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MEASURING THE TECHNICAL EFFICIENCY OF PADDY-PRODUCING FARMERS' ORGANIZATIONS IN THE NORTHERN REGION OF MALAYSIA: A STOCHASTIC FRONTIER ANALYSIS APPROACH

(*Mengukur Kecekapan Teknikal Organisasi Petani Pengeluar Padi di Wilayah Utara Malaysia: Pendekatan Analisis Perbatasan Stokastik*)

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ABSTRACT

This study investigates the technical efficiency of paddy production among 27 Area Farmers' Organizations (Pertubuhan Peladang Kawasan, PPKs) operating under the Muda Agricultural Development Authority (MADA), Malaysia, using an output-oriented Stochastic Frontier Analysis (SFA) approach. The analysis spans four planting seasons: Season 2 (2020), Season 1 (2021), Season 2 (2021), and Season 1 (2022) and incorporates six input variables: number of farmers, land area, compound fertilizer, urea, NPK, and pesticide cost, with total average paddy yield serving as the output. The Cobb-Douglas functional form with half-normal inefficiency distribution was selected via the Akaike Information Criterion. Pesticide cost had a strong positive effect on output, highlighting the role of pest management. Region III (Pendang) recorded the lowest average efficiency at 86.56%. Among all PPKs, Kubang Sepat achieved the highest average efficiency (98.04%), while Titi Haji Idris recorded the lowest (74%). The estimated gamma value (0.4426; p = 0.0058) indicates that 44.26% of the variation in output is attributable to inefficiency. The results reveal efficiency disparities, the need for targeted policies, and the influence of weather and pests, which limit yield growth despite efficiency gains. This study provides evidence-based recommendations to improve resource use, productivity, and food security in Malaysia's paddy sector.

Keywords: technical efficiency; paddy production; stochastic frontier analysis; MADA

ABSTRAK

Kajian ini meneliti kecekapan teknikal pengeluaran padi dalam kalangan 27 Pertubuhan Peladang Kawasan (PPK) yang beroperasi di bawah Lembaga Kemajuan Pertanian Muda (MADA), Malaysia, dengan menggunakan pendekatan Analisis Perbatasan Stokastik (APS) berorientasikan output. Analisis ini merangkumi empat musim penanaman: Musim 2 (2020), Musim 1 (2021), Musim 2 (2021), dan Musim 1 (2022), serta melibatkan enam pemboleh ubah input iaitu bilangan petani, keluasan tanah, baja campuran, urea, NPK, dan kos racun perosak, manakala hasil purata keseluruhan padi digunakan sebagai output. Bentuk fungsi Cobb-Douglas dengan taburan separa normal bagi ketidakcekapan dipilih berdasarkan Akaike Information Criterion. Kos racun perosak memberi kesan positif yang ketara terhadap pengeluaran, menekankan peranan pengurusan perosak. Wilayah III (Pendang) mencatat purata kecekapan terendah iaitu 86.56%. Dalam kalangan semua PPK, Kubang Sepat mencapai purata kecekapan tertinggi (98.04%), manakala Titi Haji Idris mencatat yang terendah (74%). Nilai gamma (0.4426; p = 0.0058) menunjukkan bahawa 44.26% variasi output berpunca daripada ketidakcekapan. Dapatan ini mendedahkan perbezaan kecekapan antara PPK, keperluan dasar bersasar, serta pengaruh cuaca dan perosak yang mengehadkan pertumbuhan hasil walaupun kecekapan meningkat. Kajian ini memberikan cadangan berasaskan bukti untuk meningkatkan penggunaan sumber, produktiviti, dan keselamatan makanan dalam sektor padi Malaysia.

Kata kunci: kecekapan teknikal; pengeluaran padi; analisis perbatasan stokastik; MADA

1. Introduction

Rice remains a fundamental staple food and a strategic agricultural commodity in Malaysia, playing a vital role in ensuring national food security, supporting rural livelihoods, and contributing to socio-economic stability. Since rice is produced primarily through paddy cultivation, the performance of the paddy production sector directly determines the nation's rice availability. The Malaysian government has long prioritized rice self-sufficiency, investing heavily in irrigation infrastructure, mechanization, subsidy schemes, and research and development to strengthen the paddy sector. Despite these efforts, the sector continues to face persistent challenges, including stagnant harvests where farmers consistently produce the same amount of paddy each year despite their hard work declining farm incomes, rising production costs, and inefficient use of agricultural inputs. A key challenge is that many farmers are not realizing the full potential yield of their paddy fields, which in turn limits the overall rice supply. Improving the efficiency of paddy production is therefore crucial to increasing rice output, keeping the industry competitive, and reducing the country's dependence on rice imports.

Technical efficiency refers to a producer's ability to maximize output given a set of inputs under existing technology (Coelli *et al*. 2005; Kumbhakar & Lovell 2000). Measuring the technical efficiency of paddy producers is crucial because it helps identify production shortfalls and guides interventions to close the efficiency gap (Battese & Coelli 1995). Traditionally, technical efficiency in agricultural production has been analyzed using parametric frontiers, particularly Stochastic Frontier Analysis (SFA) models, which have been widely applied in rice production studies (Mailena *et al*. 2014; Ghee-Thean *et al*. 2012).

The stochastic frontier model's error structure consists of a two-sided symmetric error term, capturing random effects beyond the producer's control such as measurement errors or environmental factors, and a one-sided non-negative component that reflects technical inefficiency (Battese & Coelli 1995). This framework allows researchers to estimate the performance of each production unit and investigate the factors influencing efficiency, under the assumption that the two error components are independent (Kumbhakar & Lovell 2000).

Previous studies have applied both SFA and Data Envelopment Analysis (DEA) to assess the technical efficiency of rice production in Malaysia. For instance, Mailena *et al*. (2014) utilized SFA to evaluate rice farms in the Muda Agricultural Development Authority (MADA) region. The average technical efficiency was 85.4%, indicating potential for output improvement through better input utilization. Similarly, Ghee-Thean *et al*. (2012) employed a Translog stochastic production frontier to analyze 230 paddy farmers in Peninsular Malaysia. They reported a mean technical efficiency of 85.8% and emphasized the importance of farmer education and access to extension services. On the other hand, Nodin *et al*. (2021) applied DEA to compare efficiency between granary and non-granary areas. They revealed disparities that suggest room for efficiency enhancements across regions.

