

MEASURING EFFICIENCY IN MALAYSIAN PALM OIL PRODUCTION USING CCR AND BCC DEA MODELS

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Abstract: *This study aims to determine the top ten palm oil-producing states in Malaysia by analyzing a dataset comprising inputs and outputs of palm oil production from various sources in the year 2022. The study unfolds in three phases: the application of BCC and CCR Input-oriented data envelopment analysis model were used to identify the most efficient state of crude oil production in Malaysia individually and a comparative analysis using Super Efficiency Model in the final phase to rank the efficient DMUs from first and second phase. The conclusive findings identify Perak as the most efficient state consistently across both models. The study emphasizes the importance of selecting an appropriate DEA model for precise efficiency evaluations. Recommendations for future research include a focus on firm-level factors influencing efficiency in industrial palm oil production. This journal article contributes valuable insights into the palm oil industry, facilitating informed decision-making for sustainable and efficient production practices.*

Keywords: *Data Envelopment Analysis, CCR Model, BCC Model, Super-Efficiency, Technical Efficiency, Palm Oil, Malaysia*

Introduction

Palm oil has grown to become the world's primary vegetable oil, both produced and consumed globally. It is found in numerous consumer goods as well as biofuels, indicating its extensive multifunctional industrial footprint worldwide (Murphy et al., 2021). Malaysia has established itself as the world's second-largest producer of palm oil, accounting for around one-third of global production and representing a critical single sector that contributes 2.5% to the nation's total Gross Domestic Product (GDP) (Statista Research Department, 2023). However, in recent years, the Malaysian palm oil sector has encountered mounting environmental and economic challenges, including shifting weather patterns, increasing awareness of the environmental impacts of monoculture plantations, and an excessive reliance on foreign labor (Sabar, 2019). These vulnerabilities were further exacerbated by the COVID-19 pandemic, which disrupted commodity production, inventories, and export prices (Statista Research Department, 2023).

As the global population expands, the demand for palm oil continues to rise, necessitating enhanced yields and more productive management frameworks (Mahmud & Chong, 2022). In Peninsular Malaysia, which hosts over fifty percent of all palm oil planted lands, the palm oil industry serves as a major socio-economic pillar (Statista Research Department, 2023). Cultivation and downstream processing employ more than 500,000 Malaysians and engage nearly 640,000 smallholders who own 40% of Malaysia's oil palm agricultural land, thereby playing a fundamental role in rural poverty alleviation (Murphy et al., 2021). The major single export markets for Malaysian palm oil products are China and India, while the European Union remains the largest import region (Statista Research Department, 2023).

The expansion of palm oil production in Malaysia faces severe structural constraints. Chief among these is the slowing rate of land expansion due to an acute shortage of suitable, accessible land (Mohamad et al., 2013). Consequently, the primary path for future growth relies heavily on maximizing the operational efficiency and productivity of current planted areas (Sari et al., 2021). Efficiency in agriculture is generally defined as the relationship between inputs utilized and outputs obtained; however, there is currently no standardized definition or methodology for measuring and maintaining land use efficiency (Sari et al., 2021). Productivity levels differ significantly among various plantations due to factors such as agricultural practices, soil quality, pests, diseases, and localized resource management (Sathinee et al., 2019). Without precise, reliable efficiency measurements, policymakers and producers cannot identify underperforming regions or optimize resource allocation. This study addresses this gap by applying and comparing two primary non-parametric models under the Data Envelopment Analysis (DEA) framework: Super-Efficiency CCR input-oriented model and the Super-Efficiency BCC input-oriented model.

This project is highly significant for both academic and industrial stakeholders. Malaysia remains a dominant force in the global vegetable oil market, and optimizing resource allocation minimizing inputs such as planted area and mills while maintaining high crude palm oil (CPO) and fresh fruit bunch (FFB) yields is essential to preserve international competitiveness (Ahmad Parveez et al., 2021). By comparing CCR and BCC models, this study offers a clear methodology for benchmarking agricultural performance across regional divisions. Furthermore, identifying the most efficient regions provides operational models from which other states can learn, facilitating the transfer of best management practices. In terms of sustainability, improving resource efficiency directly aligns with sustainable development goals (SDGs) by reducing the pressure on forest clearing, optimizing land use, and lowering the environmental footprint of cultivation (Murphy et al., 2021).

