Including Exogenous Factors in the Evaluation of Harvesting Crew Technical Efficiency using a Multi-Step Data Envelopment Analysis Procedure

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Abstract

The performance of a harvesting crew in terms of its ability to transform inputs into outputs is influenced by discretionary factors within the unit's control, such as the selection of machines and operators. However, factors associated with the operating environment, such as terrain slope and tree size that are outside the direct control of management, can also influence harvesting system efficiency. Using data on forest harvesting operations in New Zealand, this paper applies an established four-stage Data Envelopment Analysis (DEA) procedure to estimate the managerial efficiency of independent forest harvesting contractors, while taking into account the influence of the operating environment. The performance of 67 harvesting contractors is evaluated using seven inputs, one output (system productivity) and three operating environment factors in an input-oriented, variable return to scale DEA. The results show that the operating environment including terrain slope, log sorts and piece size influence the efficient use of inputs by harvesting contractors. A significant difference is observed between the mean managerial efficiency of the crews before and after controlling for the influence of the operating environment, the latter being higher by 11%. This study provides evidence that without accounting for the influence of the operating environment, the resulting DEA efficiency estimates will be biased; the performance of crews in favourable operating environment would be overestimated and those in unfavourable environment underestimated.

Keywords: data envelopment analysis, operating environment, forest harvesting, performance evaluation

1. Introduction

Data envelopment analysis (DEA) has over the years evolved into a widely accepted research technique that the operations research community is increasingly applying to analyse and improve relative performance of private and public production entities (Liu et al. 2013). DEA is a non-parametric mathematical programming-based approach for performance estimation of production or decision making units (DMUs) addressed in Charnes et al. (1978) (Charnes, Cooper and Rhodes model – »CCR«) and extended by Banker et al. (1984) (Banker, Charnes and Copper model – »BCC«). It provides a framework for the estimation of best-practice frontier for production entities involving multiple inputs and outputs to allow for benchmarking and performance evaluation (Estelle et al. 2010). The overall efficiency of a production unit can be estimated using the CCR model under the assumption of constant returns to scale, while the technical or managerial efficiency of a unit can be estimated using the BCC model under the assumption of variable returns to scale. DEA classifies production units into efficient and inefficient units based on their selected inputs and outputs by maximizing the ratio between the weighted output and the weighted input (Sharma and Yu 2015). An efficient unit is assigned the maximum efficiency score of 1, while a unit with a score less than one is considered less efficient relative to its efficient peers. DEA is able to estimate the performance of production units in terms of their ability to either minimize input usage under the production of given output (input orientation) or to maximize output production with given inputs (output orientation) (Li et al. 2017). It is important to note that DEA does not suggest that a unit with a score of 1 is absolutely efficient (operating at optimum output-input ratio), however, by comparing several units' output-input ratios (i.e. benchmarking), it can estimate that one or more units are more or less efficient than others (Sherman and Zhu 2006).

Researchers in the field of logging operations have only recently began to apply DEA in estimating performance of forest harvesting operations and it is gaining attention (Obi and Visser 2017a, Hailu and Veeman 2003, LeBel and Stuart 1998). The application of DEA in forest harvesting offers opportunities in 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 production units whose performance is being estimated operate within a homogenous production environment (Carrillo and Jorge 2016). However, this assumption in practice does not hold for most harvesting operations as the ability of a harvesting crew/contractor 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) that are beyond direct managerial control (Obi and Visser 2017b, Aalmo and Baardsen 2015). These factors provide either a favourable or an unfavourable operating environment to the crews. An unfavourable operating environment would demand additional inputs from the 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 DEA studies as most performance studies 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 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); thus potentially leading to inefficient allocation of resources. 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. However, existing studies on the application of DEA in the forest harvesting sector have so far focused on assessing performance without considering non-discretionary inputs, i.e. inputs beyond the managers' control. Obi and Visser (2017a) examined the operational efficiency of 423 independent forest harvesting contractors in New Zealand over a period of 7 years using DEA. The authors considered five inputs, namely, number of harvest days, number of machines, total harvest area, number of log sorts and total volume of timber, and one output – system productivity in the production model. They reported that majority of the harvesting contractors operate at or near scale efficiency level, but the source of inefficiency in the industry is both technical and managerial. They added that investment in technology and human capital could improve the overall efficiency of the industry. LeBel and Stuart (1998) applied DEA models to measure the technical efficiency of 23 fully mechanized loggers in Canada during the period 1988–1994. The aggregate, technical, and scale efficiencies of the loggers were evaluated based on DEA models with capital, consumables, and labour as the inputs and tons of wood as output. They reported majority of the contractors to be efficient. Factors identified as influencing the technical efficiency of the loggers include low capacity utilization and scale of harvesting operations. Hailu and Veeman (2003) using panel data covering a period of 19 years (1977–1995) analysed the technical efficiency, technical change and total factor productivity in the logging industries for six boreal provinces in Canada using DEA. The study reported substantial technical efficiency differentials among the provinces. The authors identified some region-specific variables that influenced efficiency of logging operations in the regions. The variables include forest density, proportion of hardwood production, scale of operation measured as production per establishment, and engineering construction per area harvested.