While the above mentioned studies provide valuable insights, most have concentrated on individual farm-level assessments, with limited attention to the role and efficiency of farmers' organizations as key intermediaries in the paddy production system. Farmers' organizations, particularly those operating under regional agricultural development authorities such as the Muda Agricultural Development Authority (MADA), play a central role in organizing smallholder farmers, distributing inputs, providing extension services, and supporting marketing activities. The efficiency of these organizations directly impacts the productivity and profitability of the farmers they serve. However, empirical research systematically assessing how efficiently farmers' organizations manage production resources and exploring potential performance improvements remains scarce.

This study aims to address this research gap by applying the SFA approach to measure the technical efficiency of paddy production across Malaysian farmers' organizations. Specifically, the study has the following objectives: (1) to identify the key input factors that drive paddy output, (2) to estimate the technical efficiency levels of farmers' organizations (PPK) involved in paddy production, and (3) to estimate the Potential Output Gains (POG), defined as the potential increase in rice production output required by each Farmers' Organization to achieve full technical efficiency without any additional input. The use of SFA offers a significant advantage over traditional deterministic frontier methods because it accounts for both random shocks (such as weather variability or pest outbreaks) and inefficiency effects, providing a more accurate and robust efficiency estimation.

The findings of this study are expected to have important implications for agricultural policymakers, farmers' organization leaders, and other stakeholders. By identifying the magnitude and sources of inefficiency, this research can inform targeted strategies to improve resource allocation, enhance production practices, and strengthen institutional support mechanisms. Ultimately, improving technical efficiency of paddy production not only increases Malaysia's rice output and improves farmer livelihoods, but also contributes to achieving broader national goals of agricultural sustainability and food security.

2. Materials and Methods

2.1. *Data sources*

This section provides a detailed explanation of the data used in this study's analysis. This research aims to calculate and interpret the productivity of paddy yield produced in the northern region of Malaysia. The area is monitored by the Muda Agricultural Development Authority (MADA), a government agency responsible for developing and managing the irrigation and paddy farming systems within the Muda region. This study focuses on four key regions under MADA's supervision. Each of these regions consists of several Pertubuhan Peladang Kawasan (PPK) (paddy collection centers), which play a crucial role in the collection, storage, and management of harvested paddy before it is marketed or distributed to relevant parties. PPKs also serve as operational hubs that oversee paddy farming activities, including the provision of agricultural inputs, research on more efficient cultivation methods, and monitoring crop performance to ensure effective paddy production.

A total of 27 PPKs operate under the administration of MADA, ensuring the effective governance and management of the paddy farming sector across the states of Kedah and Perlis, as detailed in Table 1. The data used in this study were obtained from secondary sources, specifically official records and reports provided by MADA, covering the four planting seasons between 2020 and 2022.

To enhance oversight and streamline agricultural operations, MADA has organized these areas into four main regions: Region I (Kangar) in the state of Perlis, Region II (Jitra) in Kedah, Region III (Pendang) in Kedah, and Region IV (Kota Sarang Semut) also in Kedah. This regional division enables MADA to implement more targeted management strategies, optimize resource allocation, and strengthen the monitoring of paddy production activities across its jurisdiction. In addition, it enables more systematic and thorough monitoring of paddy farming activities across these areas. The organizational structure also supports the efficient allocation of agricultural resources and strengthens the effectiveness of strategies designed to enhance paddy yields within MADA's jurisdiction.

Table 1: List of PPK under the supervision of MADA

Region	PPK	Pertubuhan Peladang Kawasan (PPK)	Number of PPK
Region I	A-I	Arau	
(Perlis)	B-I	Kayang	
	C-I	Kangar	5
	D-I	Tambun Tulang	
	E-I	Simpang Empat	
Region II	A-II	Kodiang	
(Jitra)	B-II	Sanglang	
	C-II	Kerpan	
	D-II	Tunjang	
	E-II	Kubang Sepat	9
	F-II	Jerlun	
	G-II	Jitra	
	H-II	Kepala Batas	
	I-II	Kuala Sungai	
Region III	A-III	Hutan Kampong	
(Pendang)	B-III	Alor Senibong	
	C-III	Tajar	6
	D-III	Titi Haji Idris	
	E-III	Kobah	
	F-III	Pendang	
Region IV	A-IV	Batas Paip	
(Kota Sarang	B-IV	Pengkalan Kundur	
Semut)	C-IV	Kangkong	
	D-IV	Permatang Buluh	7
	E-IV	Bukit Besar	
	F-IV	Sungai Limau	
	G-IV	Guar Chempedak	

2.2. *Input and output selection for SFA*

Accurate measurement of technical efficiency in agriculture depends heavily on selecting appropriate inputs and outputs. In this study, the SFA framework is applied to 27 PPK in Malaysia, with variables chosen based on recent empirical evidence and established production theory to ensure both relevance and robustness.

Output Variable:

- Average paddy yield per season (kg/hectare): A widely accepted indicator of productivity, reflecting the extent to which available resources are effectively converted into harvested paddy. This measure captures the combined influence of agronomic practices, resource use, and environmental conditions.

Input Variables:

1. Number of farmers: Represents total labor input, covering the entire production cycle from land preparation to harvesting. Labor remains a key factor in paddy farming, especially in semi-mechanized and traditional systems.
2. Land area (hectares): Indicates the physical scale of cultivation, directly influencing production potential and economies of scale.
3. Compound fertilizer (bags): Provides a balanced nutrient mix to improve soil fertility and support crop growth.
4. Urea fertilizer (bags): Supplies nitrogen for vegetative growth, a critical stage for achieving higher yields.

5. NPK fertilizer (bags): Delivers essential macronutrients (N, P, K) for overall plant health and yield stability.
6. Pesticide cost (RM)**:** Represents investment in pest and disease management, a determinant of crop survival and quality.