Literature Review

Previous Research on Palm Oil Production

The efficiency of the palm oil sector has been a subject of rigorous scholastic inquiry due to its major economic and environmental significance. Globally, the rapid expansion of oil palm plantations has attracted substantial research interest, particularly in Southeast Asia, which accounts for the vast majority of international trade (Xu et al., 2020). Scholars have employed various parametric and non-parametric techniques to evaluate productivity. For instance, Anam and Suhartini (2020) evaluated the productive efficiency of palm oil companies in Indonesia using Data Envelopment Analysis (DEA). Their research highlighted that while historical focus remained on volume expansion, modern management must prioritize technical, scale, and allocative efficiencies to address resource constraints. Similarly, Sulaiman and Ismail (2021) examined the technical effectiveness of Malaysia's palm oil-based industrial sector. Using a combination of DEA and panel regression across sixteen years, they discovered that many downstream subsectors were operating at suboptimal efficiency levels, suggesting a critical need to optimize production-side inputs.

In plantation-level studies, Mohamad et al. (2013) applied DEA Window Analysis to evaluate the efficiency trends of Malaysian palm oil estates from 2001 to 2010. Their findings highlighted substantial productivity differences among plantations and emphasized the importance of benchmarking to resolve resource wastage. In Indonesia, Septiani and Setiawan (2023) utilized a robust bootstrapped DEA approach alongside panel vector autoregressions to analyze the relationships between technical efficiency, market structure, and firm growth. They noted that variable returns to scale (VRS) models are critical when comparing firms of different operational sizes to prevent scale bias. At the microeconomic level, Sathinee et al. (2019) evaluated private oil palm seed production in Surat Thani, Thailand. Using input-oriented DEA, they determined that over 44% of private seed producers were technically inefficient, reinforcing that optimizing inputs like fertilizer, labor, and land is critical for long-term sustainability.

DEA Models for Measuring Efficiency

Data Envelopment Analysis (DEA) is a widely recognized non-parametric method based on linear programming, first introduced by Charnes, Cooper, and Rhodes (1978) as a Constant Returns to Scale (CRS) model, known as the CCR model. The CCR model constructs a piecewise linear frontier, assuming that an increase in inputs results in a proportional increase in outputs (Li, 2020). However, Banker, Charnes, and Cooper (1984) extended this by incorporating Variable Returns to Scale (VRS), creating the BCC model. The BCC model relaxes the CRS assumption, allowing for increasing, constant, or decreasing returns to scale, which is particularly appropriate when units do not operate at an optimal scale due to financial, regulatory, or geographic constraints (Bournaris et al., 2019). Scale efficiency (SE) can be derived by analyzing the relationship between CCR and BCC scores. While both models are widely utilized in agricultural economics, comparing their scores under a Super-Efficiency framework, which allows the ranking of fully efficient units by excluding the unit under evaluation from the reference set, provides deeper analytical resolution (Andersen & Petersen, 1993).

Background of Malaysian Palm Oil Industry

The Malaysian palm oil industry has a rich historical trajectory, originating in 1870 when *Elaeis guineensis* was first introduced to Peninsular Malaysia as an ornamental plant (Sabar, 2019).

The commercialization of oil palm began in the early 1900s, with Henri Fauconnier establishing the first commercial estate in Tennamaram, Selangor, in 1917 (Sabar, 2019). In the 1960s, the Malaysian government introduced agricultural diversification programs to reduce national economic reliance on rubber and tin (Malaysian Palm Oil Council, 2023). This expansion was heavily supported by government land settlement schemes, such as the Federal Land Development Authority (FELDA), which aimed to uplift rural communities (Ahmad Parveez et al., 2021). Today, FELDA schemes account for 25% of total plantations, while private corporations manage the remainder (Malaysian Palm Oil Council, 2023). The primary regulatory authority is the Malaysian Palm Oil Board (MPOB), formed in 2000 through the merger of PORIM and PORLA, which oversees licensing, research, and policy enforcement (Malaysian Palm Oil Council, 2023).

