector have employed a variety of input–output factors. The selection of variables is often influenced by availability of data. Based on available data and relevant literature (Li *et al.*, 2017; Obi and Visser, 2017b; Visser *et al.*, 2010; Visser *et al.*, 2009; Amishev *et al.*, 2009), this study selects seven inputs, one output and three exogenous factors for the performance evaluation of harvesting crews.

The factors are considered to practically reflect the harvesting process, considering the available data.

*Input factors* - These are factors over which the harvesting contractors have some level of control and they include:

- (i) Number of workers (NUMWOK) - this the average number of workers in a crew engaged in the harvesting operation of a defined forest area over the entire harvesting period;
- (ii) Number of machines (NUMMCH) - defines the total number of machines deployed for a harvesting operation;
- (iii) Harvest days (HVDAYS) – this is the total number of days of harvesting by a crew in a defined forest area;
- (iv) Net stocked area (NETAREA) – being the total actual harvest area size measured in hectares;
- (v) Total recoverable volume (TRECVOL) – is the actual volume of stem harvested from a defined forest area measured in tonnes per hectare;
- (vi) Landings size (LNDSIZE) – this is the total landing size for a harvesting operation estimated from the product of average landing size and number of landings, and is measured in hectares; and
- (vii) Average haul distance (AVHULD) – this is the mean extraction haul distance measured in meters, and is obtained from the operational harvest plan.

*Output factor:* System productivity (SYSPROD) measured in tonnes per machine hour (tons/SMH) is considered the output of the harvest operations and is calculated as the total volume of harvested timber from a defined forest area divided by the total harvest time.

*Exogenous factors:* These are exogenously fixed factors within the operating environment of the harvesting crews over which they do not have direct control. Three factors are classified as exogenous factors for the purpose of this study and they include:

- (i) Terrain slope (AVSLOP) - this the average slope of the harvested forest area in percent,
- (ii) Log sort (LGSORT) - this is the number of log sorts from a defined forest area contracted to a harvesting contractor; and

- (iii) Piece size (PESIZE) – is defined as the average piece size from a harvest area measured in tons/stem. Table 4.1 presents the descriptive statistics of all the factors.

#### 4.2.4 Analysis

Efficiency scores for the harvesting crews described in terms of the technical efficiency are estimated using <sup>1</sup>DEAP software version 2.1 which also estimates radial and non-radial slacks for each production factor using a multi-stage process (Coelli, 1996). Technical efficiency refers to the ability of a unit to utilize its limited inputs to produce the desired outputs and it is influenced by the use of technology (Coelli *et al.*, 2005). The number of DMUs in a DEA should at least be twice the number of inputs and outputs combined (Golany and Roll, 1989) as a large number of inputs and outputs combined compared to the number of DMUs diminishes the discriminatory power of DEA (Cook *et al.*, 2014). This study has 67 DMUs and 8 inputs/outputs.

**Table 4.1** Descriptive statistics of the factors for performance evaluation ( $N = 67$ )

Factors	Mean	Standard deviation	Minimum	Maximum
<i>Inputs</i>				
NUMWOK	6.2	2.5	2	18
NUMMCH	5.2	1.9	2	13
HVDAYS	65.7	41	12	206
NETAREA (ha)	32.2	27.3	5.6	153.8
TRECVOL (tons/ha)	555	125	298	902
LNDSIZE (ha)	0.84	0.52	0.06	2.4
AVHULD (m)	256.6	227.3	0	1937
<i>Output</i>				
SYSPROD (tons/SMH)	31.7	11.2	9.6	59.5
<i>Exogenous</i>				
AVSLOP (°)	18.6	7.7	11	39.3
LGSORT	11.6	2.1	7	17
PESIZE (ton/stem)	1.4	0.5	0.5	3.1

<sup>1</sup> <http://www.uq.edu.au/economics/cepa/deap.php>

## 4.3 Results and Discussion

### 4.3.1 First stage DEA without exogenous factors

The first stage DEA results presented in Table 4.2 shows a large variation in efficiency estimates of the harvesting contractors. The mean efficiency score for the contractors of 0.79 theoretically suggests that the crews efficiently utilized about 79 % of their current input levels. Conversely, on average a harvest crew could reduce its current input usage by approximately 21 %, were it to perform on the efficient frontier. A total of 18 crews (27 %) are estimated as efficient, i.e. efficiency score = 1, while 14 crews (20 %) have efficiency scores in the range of 0.8 to 0.99. About 43 % ( $N = 29$ ) are estimated to have efficiency scores of 0.60 to 0.79 (i.e. 60 to 79 %). However, operations of independent harvesting contractors are often influenced by environment factors outside the control of the crews (Hoffmann *et al.*, 2016; Aalmo and Baardsen, 2015). Crews operating in difficult environments may find it difficult to equal the performance of their counterparts in more favourable operating environment.

**Table 4.2** Stage one efficiency scores statistics ( $N = 67$ )

Statistics	Efficiency rankings	N	% of DMUs
Mean	0.794	100%	18
SD	0.158	80 – 99%	14
Median	0.784	60 – 79%	29
Min	0.519	40 – 59%	6
Max	1		9

### 4.3.2 Second stage analysis

In the second stage, total slacks representing potential input saving for each of the inputs is regressed against the set of exogenous factors (independent variables) namely, average slope, log sorts and piece size using Tobit regression. There are seven regression models, one for each input. The parameters estimated are presented in Table 4.3. A positive exogenous factor coefficient on a total input slack suggests that the factor constitutes an unfavourable environment resulting in excess use of the input by the harvest crews; the reverse being the case for a negative coefficient. In other words, an operating environment with a positive (negative) coefficient on a total input slack is associated with the inefficient (efficient) use of the input, and the sign and statistical significance can differ across the inputs (Fried *et al.*,

1999). Consequently, an operating environment with a positive coefficient on an input slack tends to reduce harvesting efficiency as its measure increases, and vice versa for an operating environment with a negative coefficient.

As shown in Table 4.3, average slope (AVSLOP) has a positive coefficient on all the input slacks but is significant only on the number of workers (NUMWOK), number of machines (NUMMCH) and the average haul distance (AVHULD). Its positive coefficient on all slacks can be attributed to the enormous challenge it presents to forest harvesting operations irrespective of the harvesting system adopted. Number of log sorts (LGSORT) has a negative coefficient on all the total input slacks except on AVHULD slack, and it is significant on the NUMWOK and the total recoverable volume (TRECVOL) slacks. This suggests an increase in log sorts is favourable to the efficient use of all the inputs in the production model except AVHULD. Log sorts, thus can be said to improve harvesting efficiency as it increases. This makes practical sense in that harvest operations in New Zealand with high log sorts are usually associated with large forest areas, and is often characterized by high system productivity. Piece size on the other hand has an insignificant positive coefficient on NUMWOK slack and a significant positive coefficient on TRECVOL slack. The coefficient is negative and insignificant on all other input slacks. The varying effects of the exogenous factors on the input slacks justifies the need to correct the initial DEA scores for the influence of the factors. Otherwise, the impact of the operating environment on harvesting operations may consistently result in estimating crews in good operating environments as more efficient than those in harsh environments. In practical terms, the main benefit of these results is to provide numeric correction factors for recalibrating the analysis as a function of the specific levels of selected exogenous factors unique to individual operations.

#### **4.3.3 Third stage analysis**

The estimated regression parameters presented in Table 4.3 are used in the third stage analysis to predict a new set of total input slacks for each of the crews according to the factors characterizing their operating environment (Equation 4.3), and to adjust the initial input data for each crew according to Equation 4.4. The maximum predicted slack is used to set a baseline for the least favourable operating environment (Fried *et al.*, 1999). A crew with a predicted total input slack less than this value for an input will have its corresponding input

factor adjusted upward. Table 4.4 presents a summary statistics of the adjusted inputs for the harvesting contractors. It can be seen that the mean value for each of the adjusted inputs (Table 4.4) is higher than its corresponding original mean value presented in Table 4.1. This is because the adjusted input data controls for the influence of the three exogenous factors considered in this study, thus giving no advantage or disadvantage to any crew owing to a favourable or unfavourable operating environment in terms of input usage.

**Table 4.3** Estimation results of total input slacks using Tobit regression. Standard errors are shown in brackets

Regressor	Dependent variables, Slacks						
	NUMWOK	NUMMCH	HVDAYS	NETAREA	TRECVOL	LNDSIZE	AVHULD
Constant	5.36 (2.35)	3.21 (1.73)	78.8 (43.9)	28.5 (24.2)	201 (112)	0.58 (0.47)	-207 (219)
AVSLOP	0.12** (0.04)	0.07* (0.03)	0.99 (0.86)	0.31 (0.47)	1.44 (2.19)	0.012 (0.01)	9.90* (4.23)
LGSORT	-0.52** (0.18)	-0.22 (0.13)	-2.85 (3.28)	-0.36 (1.80)	-18.3* (8.43)	-0.03 (0.04)	15.0 (16.3)
PESIZE	0.23 (0.68)	-0.42 (0.50)	-21.3 (12.9)	-11.8 (7.07)	69.0* (32.2)	-0.05 (0.14)	-70.1 (63.5)
Log-Likelihood	-132	-117	-287	-256	-337	-55.3	-365

\*significant at 95 %, \*\*Significant at 99 %

**Table 4.4** Summary statistics of the adjusted input factors of the harvesting contractors

Variables	Statistics			
	Mean	SD	Minimum	Maximum
NMWOK	9.6	2.2	4.8	19.2
NMMCH	7	1.7	4.5	14
H DAYS	98.3	41.6	36.5	231.3
NETAREA, ha	44.2	26.8	14.9	162.4
TRECVOL, ton/ha	704	109	500.5	1003
LNDSIZE, ha	1.1	0.5	0.2	2.8
AVHUD, m	438.7	216.8	198.9	1950

SD – Standard deviation

#### 4.3.4 Final Stage DEA with exogenous factors

The fourth and final stage of the approach is to re-run the DEA based on the initial input-output specification using the adjusted input data. This produces new efficiency estimates for the contractors attributable purely to managerial inefficiency which incorporates both technical inefficiency and the effects of the operating environment (Kontodimopoulos *et al.*, 2010). Descriptive statistics of the results of the final stage DEA adjusted for the influence of the operating environment is presented in Table 4.5. Adjusting the inputs for the effect of exogenous factors on the performance of the harvesting crews results in an increase in the number of crews estimated as efficient, and in the number crews in the 80 to 99 % efficiency range. Before the adjustment (stage 1), 18 of the 67 contractors (27 %) were efficient (Table 4.2) and after the adjustment (stage 4) 23 crews (34 %) were estimated to be efficient (Table 4.5). The mean and minimum efficiency estimates in stage four DEA also show that efficiency estimates are higher after adjusting for exogenous factors. The results indicate that it is important to include the effect of exogenous factors in the performance evaluation of harvesting operations.

**Table 4.5** Stage four estimated efficiency score statistics

Statistics ( <i>N</i> = 67)	Efficiency range	<i>N</i>	% of DMUs	
Mean	0.90	100 %	23	34
SD	0.095	80 – 99 %	32	48
Median	0.915	60 – 79 %	12	18
Min	0.68			
Max	1			
Returns to Scale	Constant	19 %		
	Increasing	78 %		
	Decreasing	3 %		

A smaller variation in performance among the crews is observed as evident in the lower standard deviation of the performance estimates in the stage four DEA results (Table 4.5) compared to the stage 1 results (Table 4.2) having removed the variation attributable to exogenous factors. The average efficiency score increased by approximately 12% (79.4 % to 90 %) after controlling for environment effects on the efficiency score.

Approximately 19 % of the crews operate under constant returns to scale while 78 % operate under increasing returns to scale. This suggests that majority of the harvesting crews possess the capacity to improve their system productivity. It is important to note that a harvesting contractor estimated to be efficient (i.e. efficiency score = 1) based on the four-stage DEA technique applied in this study does not necessarily reach its maximum production efficiency or capacity. The DEA efficiency estimate of 1 assigned to the unit means that among its peers based on their current input utilization in the face of influential operating environment, and their production outputs, the unit outperformed its peers and can act as a benchmark for others in improving their managerial efficiency. The high percentage of contractors operating under increasing returns to scale even among efficient units suggests the existence of opportunities to improve input utilization efficiency and consequently improve overall harvesting efficiency.

To statistically establish a difference between stages 1 and 4 DEA efficiency estimates, the Mann–Whitney *U*-test is applied. The Mann-Whitney *U*-statistics reject the null hypothesis of equality of the first and fourth stage efficiency scores (*p*-value = 0.0001). This implies that there exists a significant difference between the unadjusted and adjusted performance measures of the harvesting contractors. The slack adjusted new efficiency estimates represent potential minimum reduction in inputs if a crew operated in the worst environment and performed up to the efficient frontier (Fried *et al.*, 1999). The overall increase in the mean efficiency score in the fourth stage DEA suggests that crews in difficult operating environment exhibit better management skills but were adjudged poorly in the first stage DEA. In summary, incorporating the operating environment in performance evaluation does make a significant difference in the final efficiency estimates in forest harvest operations.

#### **4.4 Limitations of the Study and Future Research**

Although this study achieved its objective of measuring impartially the technical efficiency of forest harvesting contractors including quantitative environment factors, it presents some limitations worth acknowledging. The production model for forest harvesting operations incorporated only seven inputs, one output and three environment factors. These factors are not exhaustive and is limited largely by availability of data. It would be interesting to incorporate additional factors in future studies to include those endogenous to harvesting

crews such as training, years in business, operator age, etc. The study did not consider statistical noise which is another phenomenon capable of influencing performance (described as the impact of good luck and bad luck), omitted variables and other related phenomena (Fried *et al.*, 2002). Statistical noise is reflected in a random error term in stochastic frontier analysis-based performance evaluation of production units. This is left as a future line of study in performance evaluation within the forest harvesting industry.

#### **4.5 Conclusions**

The four-stage DEA approach proposed by Fried *et al.* (1999) is applied in this study to account for the effect of non-discretionary factors, often exogenously fixed, on the performance of independent forest harvesting contractors. The very few studies on performance within the harvesting sector have focused simply on estimating performance in terms of efficiency without taking into account the possible influence of the operating environment. The four-stage DEA approach simultaneously adjusts input factors to control for the operating environment and produces efficiency index attributable purely to managerial skills free of the bias introduced by the operating environment. Using data on 67 forest harvesting operations in New Zealand, this study demonstrates that employing benchmarking for performance evaluation without accounting for the operating environment could lead to biased, inaccurate and misleading estimates. Significant difference ( $p < 0.01$ ) was observed between the efficiency estimates unadjusted and adjusted for the effect of the operating environment with a mean increase of 12 % indicating the significant impact of the operating environments considered in this study. This study thus demonstrates that with the right data, forest management companies, policymakers, and general industry stakeholders involved in the measurement and overall improvement of forest harvesting operations can estimate and provide an unbiased performance metric, and promote excellence within the sector.



# **Chapter 5**

## **Conclusion**

### **5.1 Summary of the Thesis**

The forest harvesting industry plays an important role in the forestry product value chain particularly with respect to the supply of wood logs to the downstream sectors. Today's increasingly competitive forestry markets make the continuous measurement and improvement of the performance of the forest harvesting sector imperative for maintaining a continued relevance in the global markets. The forest industry is one of the key economically relevant industries in New Zealand, and its competitiveness is of interest to investors as well as the New Zealand government. The competitiveness of an industry is often measured by means of benchmarking techniques that aim to identify the 'best' producers, or the 'best' practices within an industry. Such techniques provide an opportunity for underperforming producers to learn from the best in order to improve their productivity. One such benchmarking technique is data envelopment analysis (DEA), which is applied in this thesis to the New Zealand forest harvesting industry with the goal of benchmarking the production performance of the independent forest harvesting contractors in the sector. DEA is able to simultaneously analyse the efficiency with which a crew is able to utilize its production inputs to achieve a certain level of productivity and then assign an estimated efficiency index to the crew representing the crew's performance rating. This thesis utilized data retrieved from two databases on actual contracted harvesting operations in New Zealand which entail information on harvesting crews, productivity, cost, terrain and stand parameters. The databases include the cost and productivity benchmarking database managed by the University of Canterbury (UC) on contract to Future Forest Research (now Forest Growers Research, FGR) and a harvesting benchmarking database of a large forestry company in New Zealand. Due to the sensitivity of the information in these databases as well as the confidentiality agreement binding on them, none of the contractors are named in this thesis and only mean data were presented in the results.

This thesis focuses on three main objectives. The first applied an advanced benchmarking technique in extending the capacity of assessing the performance of independent forest harvesting contractors (Chapter 2). This illustrated the application of DEA in estimating forest harvesting performance using multiple inputs and outputs, and the interpretation of the results for improved harvesting efficiency. The second objective was to assess the potential influence of external factors on the harvesting efficiency of the crews (Chapter 3). External factors are those exogenously fixed within the operating environment of the contractors but outside of their managerial control, that is, they are not able to manipulate such factors to favour their productivity. The third objective was to demonstrate the application of a benchmarking approach capable of adjusting forest harvesting inputs to accommodate the effect of potential external factors in measuring harvesting operations performance (Chapter 4). This is quite important as harvesting crews often operate in environments that offer different levels of difficulty to harvesting operations thus resulting in biased performance estimates. Performance of crews in relatively favourable operating environments are often overestimated because of their low input usage; and those in relatively difficult environment underestimated due to the additional demand on inputs by their operating environment factors. Hence, the need to adjust the inputs to reflect individual crew operating environment for an unbiased performance estimate.

## **5.2 Main Conclusions**

DEA presents an excellent opportunity to effectively assess the competitiveness of the forest harvesting industry vis-à-vis the performance of the harvesting crews in the industry. Information on the harvesting efficiency of the crews, which describes the efficiency with which the crews utilize their inputs to produce outputs, can be obtained as well as the production targets for underperforming crews to become efficient. DEA performance estimates can provide an indication of the efficiency of harvesting operations; low performing crews often experience high production costs as opposed to high performing crews due to the poor management of input resources resulting in poor performance ratings. Although DEA utilizes inputs managed by the crews in estimating harvesting performance, external factors outside the direct control of the crews but present within the operating environment can significantly influence forest harvesting operations. The differences in the estimated

performance of the crews can be attributed to the unique operating environment differences among the crews. In addition, the study showed the potentially biased nature of the DEA forest harvesting performance estimates. The inclusion of the external factors in the performance measuring process can effectively correct the bias in the DEA efficiency estimates introduced by differences in the operating environment of the crews. This can be achieved through a multi-stage DEA approach that incorporates regression analysis in the estimation procedure. Significant difference was identified in the harvesting performance of the New Zealand harvesting crews estimated with and without the inclusion of the external factors. With the right input and output data, forest companies can effectively measure and rate the performance of forest harvesting operations, provide a metric for continuous improvement, as well as identify and promote excellence in the industry.

### **5.3 Future Research Opportunities**

The backbone of effective application of DEA technique is data, thus for the effective integration of this technique within the business model of forest management companies, the emphasis must be on the collection of accurate and appropriate data. With large data on a wide number of factors including discretionary and nondiscretionary factors, a general guiding protocol could be developed on the application of DEA in estimating harvesting system performance. DEA offers a number of future research opportunities within the forest industry as a whole. An interesting area of study not covered in this thesis is the assessment of influential endogenous factors that could potentially improve harvesting performance of crews. This could potentially identify key endogenous variables that forest management companies could invest in through continuous training towards improving overall harvesting efficiency. It would be interesting to ascertain the level of training received by harvesting crews with respect to the influx of new harvesting technologies in New Zealand. This is important, as training is a key factor in how well improved technologies translate into improved performance. Although DEA generally targets to improve output, it is capable of incorporating both desirable and undesirable outputs as in the case environmental impacts during forest harvesting operations. If inefficiency exists, DEA can be used to improve performance by increasing desirable outputs and reducing undesirable outputs. This offers research opportunities in assessing ways of reducing environmental impacts associated with

forest harvesting operations, and including safety as output metric in harvesting operations. A number of models have been developed to accommodate undesirable outputs, however, the appropriateness or the need for modification of existing models to suit forest harvesting production technology requires some exploratory research.

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