The choice of these variables is supported by both empirical studies and agricultural production economics theory. Fertilizers, pesticides, land size, and labor are consistently identified in the literature as core determinants of paddy productivity. For example, Maidin *et al*. (2023) reported significant effects of fertilizer use, pesticide application, and land area on technical efficiency among Malaysian paddy farmers. Kamaruddin and Abd. Rashid (2025) stressed the importance of optimized fertilizer management and integrated pest control in minimizing input waste, while Kalimuthu and Applanaidu (2024) highlighted the central role of land size in output variation, particularly in MADA areas.

The selected variables align with the structure of commonly used production functions in SFA, such as Cobb–Douglas and Translog, where land, labor, and agrochemical inputs are principal explanatory factors. This configuration allows the model to identify efficiency gaps and provide policy-relevant insights, enabling targeted interventions that improve resource utilization and enhance the overall performance of paddy production systems.

2.3. *Methodology*

This study employs the SFA method to estimate the technical efficiency of 27 PPK under the administration of MADA. The SFA approach is particularly suitable for this analysis as it allows for the separation of random errors (such as weather or unforeseen disruptions) from inefficiency effects, providing a more accurate measurement of each PPK's performance. By using this method, the study assesses how efficiently each PPK transforms inputs into paddy production outputs, identifying potential output gain and variations in efficiency levels across centers.

2.3.1 Stochastic Frontier Analysis (SFA)

A stochastic model was proposed by Aigner *et al*. (1977) and Meeusen and van Den Broeck (1977). SFA decomposes the error terms into two components. One part represents random events outside of the decision making unit's control and another part is a non-negative term that capturing inefficiency. SFA model is a parametric technique, which requires assumptions about the functional form of the production function and the distribution of the error ters. The panel data models of SFA distinguish two approaches, concerning the assumption of whether or not efficiency changes over time. Time-invariant efficiency models assume efficiency to be constant over time. To observe changes over time, panel data need to consider as well as data of several firms at several time points. The panel form used is :

$$y_{it} = x_{it}\beta + v_{it} - u_{it} \tag{1}$$

Battese and Coelli (1992) proposed to represent the preceding u_{it} as:

$$u_{it} = \exp\left[-\eta\left(t-T\right)u_i\right] \tag{2}$$

where eta, η is an unknown scalar parameter to be estimated which will determine whether inefficiencies are time-varying or time-invariant effects and u_i as technical inefficiency error that assumed to be independent and identically distributed (i.i.d) as truncated at zero of the $N\left(\mu,\sigma_u^2\right)$ distribution. If η is zero, it represents time-invariant inefficiency effects.

Farm-specific inefficiency represents the structural residual between observed paddy output and the stochastic production frontier, distinguishing inefficiency from random shocks. In the absence of substantial changes in the agricultural and economic environment (e.g., deregulation or significant policy reforms), the efficiency levels of paddy-producing farms and their relative rankings are expected to remain largely stable over short time spans. On the other hand, positive η indicates decreasing inefficiency effects, and a negative η represents increasing effects. Hence, the parameter β can be estimated using maximum likelihood estimator (MLE) method. Battese and Corra (1977) parameterized the loglikelihood function using $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and total variation in output from the frontier level of output, atributed to technical efficiency defined by:

$$\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right) \tag{3}$$

The parameter gamma, γ lies between zero and one; $\gamma = 0$ indicates that all deviations from the frontier are due to random errors and $\gamma = 1$ means all deviation results are due to technical inefficiency.

In SFA, the production function needs to be defined. Production function is the technological relationship between the level of inputs and the resulting level of outputs. If estimated econometrically from data on observed output and input usage, it indicates the average level of output that can be produced from a given level of inputs. The two functional forms of production function that are most widely applied in the literature to evaluate inefficiency in paddy production are the Cobb-Douglas (CD) and Translog (TL) function. The Cobb-Douglas form is easy to estimate, interpret and requires estimation of few parameters. The main drawback is that it assumes all PPK would have a constant input of elasticity that substitute elasticity equals one and return to scale for all PPKs. On the other hand, the Translog form does not impose these restrictions and it tends to be more flexible. However, it is susceptible to certain degrees of freedom and multicollinearity. Multicollinearity occurs when the independent variables are too highly correlated with each other. In this study, we implemented the CobbDouglas form.

For estimating the parameters, the method of maximum likelihood was applied. The u_{it} term is a non-negative random variable associated with technical inefficiency in production. For this study, truncated-normal and half-normal distribution were chosen for Cobb-Douglas form because both distributions are easier and simpler for estimation and comparison with other types of distribution. For the assumption of technical inefficiency, it was assumed that the technical inefficiency has time-varying and time invariant effect. Estimation of technical efficiency of PPKs was computed by statistical R-Programing, employing *Frontier* package. The empirical model of Cobb-Douglas prior to the estimation of PPK performance is presented in Eq. (4):

$$\begin{aligned} \ln\left(y\right)_{it} &= \beta_0 + \sum_{j=1}^{6} \beta_j \ln x_{jit} + e_{it} \\ \ln\left(y\right)_{it} &= \beta_0 + \sum_{j=1}^{6} \beta_j \ln x_{jit} + v_{it} - u_{it} \end{aligned} \tag{4}$$

The Cobb-Douglas functional model is presented in Eq. (5).

$$\begin{aligned}\ln(y)_{it} &= \beta_0 + \beta_1(\text{No. of Farmer})_{it} + \beta_2(\text{Land Area})_{it} + \beta_3(\text{Compound Fertilizer})_{it} \\ &+ \beta_4(\text{Urea Fertilizer})_{it} + \beta_5(\text{NPK Fertilizer})_{it} + \beta_6(\text{Perticide cost})_{it} + v_{it} - u_{it}\end{aligned} \tag{5}$$

where,

subscript i : the i^{th} Pertubuhan Peladang Kawasan (PPK) for $i = 1, 2, \ldots\ldots\ldots, 27$;
subscript t: t^{th} season of observation for t = 1, 2, 3, 4;
(season 2 (2020); season 1(2021); season 2(2021); season 1(2022));
y_{it} : the average yield paddy (output production). "ln" represents the natural logarithm;
β : vector of unknown parameters to be estimated;
$e_{it} = v_{it} - u_{it}$: a stochastic composite error term.