Selection of Inputs and Outputs

Selecting appropriate input and output variables is a cornerstone of robust DEA modeling. Prior literature shows a wide range of variables depending on data availability. As shown in historical studies, inputs typically include land, labor, fertilizer, and physical capital, while outputs center on CPO, FFB, or sales revenue (Anam & Suhartini, 2020; Sulaiman & Ismail, 2021; Mohamad et al., 2013). Because this study utilizes official secondary data, the variables were selected by matching physical resources to production outcomes. The physical inputs are Planted Area (representing land capital) and Total Mills (representing processing infrastructure) (Data Statistics on Commodities of Palm Oil, 2022; The Malaysian Oil Palm Industry Performance, 2022). The output variables are CPO Production (representing the primary processed product) and FFB Yield Received by Mills (representing raw agricultural output) (Data Statistics on Commodities of Palm Oil, 2022; The Malaysian Oil Palm Industry Performance, 2022). This multi-input, multi-output specification ensures a holistic capture of both cultivation and milling efficiencies across states.

Methodology

Data Collection and Sample Selection

This study utilizes secondary, state level data for the year 2022, collected directly from the official databases of the Malaysian Palm Oil Board (MPOB). The datasets include 'Data Statistics on Commodities of Palm Oil' and 'The Malaysian Oil Palm Industry Performance'. The sample comprises ten distinct palm oil-producing states, which act as the Decision-Making Units (DMUs) in the DEA models. Evaluating these states as DMUs allows for a macro-level comparison of regional efficiency within Malaysia.

Decision-Making Units and Dataset

The 10 states evaluated are Johor, Kedah, Kelantan, Negeri Sembilan, Pahang, Perak, Selangor, Terengganu, Sabah, and Sarawak. The complete raw dataset of inputs and outputs for these DMUs is compiled in Table 1.

Table 1: State Level Input and Output Data for Malaysian Palm Oil Production in 2022

State (DMU)	Inputs		Outputs	
	Planted Area (Hectares)	Total Mills	CPO Production (Tonnes)	FFB Received (Tonnes)
Johor (DMU 1)	676,853	62	2,969,525	15,320,227
Kedah (DMU 2)	86,487	6	237,382	1,200,812
Kelantan (DMU 3)	161,852	10	336,061	1,624,993
Negeri Sembilan (DMU 4)	178,560	15	675,767	3,565,162
Pahang (DMU 5)	749,813	67	3,013,107	15,888,833
Perak (DMU 6)	352,098	44	1,866,423	9,717,282
Selangor (DMU 7)	106,008	16	498,904	2,666,802
Terengganu (DMU 8)	170,825	12	407,500	2,072,112
Sabah (DMU 9)	1,508,060	127	4,286,665	21,323,835
Sarawak (DMU 10)	1,622,374	83	4,005,425	20,645,487

Source: Adapted From Data Statistics on Commodities of Palm Oil (2022) and The Malaysian Oil Palm Industry Performance (2022)

Mathematical Formulations of DEA Models

To evaluate the relative technical efficiency of the 10 states, this study employs both the CCR input-oriented model (Constant Returns to Scale) and the BCC input-oriented model (Variable Returns to Scale). Under an input-oriented framework, the objective is to minimize input utilization while maintaining a constant level of outputs, which is highly relevant given the physical constraints on land expansion in Malaysia (Septiani & Setiawan, 2023).

Model 1: Input-Oriented CCR (CCR-I) Model

The CCR-I model for DMU₀ set up, respectively as follows:

$$\text{Max}, \theta_0 = \sum_{j=1}^m u_j y_{j0}$$

Subject to:

$$\begin{aligned} \sum_{i=1}^s v_i x_{i0} &= 1, \\ \sum_{j=1}^m u_j y_{jk} - \sum_{i=1}^s v_i x_{ik} &\leq 0, \\ u_j &\geq 0, v_j &\geq 0 \end{aligned}$$

where $u_i (i = 1, \dots, m)$ and $v_j (j = 1, \dots, s)$ be the weights attached to the i th input and j th output, respectively. For this model, $i = 1, \dots, s$ is the total number of inputs, $j = 1, \dots, m$ is the total number of output. x_{i0} and y_{j0} are the input and output vector of DMU_0 respectively. x_{ik} and y_{jk} are the actual amount of input and output for DMU_k .

Model 2: Input-Oriented BCC (BCC-I) Model

The BCC-I model for DMU_0 set up, respectively as follows:

$$Max, \theta_0 = \sum_{j=1}^m u_j y_{j0} + u_0$$

Subject to:

$$\begin{aligned} \sum_{i=1}^s v_i x_{i0} &= 1, \\ \sum_{j=1}^m u_j y_{jk} - \sum_{i=1}^s v_i x_{ik} + u_0 &\leq 0, \\ u_j &\geq 0, v_j &\geq 0 \end{aligned}$$

where $u_i (i = 1, \dots, m)$ and $v_j (j = 1, \dots, s)$ be the weights attached to the i th input and j th output, respectively. For this model, $i = 1, \dots, s$ is the total number of inputs, $j = 1, \dots, m$ is the total number of output. x_{i0} and y_{j0} are the input and output vector of DMU_0 respectively. x_{ik} and y_{jk} are the actual amount of input and output for DMU_k .

Model 3: Super-Efficiency Model

The Super-Efficiency Model is used for ranking the efficient DMUs. This model is defined as:

$$Max, \theta_0 = \sum_{j=1, j \neq 0}^m u_j y_{j0} + u_0$$

Subject to:

$$\begin{aligned} \sum_{i=1}^s v_i x_{i0} &= 1, \\ \sum_{j=1, j \neq 0}^m u_j y_{jk} - \sum_{i=1}^s v_i x_{ik} + u_0 &\leq 0, \\ u_j &\geq 0, v_j &\geq 0 \end{aligned}$$

where $u_i (i = 1, \dots, m)$ and $v_j (j = 1, \dots, s)$ be the weights attached to the i th input and j th output, respectively. For this model, $i = 1, \dots, s$ is the total number of inputs, $j = 1, \dots, m$ is the total number of output. x_{i0} and y_{j0} are the input and output vector of DMU_0 respectively. x_{ik} and y_{jk} are the actual amount of input and output for DMU_k .

Because standard DEA models often yield multiple efficient DMUs with a score of 1.0, ranking them is impossible. To resolve this, the Super-Efficiency model developed by Andersen and Petersen (1993) is employed. The Super-Efficiency model ranks efficient DMUs by excluding the unit under evaluation from the reference set constraints (i.e., $k \neq 0$). This allows the

efficiency score of an efficient unit to exceed 1.0, reflecting the maximum proportional increase in inputs that would still allow the unit to remain efficient (Pan et al., 2020).

Software and Computational Setup

The mathematical programming models were formulated and solved using LINGO 19.0 software. LINGO is a powerful tool designed to build and solve linear (LINDO Systems, 2023), non-linear, and integer optimization models, offering high computational speed, simplicity, and accuracy for DEA formulations compared to alternative programs.

Results and Discussion

Results of Phase 1: CCR Input-Oriented Model

The standard CCR model was first applied to evaluate the technical efficiency of the ten states. The resulting efficiency scores are shown in Table 2. Out of the ten states, only three achieved an efficiency score of 1.0, indicating they are technically efficient and lie on the production frontier: Johor, Perak, and Sarawak. The remaining seven states are inefficient, with scores below 1.0. For instance, Negeri Sembilan achieved a high score of 0.9611, indicating near-efficiency, whereas Kelantan was identified as the most inefficient state with a score of 0.6984. These inefficient states did not fully optimize their input physical resources planted area and mills to achieve their respective output yields (Hesampour et al., 2022).

To rank the three efficient states, the Super-Efficiency CCR model was applied. The super-efficiency scores compiled in Table 2 indicate that Perak (DMU 6) is the most efficient state under the constant returns to scale assumption, with an impressive super-efficiency score of 1.2193. Johor (DMU 1) ranked second with a score of 1.0912, and Sarawak (DMU 10) ranked third with a score of 1.0076.

Results of Phase 2: BCC Input-Oriented Model

The BCC model, assuming variable returns to scale, was subsequently applied. By allowing for scale variance, the number of efficient states increased from three to six, as shown in Table 2. The efficient states under the BCC model include Johor, Kedah, Negeri Sembilan, Perak, Selangor, and Sarawak. This increase is consistent with DEA theory, which holds that the BCC frontier is more flexible and tightly envelops the data, resulting in technical efficiency scores that are greater than or equal to their CCR counterparts (Coelli, 1992).

The Super-Efficiency BCC model was then applied to rank these six efficient states. As shown in Table 2, Kedah (DMU 2) emerged as the top-ranked efficient state under the variable returns to scale assumption, with a high super-efficiency score of 2.5000. Selangor (DMU 7) ranked second super-efficiency score of 1.2472, Perak (DMU 6) ranked third with super-efficiency score 1.1608, Negeri Sembilan (DMU 4) ranked fourth with super-efficiency score 1.0298, Johor (DMU 1) ranked fifth with super-efficiency score 1.0791, and Sarawak (DMU 10) ranked sixth obtained the lowest super-efficiency score of 1.0076.

Results of Phase 3: Comparative Analysis and Discussion

To determine the most appropriate model and identify the overall benchmark state for palm oil production in Malaysia, a comparative analysis was conducted between the CCR and BCC results. This evaluation utilizes two analytical techniques: evaluating the discriminatory power of the models and analyzing score correlations. First, Ghasami et al. (2014) demonstrated that a model's accuracy is enhanced by its ability to discriminate among DMUs, resulting in a

smaller, more focused set of efficient units. The result show that out of 10 , states , only three achieved an efficiency score of 1 under CCR model. This efficiency states are Johor, Perak, and Sarawak. Based on the CCR model, Perak (DMU 6) is consistently identified as the overall benchmark state with a super-efficiency score of 1.2193. Based on the BCC model, Kedah (DMU 2) is the top-ranked efficient state under the variable returns to scale assumption, with a high super-efficiency score of 2.5000, Selangor (DMU 7) ranked second super-efficiency score of 1.2472, Perak (DMU 6) ranked third with super-efficiency score 1.1608, Negeri Sembilan (DMU 4) ranked fourth with super-efficiency score 1.0298, Johor (DMU 1) ranked fifth with super-efficiency score 1.0791, and Sarawak (DMU 10) ranked sixth obtained the lowest super-efficiency score of 1.0076. This finding is empirically supported by MPOB yield statistics, which confirm that Perak recorded the highest monthly average CPO yield in 2022 (Data Statistics on Commodities of Palm Oil, 2022), validating the model's accuracy.

Table 2: Comparison of CCR and BCC Efficiency Scores and Super-Efficiency Rankings for 2022

State (DMU)	CCR Score	CCR SE Rank	BCC Score	BCC SE Rank
Johor (DMU 1)	1.00000	2 (Score: 1.09119)	1.00000	4 (Score: 1.07909)
Kedah (DMU 2)	0.82351	Inefficient	1.00000	1 (Score: 2.50000)
Kelantan (DMU 3)	0.69843	Inefficient	0.80165	Inefficient
Negeri Sembilan (DMU 4)	0.96114	Inefficient	1.00000	5 (Score: 1.02975)
Pahang (DMU 5)	0.95955	Inefficient	0.95952	Inefficient
Perak (DMU 6)	1.00000	1 (Score: 1.21930)	1.00000	3 (Score: 1.16077)
Selangor (DMU 7)	0.91153	Inefficient	1.00000	2 (Score: 1.24715)
Terengganu (DMU 8)	0.70695	Inefficient	0.79026	Inefficient
Sabah (DMU 9)	0.70414	Inefficient	0.70414	Inefficient
Sarawak (DMU 10)	1.00000	3 (Score: 1.00757)	1.00000	6 (Score: 1.00757)

Source: Compiled From LINGO 19.0 Computational Results

Conclusions and Recommendations

Conclusions of the Study

Based on the CCR and BCC models, Perak (DMU 6) is consistently identified as the overall benchmark state, with a super-efficiency score of 1.2193 and 1.16077 respectively. This finding is empirically supported by MPOB yield statistics, which confirm that Perak recorded the

highest monthly average CPO yield in 2022 (Data Statistics on Commodities of Palm Oil, 2022), validating the model's accuracy.

Recommendations for Future Research

Based on the findings, several recommendations are proposed. First, because states like Kedah, Negeri Sembilan, and Selangor are technically efficient but scale inefficient, local authorities must focus on adjusting plantation sizes and consolidation to operate at an optimal scale. Second, future research should expand on these macroeconomic findings by analyzing firm level or estate level data (Septiani & Setiawan, 2023). Investigating company level factors, such as specific agricultural techniques, fertilizer application rates, and management styles, would provide granular, actionable insights into how individual operations can achieve the benchmark efficiency demonstrated by Perak.

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