Literatures on performance evaluation that account for the effects of exogenous factors on the efficiency of production entities in different industries exist (Zhu et al. 2016, Ferrera et al. 2014, Macpherson et al. 2013). There is however no literature controlling for the effects of the operating environment on efficiency estimates of forest harvesting operations. 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 their operating environment. This removes the environment bias, and the resulting performance estimates are attributable purely to managerial efficiency. This is accomplished by applying the four-stage DEA procedure. This study extends the previous work of Obi and Visser (2017a) by introducing the operating environment factors in the performance evaluation procedure.

2. Methodology

2.1 The four-stage DEA procedure

Fried et al. (1999) developed an empirical technique termed the four-stage DEA procedure to separate managerial inefficiency from other inefficiency components beyond managerial control. The four-stage DEA procedure rests on the premise that production units 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 operating environment factors by compensating for their effects, and has been applied in previous literatures (Zhu et al. 2016, Ferrera et al. 2014, 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 detailed description of the four-stage DEA procedure, readers are referred to Fried et al. (1999).

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 which in the case of this study are independent forest harvesting contractors. 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 exogenous factors. This establishes a best-practice frontier for the harvesting crews based on the inputs and outputs included in the DEA. However, the efficiency estimates of crews operating in »good« operating environment are overestimated and that of the harvesting crews in »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):

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

Subject to

$$\sum_{j=1}^{n}\lambda_j x_{ij} + s_i^{-} = \theta_0 x_{ij0} \quad (1)$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_{r0}^{+} = y_{rj0}$$

$$\sum_{j=1}^{n}\lambda_j = 1$$

$$\lambda_j, s_i^{-}, s_r^{+} \geq 0, i = 1,2,\ldots,m; r = 1,2,\ldots,s; j = 1,2,\ldots,n$$

Where:

x_{ij} vector of inputs for unit *j*
y_{rj} vector of outputs for unit *j*
θ_0 efficiency score
ε infinitesimal non-Archimedean constant
λ_j weightings
s_r^{-} inputs slacks
s_r^{+} outputs slacks.

2.1.2 Stage two

The second stage is to estimate *N* input equations using an appropriate econometric method such as 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. This quantifies the effect of the exogenous factors as it affects the excessive use of inputs so they can be adjusted accordingly. The radial input slack represents the reduction in the inputs of a relatively inefficient DMU were it to operate efficiently beyond which no further reduction in inputs is possible without reducing output; whereas the non-radial slack represents the potential additional reduction in the inputs of a relatively inefficient DMU after proportionally reducing its current inputs to become efficient (Fried et al. 1999). 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 provide 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, Avkiran 2009, Fried et al. 1999). The N input equations are specified as follows:

$$ITS_{\mathrm{j}}^{\mathrm{k}} = f_{\mathrm{j}}\left(Q_{\mathrm{j}}^{\mathrm{k}},\ \beta_{\mathrm{j}},\ u_{\mathrm{j}}^{\mathrm{k}}\right), j=1,\ldots..,N; k=1,\ldots..,K \quad (2)$$

Where:

$ITS_{\mathrm{j}}^{\mathrm{k}}$ unit k's total slack for input j based on the DEA efficiency estimates from the first stage

$Q_{\mathrm{j}}^{\mathrm{k}}$ vector of variables characterizing the external environment for unit k that may affect the utilization of input j

β_{j} vector of coefficients

$u_{\mathrm{j}}^{\mathrm{k}}$ disturbance term.