The v_{it} term corresponds to statistical noise, measurement error and other random events that are beyond the PPK's control and it is assumed to be independently and identically distributed (i.i.d) normal random variables with zero means and variances; $v_{it} \sim N(0, \sigma_v^2)$ and the u_{it} term is a non-negative random variable associated with technical inefficiency in production and are assumed to be independently and identically distributed (i.i.d). It is further assumed that v_{it} and u_{it} is independently distributed from each other.

The technical efficiency for the i-th company in the t-th year can be defined in the context of stochastic frontier model as shown in Eq. (6).

$$TE_{it} = \left(e^{-u_{it}}\right) \tag{6}$$

The technical efficiency scores (TE_{it}) for each PPK were calculated across the four planting seasons, and the average technical efficiency for each PPK, (TE_i) was subsequently derived. Based on these average values, in an output-oriented approach, the potential output gain, (POG_i) was computed to estimate the percentage increase in output that could be achieved if the organization operated at full technical efficiency using the following formula (Kumbhakar & Lovell 2000):

$$POG_i(\%) = \left(\frac{1}{TE_i} - 1\right) \times 100 \tag{7}$$

Eq. (7) estimates the percentage increase in output that could be achieved if the respective PPK operated at full technical efficiency throughout the study period. This concept is supported across various studies highlighting that the difference between actual and potential output can be significant (Jote *et al*. 2018; Dlamini *et al*. 2018).

2.3.2 Selection function, distribution and time effect for inefficiency

In this study, four stochastic frontier models were set up and compared to analyze PPK inefficiency by varying the choice of inefficiency distribution and the treatment of time effects. All models apply the Cobb-Douglas production function due to its simplicity, interpretability, and suitability for capturing the multiplicative relationship between inputs and output. Specifically, Model 1 uses a Cobb-Douglas functional form with a half-normal distribution for inefficiency effects, assuming these effects are time-invariant, following the approach of Battese and Coelli (1988). Model 2 employs the same production function but allows inefficiency effects to follow a truncated-normal distribution, still treating them as constant over time. Model 3 retains the half-normal assumption but introduces time-varying inefficiency effects as described by Battese and Coelli (1992), capturing potential performance changes over time. Finally, Model 4 combines a truncated-normal distribution with time-varying inefficiency, offering the most flexible framework to account for both cross-sectional heterogeneity and temporal dynamics. The Cobb-Douglas functional form was chosen because it provides a straightforward log-linear structure, enabling easy estimation and interpretation of input elasticities. It also helps avoid the risk of over-parameterization and multicollinearity associated with more flexible forms like the translog, which is particularly important when working with six input variables and a limited sample size.

To select the best-fitting model for the dataset, the Akaike Information Criterion (AIC) was used. AIC is widely recognized for balancing the trade-off between model fit and complexity, thereby helping to prevent overfitting. The likelihood ratio (LR) test was not used because some models are non-nested, making LR inappropriate for direct comparison. Although LR may yield similar results for some models, AIC is methodologically more suitable as it allows comparison across both nested and non-nested models while accounting for model complexity. It enables direct comparison between non-nested models, such as those differing in inefficiency distributions or time effect treatments and provides a clear decision rule where the model with the lowest AIC value is considered the most appropriate. This criterion is computationally efficient, well-established in econometric and efficiency analysis research, and ensures that the selected model achieves the best explanatory power while maintaining parsimony. In this study, the AIC was employed to select the best-fitting stochastic frontier model rather than using the likelihood ratio (LR) test or formal hypothesis testing. AIC is particularly suited for comparing non-nested models such as models with different inefficiency distributions (half-normal vs truncated-normal) and different treatments of time effects (time-invariant vs time-varying) where LR tests are not applicable.

The Cobb-Douglas production function was selected over the Translog specification because the study involves six input variables, and using a Translog functional form would require estimating a large number of additional interaction and squared terms. Specifically, a translog with six inputs would need to estimate 6 first-order, 6 squared, and 15 pairwise interaction terms, significantly increasing the number of parameters and the risk of overfitting, especially with a limited sample size. This could lead to multicollinearity and less precise parameter estimates. The Cobb-Douglas form, on the other hand, offers a parsimonious and interpretable log-linear structure that provides constant output elasticities and allows for the estimation of returns to scale without unnecessary model complexity. Given these considerations, the Cobb-Douglas specification was deemed more appropriate and reliable for the objectives of this study.

The Akaike Information Criterion (AIC) is calculated as:

$$AIC = -2\ln(L) + 2k \tag{8}$$

where,

L = the maximum value of the likelihood function for the model,
ln(L) = the log-likelihood,
k = the number of estimated parameters in the model.

3. Results and Discussions

3.1. *Model comparison using AIC results*

Table 2 reports the AIC values for four competing SFA models. Among these, Model 3 (Cobb-Douglas, half-normal distribution, time-variant inefficiency) has the lowest AIC value (-248.7883), indicating the best balance between model fit and parsimony. Therefore, Model 3 was selected as the preferred specification for subsequent analysis.

Table 2: Model comparison based on AIC

Model	Spesification	AIC
Model 1	Cobb-Douglas, Half-Normal, Time-Invariant	-210.8509
Model 2	Cobb-Douglas, Truncated-Normal, Time-Invariant	-211.0341
Model 3	Cobb-Douglas, Half-Normal, Time-Variant	**-248.7883**
Model 4	Cobb-Douglas, Truncated-Normal, Time-Variant	-247.0763

3.2. *Efficiency analysis*

Model 3 SFA results (Table 3) provide important insights into production efficiency. The model employs a Cobb-Douglas production function with a half-normal distribution for the inefficiency term and time-variant inefficiency, which allows capturing changes in efficiency across different seasons. This functional form provides a clear and interpretable framework for understanding how inputs influence output while avoiding over-parameterization.

Table 3: Estimated maximum likelihood SFA parameter results

Variable		Coefficient	$P_r(>\lvert z \rvert)$
Constant	β_0	7.3716	0.7369
ln (No. of Farmer)	β_1	0.2104	0.2246
ln (Land Area)	β_2	-2.9378	0.7563
ln(Compound Fertilizer)	β_3	-1.2341	0.8625
ln(Urea Fertilizer)	β_4	3.8084	0.0805 .
ln (NPK Fertilizer)	β_5	0.7067	0.8341
ln (Pesticide Cost)	β_6	0.5357	<2.2e-16***
Sigma-Squared	σ^2	0.0055	0.0002***
Gamma	γ	0.4426	0.0058**
Time	η	0.4611	9.02e-09***
Log-likelihood function		134.3942	
Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '			

The gamma ($\gamma = 0.4426$, $p = 0.0058$) indicates that approximately 44% of the variation in output is attributable to inefficiency rather than random noise or measurement errors. Similarly, eta ($\eta = 0.4611$, $p < 0.001$) reflects the substantial contribution of unobserved inefficiency to total inefficiency. Together, these results demonstrate that inefficiency is a major factor affecting production outcomes. From a practical perspective, addressing these inefficiencies through improved resource allocation, adoption of better technologies, or enhanced management practices could lead to significant gains in technical efficiency.

Among the explanatory variables, pesticide cost and time are highly significant, highlighting their strong influence on production efficiency and the positive effects of temporal improvements in farming practices. Other factors, such as the number of farmers, land area, fertilizer, urea, and NPK, are non-significant ($p > 0.05$) and are therefore not discussed in detail, keeping the focus on the most impactful determinants. Overall, these findings provide a robust basis for understanding the sources of inefficiency in Malaysian agriculture and for guiding future interventions aimed at improving productivity. The technical efficiency scores presented in Table 4 for the 27 PPK across four seasons provide valuable insights into the performance of agricultural production across different regions of Malaysia over time.

Table 4 presents the technical efficiency (TE) scores for 27 PPKs across four key periods: Season 2 (2020), Season 1 (2021), Season 2 (2021), and Season 1 (2022). The data are structured by region, which facilitates comparisons of performance both within and across regions. In Region I (Perlis), the technical efficiency scores show a consistent improvement over time. For instance, Arau (A-I) begins with a score of 0.8638 in Season 2 (2020) and increases to 0.9638 by Season 1 (2022), while other PPKs such as Kayang and Kangar exhibit similar upward trends. The regional mean scores also improve steadily, ranging from 0.8600 to 0.9627, reflecting effective productivity measures and better resource management implemented over the study period.

Region II (Jitra) records the highest average efficiency across all seasons, with mean values of 0.8875, 0.9267, 0.9528, and 0.9699. PPKs such as Kerpan, Kubang Sepat, and Jerlun maintain high efficiency levels (often above 0.95 in later seasons), suggesting that the management practices, resource allocation, and support mechanisms in this region are particularly effective. In contrast, Region III (Pendang) displays the lowest mean efficiency values, 0.7759, 0.8495, 0.9011, and 0.9360 and greater variability among PPKs. While Pendang itself shows steady improvement from 0.9316 to 0.9823, other PPKs such as Titi Haji Idris start from a much lower base (0.5776) and only improve gradually (0.8713). Similarly, Alor Senibong increases from 0.7069 to 0.9165, reflecting progress but still trailing behind the other regions. These disparities indicate uneven resource access and management capacities within the region, highlighting the need for targeted improvement efforts.

Region IV (Kota Sarang Semut) exhibits strong and stable performance, comparable to Region II. The regional average scores of 0.8932, 0.9309, 0.9557, and 0.9717 reflect sustained efficiency growth. PPKs such as Kangkong and Bukit Besar consistently score above 0.92, while Guar Chempedak improves from 0.8260 to 0.9530, signaling continuous progress. When viewed across seasons, a general upward trend in technical efficiency is evident for all regions, culminating in the highest overall values during Season 1 (2022). This improvement suggests that efficiency-enhancing measures such as technology adoption, improved farming techniques, and optimized resource management have had cumulative and lasting impacts.

The findings also reveal significant regional disparities, particularly between the high-performing Regions II and IV and the lower-performing Region III. Such differences underscore the importance of considering spatial and contextual factors such as production environment, access to technology, and management practices when formulating agricultural policies. Regions with higher TE scores can serve as benchmarks for best practices, while underperforming regions would benefit from targeted interventions, including farmer training, resource optimization programs, and access to improved technologies. Overall, the sustained efficiency growth across all regions reflects a positive trend in the sector's adaptability and productivity improvement over time.

Table 4: Technical efficiency scores for 27 PPK across four seasons by region

Region	Pertubuhan Peladang Kawasan (PPK)		Season 2 (2020)	1 (2021)	2 (2021)	1(2022)
Region I (Perlis)	A-I	Arau	0.8638	0.9116	0.9433	0.9638
	B-I	Kayang	0.8362	0.8931	0.9311	0.9560
	C-I	Kangar	0.8587	0.9082	0.9410	0.9624
	D-I	Tambun Tulang	0.8687	0.9149	0.9454	0.9652
	E-I	Simpang Empat	0.8726	0.9175	0.9471	0.9663
	Average (Region 1)		0.8600	0.9091	0.9416	0.9627
Region II (Jitra)	A-II	Kodiang	0.8842	0.9251	0.9520	0.9695
	B-II	Sanglang	0.8181	0.8809	0.9231	0.9507
	C-II	Kerpan	0.9554	0.9715	0.9819	0.9885
	D-II	Tunjang	0.8212	0.8830	0.9245	0.9517
	E-II	Kubang Sepat	0.9659	0.9783	0.9862	0.9913
	F-II	Jerlun	0.9645	0.9774	0.9857	0.9909
	G-II	Jitra	0.7756	0.8518	0.9037	0.9381
	H-II	Kepala Batas	0.8836	0.9248	0.9518	0.9693
	I-II	Kuala Sungai	0.9188	0.9478	0.9667	0.9788
	Average (Region II)		0.8875	0.9267	0.9528	0.9699
Region III (Pendang)	A-III	Hutan Kampong	0.8856	0.9261	0.9526	0.9698
	B-III	Alor Senibong	0.7069	0.8033	0.8710	0.9165
	C-III	Tajar	0.8353	0.8925	0.9307	0.9557
	D-III	Titi Haji Idris	0.5776	0.7073	0.8037	0.8713
	E-III	Kobah	0.7183	0.8115	0.8765	0.9202
	F-III	Pendang	0.9316	0.9561	0.9721	0.9823
	Average (Region III)		0.7759	0.8495	0.9011	0.9360
Region IV (Kota Sarang Semut)	A-IV	Batas Paip	0.8582	0.9079	0.9408	0.9622
	B-IV	Pengkalan Kundur	0.9262	0.9527	0.9698	0.9808
	C-IV	Kangkong	0.9416	0.9626	0.9762	0.9849
	D-IV	Permatang Buluh	0.8859	0.9263	0.9528	0.9699
	E-IV	Bukit Besar	0.9269	0.9531	0.9701	0.9810
	F-IV	Sungai Limau	0.8876	0.9274	0.9535	0.9704
	G-IV	Guar Chempedak	0.8260	0.8863	0.9266	0.9530
	Average (Region IV)		0.8932	0.9309	0.9557	0.9717

Results in Table 5 present the mean technical efficiency scores and rankings of the 27 Pertubuhan Peladang Kawasan (PPK) across four regions based on the Stochastic Frontier Analysis (SFA) model. The mean efficiency values reflect the average ability of each PPK to transform inputs into outputs relative to the best performers, while the ranking indicates how each PPK compares to others nationwide. In Region I (Perlis), the mean technical efficiency scores range from 0.9041 (Kayang, ranked 19th) to 0.9259 (Simpang Empat, ranked 14th), showing moderate efficiency levels but none reaching the top ten nationally. The results suggest that although these PPKs operate with fairly good efficiency, they lag slightly behind the best-performing areas. Region II (Jitra) stands out with exceptionally high performers. Kubang Sepat (0.9804) and Jerlun (0.9796) take the top two national rankings, while Kerpan (0.9744) ranks 3rd overall, clearly demonstrating that Region II leads in efficiency. However, this region also shows large variability, with Sanglang (0.8932, ranked 23rd) and Jitra (0.8673, ranked 24th) falling behind, indicating that despite the region's overall strength, certain PPKs still underperform and require targeted improvements.

Table 5: Mean, Potential Output Gain (POG) and ranking of PPK by region

Region	Pertubuhan Peladang Kwasan (PPK)		Mean (TE)	POG (%)	Rank
Region I (Perlis)	A-I	Arau	0.9206	8.62	16
	B-I	Kayang	0.9041	10.61	19
	C-I	Kangar	0.9176	8.98	17
	D-I	Tambun Tulang	0.9235	8.28	15
	E-I	Simpang Empat	0.9259	8.00	14
	Average (Region 1)		0.9183	8.90	
Region II (Jitra)	A-II	Kodiang	0.9327	7.22	12
	B-II	Sanglang	0.8932	11.96	23
	C-II	Kerpan	0.9744	2.63	3
	D-II	Tunjang	0.8951	11.72	22
	E-II	**Kubang Sepat**	0.9804	**2.00**	1
	F-II	Jerlun	0.9796	2.08	2
	G-II	Jitra	0.8673	15.30	24
	H-II	Kepala Batas	0.9324	7.25	13
	I-II	Kuala Sungai	0.9530	4.93	8
	Average (Region II)		0.9342	7.23	
Region III (Pendang)	A-III	Hutan Kampong	0.9335	7.12	11
	B-III	Alor Senibong	0.8244	21.30	26
	C-III	Tajar	0.9036	10.67	20
	D-III	**Titi Haji Idris**	0.7400	**35.14**	27
	E-III	Kobah	0.8316	20.25	25
	F-III	Pendang	0.9605	4.11	5
	Average (Region III)		0.8656	16.43	
Region IV (Kota Sarang Semut)	A-IV	Batas Paip	0.9173	9.02	18
	B-IV	Pengkalan Kundur	0.9574	4.45	7
	C-IV	Kangkong	0.9663	3.49	4
	D-IV	Permatang Buluh	0.9337	7.10	10
	E-IV	Bukit Besar	0.9578	4.41	6
	F-IV	Sungai Limau	0.9347	6.99	9
	G-IV	Guar Chempedak	0.8980	11.36	21
	Average (Region IV)		0.9379	6.69	

In Region III (Pendang), the performance is mixed. While Pendang PPK ranks 5th overall with a high mean efficiency score of 0.9605, other PPKs in the region perform poorly: Titi Haji Idris (0.7400) ranks last at 27th, and Alor Senibong (0.8244) is at 26th. This wide performance gap highlights critical disparities in management practices, resource use, or operational challenges within the region. Region IV (Kota Sarang Semut) shows consistently strong performance, with Kangkong (0.9663, ranked 4th), Bukit Besar (0.9578, ranked 6th), and Pengkalan Kundur (0.9574, ranked 7th) all positioned in the top ten. Other PPKs in this region, such as Sungai Limau (0.9347, ranked 9th) and Permatang Buluh (0.9337, ranked 10th), also demonstrate high efficiency, suggesting that Region IV, alongside Region II, forms the backbone of top-performing agricultural units nationally. Overall, the results indicate that the paddy sector under MADA has pockets of excellence, particularly concentrated in Regions II and IV, where several PPKs achieve near-best-practice efficiency levels. However, the presence of underperforming PPKs, especially in Regions III and certain parts of Region II, suggests uneven progress that requires focused policy intervention, capacity building, and resource optimization. By addressing the weaker units, MADA can work toward achieving more balanced and widespread improvements in agricultural efficiency across all regions.

Table 5 also presents the Potential Output Gain (POG) values for all 27 PPKs, representing the percentage of output that could be increased over the four-season study period if full technical efficiency were achieved. Kubang Sepat recorded the highest average technical efficiency score of 0.9804, indicating that its actual output was only 2.00% below the estimated production frontier. In contrast, Titi Haji Idris had the lowest average score of 0.7400, suggesting a potential output gain of 35.14% under full efficiency. Other PPKs with notable efficiency gaps include Alor Senibong (POG = 21.30%) and Kobah (POG = 20.25%), highlighting the need for targeted improvements in resource management and production practices in these areas.

Furthermore, Table 5 includes the average TE values by region, where Region I achieved a mean of 0.9183, Region II 0.9342, Region III 0.8656, and Region IV 0.9379. These results reinforce the earlier findings that Region IV recorded the highest overall efficiency, closely followed by Region II. In contrast, Region III exhibited the lowest average TE, highlighting greater inefficiencies and the need for targeted strategies to enhance management and production practices within that region.

Figure 1 illustrates the average (mean) technical efficiency scores across four seasons, with reported mean values of 0.8591 for Season 1, 0.9074 for Season 2, 0.9400 for Season 3, and 0.9615 for Season 4. The overall average across all four seasons is 0.9170. There is a clear upward trend in technical efficiency from Season 1 through Season 4, suggesting continuous improvement in production efficiency over time. The increase from 0.8591 in Season 1 to 0.9615 in Season 4 indicates that efforts to enhance resource use, adopt better agricultural practices, or implement management improvements have been effective. The overall mean efficiency of 0.9170 shows that, on average, the production units (such as PPKs) operated at around 91.7% of maximum possible efficiency across the observed period.

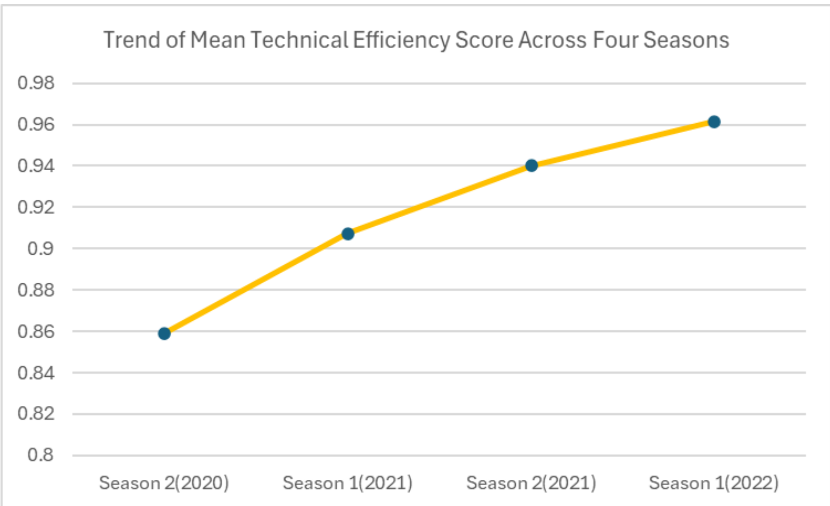

Figure 1: Seasonal trend in production efficiency

Figure 2 visualizes the average technical efficiency (TE) values for the four regions under MADA. The figure clearly shows that Region IV (Kota Sarang Semut) recorded the highest average TE (0.9379), followed closely by Region II (Jitra) at 0.9342. Region I (Perlis) achieved a moderate level of efficiency (0.9183), while Region III (Pendang) recorded the lowest average efficiency (0.8656). Overall, the visualization supports the tabulated results in Table 5, highlighting the regional variations in efficiency performance among the 27 PPK under MADA.

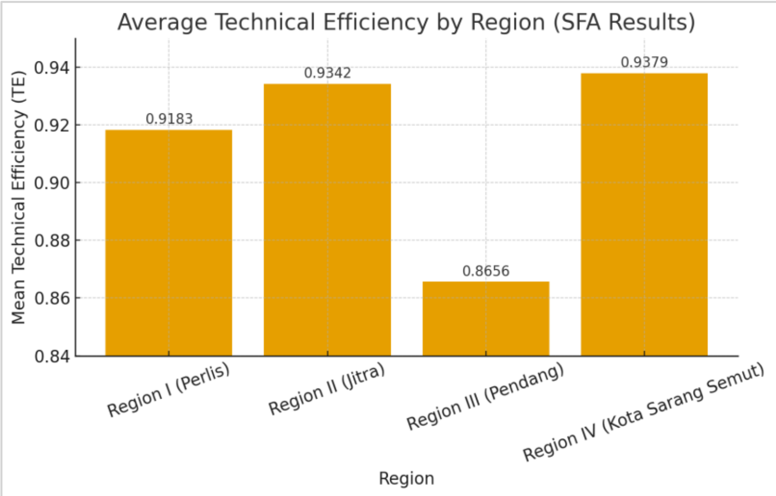

Figure 2: Average technical efficiency (TE) by region

Figure 3 presents the average Potential Output Gain (POG) across four regions under MADA: Region I (8.90%), Region II (7.23%), Region III (16.43%), and Region IV (6.69%). Region III recorded the highest POG, indicating the greatest potential for improving production efficiency, while Region IV had the lowest POG, suggesting relatively efficient resource utilization among its PPKs.

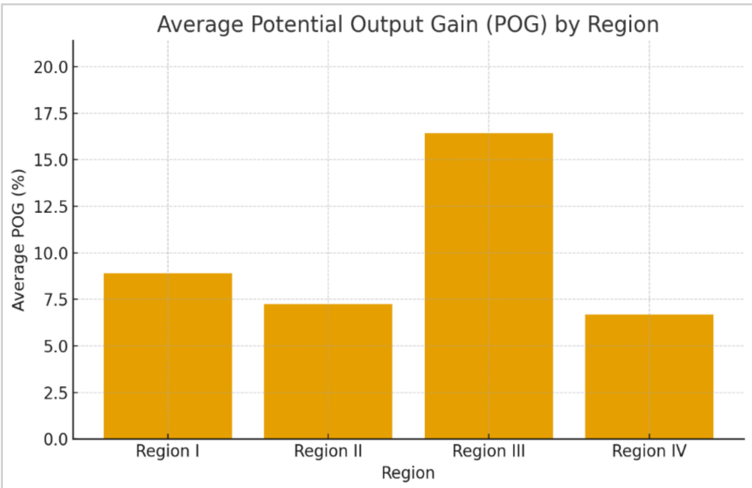

Figure 3: Average Potential Output Gain (POG) by region

Table 6 shows the value of mean technical efficiency (TE) and total paddy production (Tons) across four seasons. Over the observed period, TE consistently improved, rising from 0.8591 in Season 2 (2020) to 0.9615 in Season 1 (2022). In contrast, total paddy production fluctuated. In Season 2 (2020), production stood at 398,892 tons, which increased to 451,180 tons in Season 1 (2021) and 468,460 tons in Season 2 (2021). However, in Season 1 (2022), production decreased to 384,426 tons despite recording the highest TE during this period. The increase in TE does not always align with higher production. For example, in Season 1 (2022), while TE reached its peak, production declined when compared to the previous season. Conversely, Seasons 1 and 2 in 2021 achieved higher production levels despite having lower TE scores than Season 1 (2022).

This disparity indicates that while technical efficiency improved, it did not directly correlate with increased paddy production, particularly in Season 1 (2022). Even though the technical efficiency shows an increasing trend, it is important to note that this does not always directly correlate with physical output, such as paddy yield. Efficiency refers to how well inputs are turned into outputs, but actual production can still decrease if external factors like weather conditions, pest outbreaks, or market disruptions affect yields. Therefore, while technical efficiency has improved, further investigation is needed to understand why physical paddy output might be declining in Season 1 (2022) despite these efficiency gains. This suggests that there may be external, non-efficiency-related constraints affecting production outcomes.

Table 6: Technical efficiency (TE) scores and total paddy production by MADA

Season	Total Production Paddy (Tons)	Mean TE
Season 2 (2020)	398, 892	0.8591
Season 1 (2021)	451,180	0.9074
Season 2 (2021)	468,460	0.9400
Season 1 (2022)	384, 426	0.9615

3.3. *Discussions*

The results from Model 3, based on Maximum Likelihood Estimation (MLE) Stochastic Frontier Analysis (SFA) with a Cobb-Douglas production function and half-normal inefficiency distribution, offer valuable insights into the technical efficiency of paddy production across 27 Pertubuhan Peladang Kawasan (PPK) in MADA.The gamma (γ) value of 0.4426 ($p = 0.0058$) indicates that 44.26% of production variance is due to inefficiency, suggesting that nearly half of performance variation could be improved through better resource management, technology adoption, or targeted interventions. Its statistical significance confirms the importance of addressing inefficiency, aligning with Khatri-Chhetri *et al*. (2023), who reported similar findings in agricultural systems. The eta (η) value of 0.4611 ($p < 0.001$) highlights the substantial role of unobserved inefficiency components, with significant potential for improvement through resource optimization, efficient technologies, and better management practices. This agrees with Boddapati *et al*. (2025), who emphasized the major influence of unobserved inefficiencies on production. Among input variables, pesticide cost is a significant driver of technical efficiency ($p < 2.2e\text{-}16$), supporting the idea that effective pest control boosts productivity, as found by Tudi *et al*. (2021). Fertilizer use (urea, NPK), land area, and number of farmers showed no significant effects, suggesting these inputs do not directly influence efficiency under current usage patterns consistent with Jondrow *et al*. (1982), who noted that such effects are often context-dependent.

The time variable ($p < 0.001$) confirms that technical efficiency improves over time, reflecting better practices, resource management, and technology adoption. This upward trend aligns with Oumer *et al*. (2022), who showed that time-variant models capture productivity gains from technological and management improvements. Regional analysis reveals notable differences. Region I (Perlis) improved steadily, with Arau rising from 0.8638 (Season 2, 2020) to 0.9638 (Season 1, 2022). Region II (Jitra) performed consistently well, while Region III (Pendang) showed mixed results Pendang improved, but Titi Haji Idris and Alor Senibong lagged. Region IV (Kota Sarang Semut) maintained scores above 0.82 across seasons. These patterns mirror Färe *et al*. (1994), who linked regional efficiency variation to differences in resources, management, and policies. Although technical efficiency peaked in Season 1, 2022, paddy production declined compared to earlier seasons, indicating that external factors such as weather, pests, or market conditions can offset efficiency gains. This supports O'Donnell (2010), who found that efficiency improvements may not always translate into higher output without addressing external constraints.

Policy implications include:

- Targeted interventions for underperforming PPKs, especially in Region III and parts of Region II.
- Continued improvements in pesticide management, resource optimization, and technology adoption.
- Measures to mitigate external risks (e.g., climate, market shocks) alongside efficiency enhancement (Sundram 2023).

Overall, while MADA's agricultural technical efficiency has improved, disparities remain. A balanced approach combining internal efficiency gains with external risk mitigation is essential for sustained productivity growth.

4. Conclusion

This study evaluated the technical efficiency of paddy production across 27 Pertubuhan Peladang Kawasan (PPK) under MADA in the northern region of Malaysia using the Stochastic Frontier Analysis (SFA) with a Cobb–Douglas production function. The findings reveal that inefficiency accounts for a significant portion of the variation in paddy production, with approximately 44% of the variance attributable to inefficiency. In particular, the significant role of pesticide costs in improving efficiency underscores the importance of optimal pest management in enhancing agricultural productivity. The study also highlights that improvements in technical efficiency are occurring over time, suggesting that the ongoing adoption of better agricultural practices and resource management strategies is contributing to more efficient production. However, substantial regional disparities in efficiency remain, with certain regions exhibiting greater potential for improvement than others. The influence of external factors such as weather conditions and market fluctuations on overall production levels, despite improvements in efficiency, also points to the need for a more holistic approach to agricultural management.

Overall, while there have been notable gains in technical efficiency, addressing inefficiencies and external challenges remains crucial for sustaining long-term improvements in paddy production. Given the regional disparities in technical efficiency, policy interventions should be more targeted, particularly towards underperforming regions such as Region III, where inefficiencies are more pronounced. Adapted support, including farmer training programs and incentives for the adoption of efficient technologies, could help reduce inefficiency in these areas. Strengthening these efforts will be vital to improving productivity and ensuring the long-term sustainability of Malaysia's agricultural sector.

5. Recommendations

While this study provides valuable insights into the efficiency of paddy production, it also highlights areas for future research to further enhance agricultural productivity. Policymakers and agricultural agencies, particularly MADA, should continuously refine strategies that promote efficient and sustainable farming practices to enhance productivity and resilience in the paddy sector. Future research could explore the impact of various pest control methods, including Integrated Pest Management (IPM), on paddy production and efficiency. Moreover, the adoption of innovative agricultural technologies such as precision farming tools, drones for crop monitoring, and automated irrigation systems could further reduce inefficiencies. