Measuring Performance Efficiency of Oil Palm Plantations using Window Analysis

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ABSTRACT

Performance of a unit or an organisation is among the issues discussed as a way of helping the decision-making process. This study was aimed at determining and evaluating performance efficiency trends in the management of selected plantations in the oil palm industry. It took into account the input and output factors using data envelopment analysis (DEA). Relative efficiency was identified to set the benchmark in this case study, and as a way to improve the overall activities related to the use of input as resources by the least efficient plantation. The DEA method was used to calculate the efficiency trend score. Data collected were from the years 2001-2010 for five input and one output variables. Analysis was conducted using the Window Analysis, DEA Solver. The overall result shows significant correlations among the variables and that the average efficiency score determines efficiency trend. Two out of three plantations studied had highest average efficiency scores while the other one was the less efficient.

INTRODUCTION

Production studies are concerned with the effect of various existing critical issues, such as the lack of resources and whether human activities are using the resources optimally. In economics, production is defined as a process that combines input and converts them into output (Case and Fair, 2004). Input refer to land, human resources and man-made aids (such as tools and machinery) in a production process. Output can be categorised into products and services. To evaluate the efficiency in the use of input and output, organisations therefore need to analyse their performance.

Performance measurement has become very important and popular for organisations as a way of attaining better decision-making. One of the ways to measure performance is by looking at the efficiency level which relates to the resources used and the results achieved. Parametrics and non-parametrics are among the tools which help in measuring performance. Efficiency is often associated with the performance of an organisation as it compares between output and input. In most literature, efficiency is closely

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related to productivity as the effect of the use of input variables on output is involved.

In agriculture, studies have been conducted to measure the technical or production efficiency of farms using data envelopment analysis (DEA) (Krasachat, 2001; Padilla-Fernandez and Nuthall, 2001; Dhungana *et al*., 2004; Andreu, 2008; Minh and Long, 2008; Gul *et al*., 2009; Kilic *et al*., 2009; Theocharopoulos *et al*., 2009; Banaeian and Zangeneh, 2011; Minh, 2011; Wang and Wang, 2011). The literature shows that DEA has proven capable of measuring the efficiency of management in agriculture, thus attesting to its importance.

This article discusses the application of DEA for the purpose of formulating improvements in the management of oil palm plantations. Collection of detailed information on efficiency using DEA in collaboration with the plantation management was carried out. Generally, the article aims to rank the oil palm plantations based on their average efficiency score and to evaluate the performance efficiency trend of these plantations over 10 consecutive years.

MALAYSIAN PALM OIL INDUSTRY

As an important commodity in the Malaysian economy, palm oil contributes to a large amount of exports to the world. Global demand for palm oil has been on the rise over the past decade compared with other vegetables oils, such as soyabean, rapeseed and sunflower oils (Belai *et al*., 2011). In Malaysia, palm oil is among the 12 key sectors in the National Key Economic Areas (NKEA), which currently aim at improving upstream productivity and promoting downstream expansion, whilst focusing on sustainability. However, recent reports in 2011 by the United States Department of Agriculture (USDA), state that production growth of the Malaysian palm oil industry is uncertain and has been underperforming for a considerable number of years.

Area expansion for growing oil palm is slowing down due to the lack of available suitable land; thus, efficiency in managing the existing planted areas is the only choice left. This has caused a major challenge to the Malaysian palm oil cluster as limited availability of cultivable land (due to concerns over deforestation and environmental degradation) also limits growth in the upstream activities. At the moment, Malaysia is estimated to have four million hectares of land under oil palm cultivation, and further expansion in cultivation is expected to decrease due to the limitation of land and competing uses of land for other forms of agriculture as well as for urban development (Belai *et al*., 2011).

The main sources of growth in the cluster come from upstream efficiencies, increased downstream investment in R&D, and branding.

Productivity of the upstream activities in the coming years is also challenged by aging oil palm plantations (Belai *et al*., 2011). The Third National Agricultural Policy (NAP) states the objective of maximising income through the optimal utilisation of resources in the production process. Therefore, management should administer resource utilisation well to increase efficiency and productivity in their business operations for the palm oil industry.

Labour shortage is another factor which affects the palm oil industry performance. Malaysia relies heavily upon foreign labour, especially in the plantation sector. As has been pointed out by the Malaysian Palm Oil Board (MPOB), if the issue of labour shortage is resolved, it will then be possible to produce 18.1 million tonnes of palm oil per year (Reuters, 2010). The Malaysian Palm Oil Association has stated that:

'In Malaysia, money grows on oil palm trees but without harvesters, the money will be just hanging up there. So, there is less revenue for local plantation companies and foregone export earnings for the country.'

Harvesting which usually takes 15 days per round now takes 25 days due to an acute shortage of workers (Adna, 2010). According to Barta (2004), cited by Naziman (2010), the Malaysian palm oil industry experiences inefficiency as the country is no longer among the world's low-cost producers. Due to all these problems, Malaysia needs to improve the use of resources in order to become more efficient and thus increase the production of palm oil.

EFFICIENCY

The concept of modern efficiency was first introduced by Farrell (1957) who defined a simple measurement to gauge the efficiency of a company. The efficiency discussed covers technical efficiency and allocative efficiency. Technical efficiency reflects the ability of a firm to maximise output with given input, while allocative efficiency reflects the ability of an organisation to utilise input optimally at a predetermined price level. The definitions of technical efficiency according to Farrell (1957) result in the following:

- efficiency is the inverse function of the input variables, and any increase in these variables may indicate a decrease in efficiency; and
- efficiency has a direct relationship with the outputs such that any increase in these variables is simply an increase in efficiency too.

Any increment in the level of productivity can affect the increment in input efficiency. This means that the same level of input may produce a higher output level, thus lowering the production costs, or *vice versa*. Hence, an improvement in productivity may reflect the quality of input usage (Jajri, 2007).

In this study, efficiency refers to the ability of decision-making units (DMU) to use scarce economic resources (inputs) to produce a certain level of outputs. A hypothesis by Farrell (1957) states that efficiency can be divided into two sub-components that reflect the physical efficiency of transformation of the input-output production (technical component), and the economic efficiency of the optimal allocation of factors (price efficiency). Technical competence is a measure of the success of a firm when it is able to use a certain amount of its input to produce maximum output, while allocative efficiency measures the success of a firm in choosing the optimal amounts of input.

The most common concept used in measuring efficiency is technical efficiency (TE) where input are utilised maximally in order to produce specific amounts of output. A firm is considered as technically efficient when it is able to compare with other firms (homogeneous units) in producing the same level of output through minimising or reducing the usage of its input.

Efficiency can be measured by various methods such as ratio analysis, least square regression (LSR), total factor productivity (TFP) and data envelopment analysis (DEA). Since 1978, the DEA method has been widely accepted and been used in many subject areas in terms of application and theory. DEA is a powerful tool for managing and improving productivity. It has been extremely effective in increasing the productivity in a wide variety of organisations. DEA is well-suited to designing and managing productivity where other techniques fail (Sherman, 1992). Also, DEA is known to be an effective and powerful tool for measuring relative efficiency as the performance of each of the DMU is estimated relative to the other units in the same population (Gavirneni, 2006).

Efficiency relates to the benefits realised and the resources used (Cooper *et al.*, 2006). Efficiency is also an index showing the results of the comparison between outputs and inputs. The ratio indicates that the index of efficiency can be determined from the process, or from both input and output at the same time. Finally, efficiency can be used to measure the performance of a unit of economic activity (Budi, 2010).

DATA ENVELOPMENT ANALYSIS

DEA is a non-parametric methodology based on linear programming. It was originally developed for the measurement of performance, and now the application has been extended to various disciplines of science and operational activities (Cooper *et al*., 2006). The DEA method is used as a tool to evaluate the performance of an activity in a unit entity (*e.g.* organisation). The methodology can be applied effectively to measure the relative performance of a set of companies using the same inputs to produce the same outputs. DEA principles were introduced by Farrell (1957) and were later developed extensively by Charnes (1978). In the method, the measurement is simply between the input and the output.

DEA is an important method or approach for measuring efficiency. It can be used to evaluate the efficiency of performance of DMU, which are responsible for using a number of input to obtain a targeted output. In the context of this study, DMU refer to the oil palm plantations. DEA is a fractional programming model which can include multiple input and output without the need to determine the weightings for each variable beforehand, and without explicit mention of the functional relationships between input and output (unlike in regression).

DEA can handle multiple input and output at any one time. DMU can be compared directly with each other, while the input and output can have different units of measure. DEA may also help in terms of planning in an organisation. Statistical problems that arise from the assumptions of incorrect functional forms of the error term distribution can be avoided by using DEA.

DEA is known as a multi-productivity factor analysis-based mathematical model for measuring the relative efficiency of a homogenous set of DMU. It has also proved to be appropriate and practical for performance measurement and as a benchmarking tool, based on extensive research conducted on schools, hospitals, bank branches, production plants and other entities (Kurien and Qureshi, 2011).

One of the main objectives in DEA is to study the projection of the inefficient DMU into the production frontier. It is possible for an operating system to become a failure if the use of resources is inefficient as well as when there is inadequate customer service (Kumar and Suresh, 2009). In such cases, the utilisation of resources may reflect the organisation's loss or waste. Utilisation of resources, such as materials and labour, is closely related to productivity which in turn is linked to quality, technology and profitability. All this can be measured using DEA for improving productivity by controlling input, improving processes and by upgrading technology. Technology is one of the factors that contribute to efficiency in agriculture. The introduction of new technology has been stated as the only way to keep Virginia tobaccos in production (Theocharopoulos *et al.,* 2009).

DEA has been proven to work in determining the best practices frontier, identifying the inefficient ones, estimating the excessive amounts of resources used by inefficient DMU, and generating the benchmark for these inefficient DMU (Sherman, 1992). DEA has also been used to investigate the possibility of short-term viability of individual farms by abolishing inefficient practices. This approach does not serve only for the purpose of academic interest but also for policy-makers to formulate and experiment strategies striving to upgrade ongoing agriculture (Reig-Martíneza and Picazo-Tadeo, 2004).

In the oil palm industry, related studies have been found using the data envelopment analysis adopted by Krasachat (2001) and Zulkifli *et al.* (2010). As only a few articles have been found on this topic, there is still a gap which we can close by analysing data from this industry using Window Analysis. Studies have been found which focus on and analyse data using other models, such as those of Charnes, Cooper and Rhodes (CCR) and Banker, Charnes and Cooper (BCC).

Decision-making Units

DEA is a linear programming-based measurement of the performance efficiency levels of an organisation using DMU. The term DMU in DEA can refer to an assortment of units, such as banks, hospitals, healthcare establishments, department stores, universities, schools, libraries, and so on and so forth (Cooper *et al.*, 2006). Zulkifli *et al.* (2010) said that two factors influence the selection of DMU, namely:

- DMU must be homogeneous units, performing the same tasks and having the same objectives; and
- the relationship between the number of DMU and the number of input and output is determined based on the 'rule of thumb'. The number of DMU needs to exceed the number of input and output, and the sample size should be double or triple the total number of input and output. These assumptions are in agreement with Barnum and Gleason (2008), who stated that the judgment in selecting the number of DMU is based on DMU itself. To be able to selectively distinguish between an efficient DMU and an inefficient DMU, a larger number of DMU is required than the number of multiple input and output volumes. However, in other studies involving DEA, there is also the use of a smaller sample of DMU (Mello and Climaco 2008; Sun and Lin, 2009; Zervopoulos, 2012).

DEA Concept

The DEA technique is based on the relative performance of a group of units handling input and output. DEA can overcome some limitations of analyses of the ratios of partial and multiple regressions. DEA is a procedure designed specifically to measure the relative efficiency of DMU which uses a lot of input and output. In DMU, DEA's relative efficiency is defined as the ratio of total weighted output divided by total weighted input. The core of DEA is to determine the weights or scales for each input and output in each DMU. Weight has no negative properties and is universal, meaning that each DMU in the sample should be able to use the same set of weights to evaluate the ratio (total weighted output/ total weighted input), and that the ratio should not be more than one (*i.e.*, total weighted output/total weighted input ≤ 1).

DEA assumes that each DMU will choose weights that maximise its efficiency ratio (maximising total weighted output/total weighted input). As each DMU uses different input combinations to produce different output combinations, each DMU will select a set of weights that reflects this diversity. Weights are not the economic values of the input and output, but rather they are determinants to maximise the efficiency of a DMU. The method of measurement used in DEA is to compare the output generated by the current inputs (Ramanathan, 2003).

The ratio or efficiency score is basically calculated as follows:

$$\text{Efficiency} = \frac{\text{Weighted sum of output}}{\text{Weighted sum of input}}$$

subject to

$$\text{Maximum} = \frac{\sum_{r=1}^{s} v_r y_{r0}}{\sum_{r=1}^{m} v_i x_{i0}} = 1$$

Steps in Conducting Studies Using DEA

In conducting research using DEA as part of the methodology, several steps need to be followed as shown in *Figure 1*.

The steps start with identifying the most suitable input related to the study. Only then is identification of the output done. When determining the input and output variables for the study, it is important to ensure that the result is accurate. After data collection is done based on the selected input and output, the efficiency score for all DMU is determined using suitable software. Based on the efficiency scores, DMU with scores of 1 will be considered efficient whereas those with scores less than 1 will be categorised as inefficient. The final steps are the most important as they help in setting the projections for those inefficient DMU by balancing the proportions for the number of input utilised in relation to the number of output.

Selection of Input and Output Variables

The only difficulty in DEA application is the selection of input and output. The criteria for the selection of input and output are very subjective. There are no specific rules to help in the selection of input and output. However, Ramanathan (2003) suggested some pointers for this selection process. Input is generally defined as the resources used by DMU or the conditions that affect the performance of DMU, while output is an advantage (benefit) that is generated as a result of the operating activities of DMU. In any application of DEA, it is important to specify the input and output correctly.

DEA Window Analysis

In DEA, there have been studies where small sample numbers were used in measuring the performance in an industry. According to the rule of thumb, DMU must be twice of the number of input and output. This is to avoid misleading results in determining the efficiency level. However, in certain cases, DEA allows the use of small numbers of DMU when other models are employed which can overcome the issues of limited numbers of DMU.

The Window Analysis method was introduced by Charnes and Cooper (1985) as a way to overcome the limited or small numbers of DMU. It is known as a way to study the trend and behaviour of each of the DMU involved. The basic idea and concept of this time-dependent use of DEA are found to be suitable for dynamic situations (Cooper *et al.*, 2006). This technique was chosen to be used in this current study due to its suitability for the small number of DMU, and also because it can cater for the variations in efficiency over the time duration of the study. In other words, it can treat each of the entities differently for each time period.

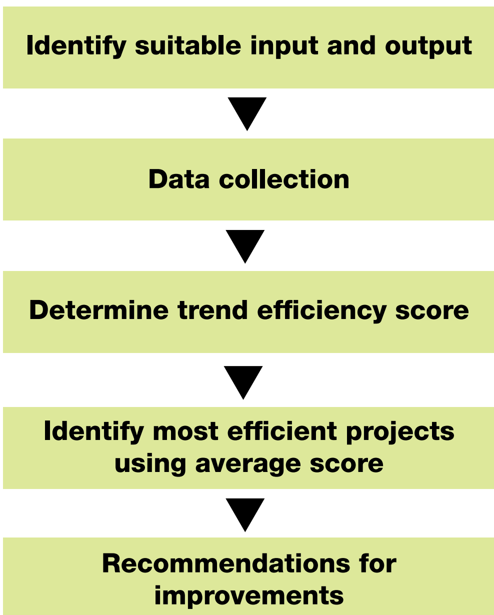

Figure 1. Steps in the methodology using data envelopment analysis (DEA).

Generally, DEA will treat DMU differently for each reporting date by comparing them to a subset data panel. It is able to assess the performance of DMU from time to time, and is able to monitor the performance of a unit or process. It can calculate the average efficiency of the CCR model (based on Charnes, Cooper and Rhodes) and of the BCC model (based on Banker, Charnes and Cooper), and is useful for detecting efficiency trends over time.

Referring to Asmild *et al.* (2004), let us assume a sample of N DMU (n = 1,….N) with a period of observation over T periods (t = 1,…T) and where inputs i are used to produce output j. With such assumptions, the sample will have N x T observations. For each observation n in the period t, DMU_t^n has an r-dimensional input vector $x_t^n = (x_{1t}^n, x_{2t}^n, \ldots, x_{rt}^n)^T$ and a dimensional s output $x_t^n = (y_{1t}^n \ldots, y_{rt}^n)^T$. The window starting at time k, $1 \leq k \leq T$ and with the width w, $1 \leq w \leq T \leq k$, is denoted by k_w, and has N x w observations.

The matrix of input in the window analysis is given by:

$$X_{kw} = (x_k^1, x_k^2, \ldots, x_k^N, x_{k+1}^1, x_{k+1}^2 \ldots, x_{k+1}^N, \ldots, x_{k+w}^1, x_{k+w}^2, \ldots, x_{k+w}^N),$$

while the matrix of outputs under this model analysis is:

$$Y_{kw} = (y_k^1, y_k^2, \ldots, y_k^N, y_{k+1}^1, y_{k+1}^2 \ldots, y_{k+1}^N, \ldots, y_{k+w}^1, y_{k+w}^2, \ldots, x_{k+w}^N)$$

No justification theory is found for the selection of the window size (Al-Eraqi *et al.*, 2008). DEA basically uses to analyse the cross-sectional data of DMU_k rather than those of other DMU in the same period of time where the time factor is ignored (Sun and Lin, 2009). Window Analysis, however, is based on the assumptions that have been made in the past and which remain feasible, and also performs an analysis of the treatment time window which is more than average.

One of the main benefits of using Window Analysis is that it can increase the discriminating power of DEA by increasing the size of DMU (Maidamisa *et al.*, 2012). Window Analysis of DEA has been used in many different fields such as in the port industry (Al-Eraqi *et al.*, 2010; Pjevcevic *et al.*, 2011), science park (Sun and Lin, 2009), wood panel industry (Hemmasi *et al.*, 2011), banking industry (Asmild *et al.*, 2004) and the automotive industry (Alshare, 2004).

METHODOLOGY

This study using DEA catered for the measurement of performance by selecting an oil palm company as a case study, and the framework is shown in *Figure* 2. The input and output variables were identified for the evaluation and analysis. Correlation analysis was performed to validate effectiveness. The DEA approach was then applied, and results from Window Analysis were presented.

Industrial Case Study

This study was conducted at one of the private companies that operate oil palm plantations in Malaysia. As the selection is based on the practices complying with the Roundtable on Sustainable Palm Oil (RSPO), this company fulfills the selection condition because it follows the safety practices guided by RSPO. Data collected from 2001 until 2010 were on five input and one output as the variables as shown in *Figure* 2. This company has three oil palm plantations that directly supply their production output [fresh fruit bunch (FFB)] to one palm oil processing mill belonging to the same company, and for that reason the number of DMU was only three. As the identity of DMU used in this study is confidential, they are thus coded by the letters *A*, *B* and *C*.

Data and Variable Description

In this case study, input and output data for the oil palm productions were obtained from the three plantations belonging to the company under study. The data were collected for 10 years beginning from 2001. There were three DMU (*A*, *B* and *C*) involved in the case study and five input variables and one output variable. The elements of land area, labour, fertiliser, capital and machinery were identified as the input variables whereas the production of FFB comprised the output, and the variables were measured as shown in *Table 1*.

Fertiliser, labour and capital were the factors analysed in this study. Productivity in Malaysia is still driven more by capital and labour inputs than by innovation; however, the palm oil industry is now plagued by a problem of labour shortage (Belai *et al.*, 2011). Fertiliser management plays an important role in the productivity and profitability of oil palm production.

Data Analysis

Data collected were first analysed using the software SPSS version 16.0 in order to understand and identify the relationships between the input and output variables. This was part of a validity test which uses correlation analysis. Once all the input and output were found to be significantly correlated with one another, the data were then analysed using DEA Solver Software Learning Version for Window Analysis. *Table* 2 shows the summary statistics of the input and output variables, covering mean, standard deviation, minimum and maximum values, and sum, for all the selected resources used (input) as well as the total production of FFB (output), for 10 consecutive years.

RESULTS AND DISCUSSION

In this section, we provide details of the correlation analysis, DEA-CCR model analysis and Window Analysis. Charnes and Cooper

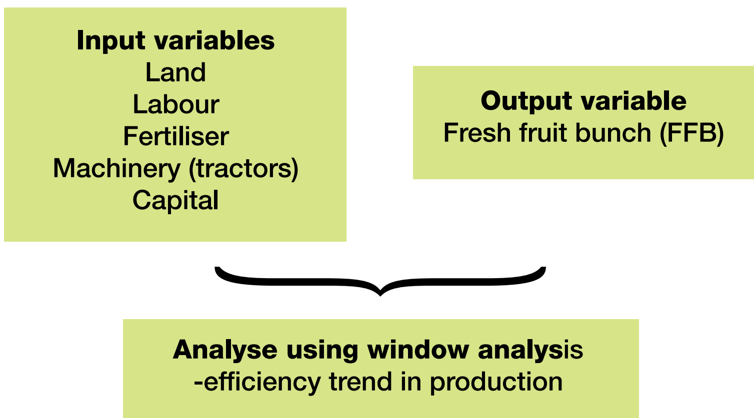

Figure 2. Research framework for the oil palm efficiency study using data envelopment analysis (DEA).

TABLE 1. VARIABLE DESCRIPTIONS FOR DATA ENVELOPMENT ANALYSIS (DEA)

Variable	Unit	Description
Fresh fruit bunch (FFB)	t	Quantity of oil palm produced per plantation
Land area	ha	Planted area per plantation
Hired labour	Man-day	Number of harvesters and drivers hired for use per plantation
Tractor	No.	Number of tractors used per plantation for the process of transportation
Fertiliser	kg	Quantity of chemical fertiliser used per plantation
Capital	RM	Cost incurred for using machines and tools per plantation, including the costs of maintenance, repairs, depreciation and interest

(1985) mentioned that in order to validate the DEA model, all input used in the model need be related to the output produced. Correlation analysis is important in testing the pattern of the data as well as analysing the relationships existing among the variables in a study.

Table 3 shows the results of the correlation analysis between the five input and output. Of all the inputs, two (fertiliser and capital) were found to have negative correlations with the rest. Land area and labour had the highest positive correlation coefficient of 0.9574. Land area and FFB also had a high positive correlation coefficient of 0.856. Land area and tractor had a medium positive correlation coefficient of 0.6854.

All the correlation coefficients were significant at probability levels of less than the 0.05 or 0.01 levels. This is important to ensure that the variables selected in this study were significantly correlated. Since fertiliser was found not significant, then it will be removed from the analysis using DEA method.

The subsequent analysis was done using the Window Analysis, DEA Solver application. Window Analysis helps to spot the most and least efficient plantation. A three-year window width was chosen as the oil palm takes this long to mature and start producing fruits for harvest from the date of transplanting to the field. In each of the windows, every plantation will be treated as an independent entity. The efficiency scores using this analysis indicate the separate observations on the three plantations in the 10 different years, and were compared against each of the entities. This also means that by choosing a three-year window width, the observations were only compared within three-year time spans.

Table 4 shows the DEA-Window Analysis scores for the three plantations by year in each of the windows presented. The efficiency scores were different for every year; each column gives the efficiency score for the same year but the scores were evaluated using different window widths.

Among the three plantations, *C* led with the highest average efficiency level (94.88), followed by *B* (93.55), while *A* recorded the least efficient level (68.24). This shows that the overall performance for *C* was relatively higher than the other two plantations. Similarly, *B* had a relatively higher overall performance than *A*; thus, both the plantations *C* and *B* had a more stable performance than *A*.

The efficiency scores for each of the years were different suggesting industry changes over time and

TABLE 2. SUMMARY STATISTICS OF THE INPUT AND OUTPUT VARIABLES

	Land area (ha)	Hired labour (man)	Tractor (No.)	Fertiliser (kg)	Capital (RM)	FFB (t)
Mean	1 929.647	102.36666	7.4	2 551.136	211 672	37 380.3
Standard deviation	649.325	33.7224813	1.220514	623.1657	178 469.3	19 432.35
Minimum	448.2	27	5	1 270.75	7 800	7 974.64
Maximum	2 641.6	141	9	3 763.5	707 544	64 752
Sum	57 889.4	3 071	222	76 534.08	6 350 160	1 121 409

Note: FFB – fresh fruit bunch.

TABLE 3. CORRELATIONS[a] BETWEEN INPUT AND OUTPUT VARIABLES

	Land area	Labour	Tractor	Fertiliser	Capital	FFB
Land area	1	0.957[b]	0.685[b]	0.280	-0.529[b]	0.856[b]
Labour	-	-	0.734[b]	0.198	-0.509[b]	0.894[b]
Tractor	-	-	-	-0.050	-0.489[b]	0.638[b]
Fertiliser	-	-	-	-	-0.081	0.360
Capital	-	-	-	-	-	-0.433[c]

Note: [a] Pearson correlation. [c] Significant at $p<0.05$ level. [b] Significant at $p<0.01$. Sample size (n) = 30.
FFB – fresh fruit bunch.

detecting performance trends over the 10-year period. Changes resulted from new technology, the amount of resources used or the replanting process, all of which will impact the final average efficiency scores among the plantations. To achieve high average efficiency scores, plantations with low scores need to know the most suitable combination of input that will result in the best volume of output.

There was an issue on the usage of resources relating to Plantation *A* as the performance trend for this plantation was quite unstable. In 2005 and 2006, the efficiency scores for *A* were particularly low (<0.5), which resulted in the low average efficiency score for this plantation.

Figure 3 shows the performance trend and the stability of the three plantations. The most stable plantation was *C*. Plantation *B* experienced higher efficiency scores in the early years but the scores then slowly declined towards the later years. For *B*, the variations through window analyses show both lower efficiency scores and unstable performance efficiency trend. In the early years, until the window width of 2007, the score was declining but it slowly recovered in the later years. It is therefore expected that Plantation *A* would be able to increase its performance efficiency score eventually, and attention needs to be focused on Plantation *B* because of the declining efficiency trend it faced in the later years.

Based on the values in *Table 5*, the highest average efficiency (score of 1) by plantation was recorded for in 2009 and 2010 for plantation *A*, in 2001 and 2004 for *B*, and in 2001, 2002 and 2009 for *C*.

As these three plantations belong to a single big private company, there is a need to identify how *A* used its resources for production in order to improve its performance level so that *A* can be at its optimum, whereas *B* and *C* can further increase their efficiency scores to the maximum level too.

It is important to improve the efficiency scores as Malaysia's closest competitor in the palm oil industry is Indonesia whose government is currently focusing on massive expansion in the production of oil palm (Susanti and Burgers, 2011). Malaysia needs to ensure that they are able to compete and respond positively to remain the top producer and exporter of palm oil in the world.

Oil palm and palm oil production has grown over time in its role in the Malaysian economy. It has contributed a large proportion to the Malaysian export earnings, thus its importance cannot be ignored. Increasing production efficiency will eliminate waste in the use of resources, and furthermore reflects productivity. The issue of labour shortage can no longer be disregarded. The shortcomings of other inputs such as land, tractor and capital also need to be addressed. The efficient utilisation of all the inputs will give an impact on production and the overall performance of a plantation. By increasing the efficiency level, the production process will be strengthened and be more astute.

CONCLUSION

Efficiency is among the common types of measurement for performance in an industry. In this study, we examined the technical efficiency of three oil palm plantations. TE means there is no wastage in the use of input while producing specific amounts of output.

Our study used the DEA Window Analysis method to measure performance trend in the oil palm industry. Window Analysis is able to capture the efficiency scores of a small number of DMU using time series data. It can identify the best performance trend in the industry under study. By using Window Analysis, the number of DMU will be increased as it treats each of the years as different entities of DMU. The suitability of using Window Analysis is when the number of DMU is small or limited; thus, Window Analysis helps to overcome small sample sizes.

Efficiency score may vary for any entity among homogenous units of

TABLE 4. EFFICIENCY LEVELS USING WINDOW ANALYSIS

Plantation	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010		Mean efficiency
A	0.6402	0.6152	0.7767	-	-	-	-	-	-	-	0.6737	0.6824
	-	0.5904	0.7313	0.7239	-	-	-	-	-	-	0.6818	-
	-	-	0.7313	0.7239	0.4241	-	-	-	-	-	0.6264	-
	-	-	-	0.7239	0.4241	0.3697	-	-	-	-	0.5059	-
	-	-	-	-	0.4480	0.3906	0.4295	-	-	-	0.4227	-
	-	-	-	-	-	0.5175	0.5746	0.8216	-	-	0.6379	-
	-	-	-	-	-	-	0.7199	1.000	1.000	-	0.9066	-
	-	-	-	-	-	-	-	1.000	1.000	1.000	1.000	-
	x	0.0248	0.0454	0	0.0239	0.1478	0.2904	0.1784	0	x	-	0.2904
B	1.000	1.000	1.000	-	-	-	-	-	-	-	1.000	0.9355
	-	0.9609	0.9965	1.000	-	-	-	-	-	-	0.9858	-
	-	-	0.9965	1.000	0.9465	-	-	-	-	-	0.9810	-
	-	-	-	1.000	0.9465	0.9767	-	-	-	-	0.9744	-
	-	-	-	-	1.000	1.000	0.6682	-	-	-	0.8894	-
	-	-	-	-	-	1.000	0.7675	0.7661	-	-	0.8445	-
	-	-	-	-	-	-	1.000	1.000	0.8352	-	0.9451	-
	-	-	-	-	-	-	-	1.000	0.8750	0.7157	0.8636	-
	x	0.0391	0.0035	0	0.0535	0.0233	0.3318	0.2339	0.0218	x	-	0.3318
C	1.000	1.000	1.000	-	-	-	-	-	-	-	1.000	0.9488
	-	1.000	0.9977	0.9218	-	-	-	-	-	-	0.9731	-
	-	-	1.000	0.9239	0.8672	-	-	-	-	-	0.9303	-
	-	-	-	0.9280	0.8711	0.8677	-	-	-	-	0.8889	-
	-	-	-	-	1.000	0.9169	0.7748	-	-	-	0.8972	-
	-	-	-	-	-	1.000	0.8995	0.9353	-	-	0.9449	-
	-	-	-	-	-	-	1.000	1.000	1.000	-	1.000	-
	-	-	-	-	-	-	-	1.000	1.000	0.8674	0.9558	-
Average	x	0	0	0.0062	0.1328	0.1323	0.2252	0.0647	0	x	-	0.1328

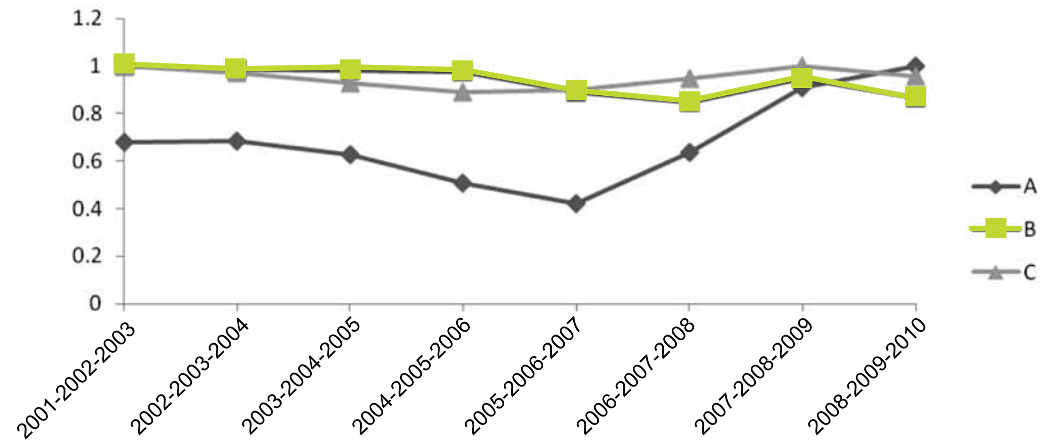

Figure 3. Variations in performance efficiency through Window Analysis.

TABLE 5. AVERAGE EFFICIENCIES BY YEAR

Plantation Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
A	0.6402	0.6028	0.7464	0.7239	0.4321	0.4259	0.5747	0.9405	1.000	1.000
B	1.000	0.9804	0.9977	1.000	0.9643	0.9922	0.8119	0.9220	0.8551	0.7157
C	1.000	1.000	0.9992	0.9245	0.9128	0.9282	0.8914	0.9784	1.000	0.8674

DMU. In oil palm plantations as well as in other industries, the efficiency score may show different values in different years. Indeed, the results from this analysis also show inefficiency scores for DMU. Thus, performance efficiency for the coming years can be predicted based on the previous performance trend.

In our study, we first conducted a correlation analysis to identify how the input related one another and to the output. Next, we applied the Window Analysis, and the results recorded different efficiency levels for the three plantations for each of the years. DMU for a period is regarded as a wholly different DMU. In such a situation, the DMU efficiency score for a certain period is placed adjacent to its own efficiency scores for other periods as well as the efficiency scores of other DMU.

The results indicate that plantations *C* and *B* has attained the highest average efficiency scores while plantation A has the lowest average efficiency score. It is suggested that instead of focusing only on *A* to increase its efficiency, the company needs also to accommodate *B* because the window variations showed declining efficiency scores in the later years of this particular plantation.

More studies are needed to improve the information reported in this article. First, this article focuses on only three plantations as a case study; thus, increasing the number of DMU will strengthen the results and the window variations by comparing DMU to more data and windows.

Second, future studies should expand on the input and output variables for measuring performance trends. By increasing the number of input, output and DMU, various combination models of CCR, BCC and Window Analysis for the palm oil industry can be done. It will lead to better final outputs by setting benchmarks for the industry as well as ranking them in order of importance so that projections can be made for the coming years.

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