2.1.3 Stage three

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

$$I\hat{T}S_{\mathrm{j}}^{\mathrm{k}} = f_{\mathrm{j}}\left(Q_{\mathrm{j}}^{\mathrm{k}}, \widehat{\beta}_{\mathrm{j}}\right), j=1,\ldots..,N; k=1,\ldots..,K \quad (3)$$

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:

$$x_{\mathrm{j}}^{\mathrm{k\ adj}} = x_{\mathrm{j}}^{\mathrm{k}} + \left[Max^{\mathrm{k}}\left\{I\hat{T}S_{\mathrm{j}}^{\mathrm{k}}\right\} - I\hat{T}S_{\mathrm{j}}^{\mathrm{k}}\right]$$

$$j=1,\ldots..,N; k=1,\ldots..,K \quad (4)$$

Where:

$x_{\mathrm{j}}^{\mathrm{k\ adj}}$ value of unit k's adjusted jth input

$x_{\mathrm{j}}^{\mathrm{k}}$ value of unit k's primary jth input

$Max^{\mathrm{k}}\{ITS_{\mathrm{j}}^{\mathrm{k}}\}$ maximum predicted slack for unit k

Eq. 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.

2.1.4 Stage four DEA

The fourth and final stage re-runs the DEA (Eq. 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.

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 harvesting operations from January 2016 to March 2017. The data was collected at individual-contract level 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 input requirement for the operations. The data were collated from the different regions of New Zealand amounting to a total of 67 entries on harvesting operations executed by independent forest harvesting crews. Due to the confidentiality agreement binding on the data, information on the identity of the harvesting contractors are not provided; each harvesting contractor is assigned a unique identifier for ease of reference. All the harvest operations were clear-fell in New Zealand Radiata pine plantations.

2.3 Production and exogenous factors

Previous studies on performance evaluation in the forest harvesting sector have employed a variety of input–output factors. Based on available data and relevant literatures (Li et al. 2017, Obi and Visser 2017a, Visser and Spinelli 2012,Visser et al. 2011, Amishev et al. 2009), this study selects seven inputs, one output and three exogenous factors for the performance evaluation of the 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 (NMWOK) – 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 (NMMCH) – defines the total number of machines deployed for a harvesting operation; (iii) Harvest days (HDAYS) – 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 (TREVOL) – 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 (AVHUD) – 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 scheduled 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 harvest crews over which they do not have direct control. Three factors are identified 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 measured in degrees, (ii) log sorts (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 ton/stem. Table 1 presents the descriptive statistics of all the factors.

Table 1 Descriptive statistics of the factors for performance evaluation (N=67)

Factors	Mean	SD	Min.	Max.
Inputs				
NMWOK	6.2	2.5	2	18
NMMCH	5.2	1.9	2	13
HDAYS	65.7	41	12	206
NETAREA, ha	32.2	27.3	5.6	153.8
TREVOL, tons/ha	555	125	298	902
LNDSIZE, ha	0.84	0.52	0.06	2.4
AVHUD, m	256.6	227.3	0	1937
Output				
SYSPROD, tons/SMH	31.7	11.2	9.6	59.5
Exogenous				
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

SD – Standard deviation

2.4 Analysis

Efficiency scores for the harvesting crews described in terms of the technical efficiency are estimated using 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 production units 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 units diminishes the discriminatory power of DEA (Cook et al. 2014). This study has 67 production units (harvesting crews) and 8 inputs/output.

3. Results and discussion

3.1 First stage DEA without exogenous factors

The first stage DEA results presented in Table 2 shows a large variation in efficiency estimates of the harvesting contractors. The mean efficiency score for the contractors is 0.79, theoretically suggests that the crews are currently operating at about 79% efficiency 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 of 0.8 to 0.99. Most, 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 operating environment factors outside the control of the crews (Obi and Visser 2017b, Hoffmann et al. 2016, Aalmo and Baardsen 2015). Crews operating in difficult environments may find it challenging to equal the performance of their counterparts in more favourable operating environment.

Table 2 Stage one efficiency scores statistics (N=67)

Statistics		Efficiency rankings	N	% of crews
Mean	0.794	100%	18	27
SD	0.158	80–99%	14	21
Median	0.784	60–79%	29	43
Min.	0.519	40–59%	6	9
Max.	1	–	–	–

SD – Standard deviation

3.2 Second stage analysis

In the second stage, total input 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 slack. The parameters estimated are presented in Table 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 3, average slope (AVSLOP) has a positive coefficient on all the input slacks but its effect is significant only on the number of workers (NMWOK), number of machines (NMMCH) and average haul distance (AVHUD) slacks. Its positive coefficient on all slacks can be attributed to the enormous challenge it presents to forest harvesting operations irrespective of the system of harvesting adopted. Number of log sorts (LGSORT) has a negative coefficient on all the total input slacks except on AVHUD slack, and it is significant on NMWOK and total recoverable volume (TREVOL) slacks. This suggests an increase in log sorts is favourable to the efficient use of all the inputs in the production model except AVHUD. 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 NMWOK slack and a significant positive coefficient on TREVOL slack. The coefficient is negative and insignificant on all other input slacks. The significant positive coefficient of piece size on

Table 3 Estimation results of total input slacks using Tobit regression. Standard errors are shown in brackets

Regressor	Dependent variables, slacks						
	NMWOK	NMMCH	HDAYS	NETAREA, ha	TREVOL, tons/ha	LNDSIZE, ha	AVHUD, m
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, ton/stem	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%

TREVOL is understandable in that for a given tree stand, increased piece size is expected to result in increased total recoverable volume. 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 results present some insights as to the direction of the effects of these exogenous factors on the usage of harvesting inputs thus providing some guide as to the inputs that should be carefully managed under certain operating environments in order to improve overall harvesting efficiency.

3.3 Third stage analysis

The estimated regression parameters presented in Table 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 (Eq. 3), and also to adjust the initial input data for each crew according to Eq. 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 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) is higher than its corresponding original mean value presented in Table 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 Summary statistics of the adjusted input factors of the harvesting contractors

Variables	Statistics			
	Mean	SD	Min.	Max.
NMWOK	9.6	2.2	4.8	19.2
NMMCH	7	1.7	4.5	14
HDAYS	98.3	41.6	36.5	231.3
NETAREA, ha	44.2	26.8	14.9	162.4
TREVOL, 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

3.4 Final stage DEA with exogenous factors

The fourth and final stage of the approach is to rerun 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 skills void of the influence of the operating environment factors considered in the analyses. Descriptive statistics of the results of the final stage DEA adjusted for the influence of the operating environment is presented in Table 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 80–99% efficiency ranking. Before the adjustment (stage 1), 18 of the 67 contractors (27%) were efficient – 100% efficiency score (Table 2) and after the adjustment (stage 4) 23 crews (34%) were estimated to be efficient (Table 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.

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 5) compared to the stage 1 results (Table 2). The decrease in standard deviation reflects an overestimation of the performance of units in favourable conditions and an underestimation of

Table 5 Stage four estimated efficiency score statistics (*N*=67)

Statistics		Efficiency rankings	N	% of crews
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%	–	–

SD – Standard deviation

those in more challenging environments in the first stage DEA. The average efficiency score increased by approximately 11% (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 = 100%) based on the four-stage DEA technique applied in this study does not interpret to mean that it has reach its maximum production efficiency or capacity. The DEA efficiency estimate of 1 assigned to the contractor means that among its peers based on their current input utilization and production outputs, the contractor outperformed its peers and can act as a benchmark for others in improving their managerial efficiency. The high percentage of the contractors operating under increasing returns to scale 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 in the managerial efficiency of the harvesting contractors adjusted and unadjusted for differences in the operating environment. 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, including the operating environment factors in performance evaluation does make a significant difference in the final technical efficiency estimates in forest harvesting operations.

4. Limitations of the study and future research

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

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 DEA 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 inputs factors to control for the operating environment factors and produces efficiency index attributable purely to managerial skills removing the bias introduced by the operating environment. Using data on forest harvesting operations contracted to 67 harvesting crews in New Zealand, this study demonstrates that benchmarking performance of harvesting crews without accounting for differences in the operating environment will lead to biased, inaccurate and misleading estimates. Significant difference (p<0.01) was observed between the mean managerial efficiency estimates unadjusted and adjusted for the effect of the operating environment with a mean increase of about 11% indicating the impact of the operating environment factors considered in this study. Previous studies also reported a difference between the mean efficiency score unadjusted and adjusted for the effect of the operating environment ranging from 10–23% (Macpherson et al. 2013, Kontodimopoulos et al. 2010, Wang et al. 2006, Fried et al. 1999). The study provides some useful decision support to forest companies, policymakers, and general industry stakeholders involved in the measurement and overall improvement of forest harvesting performance.

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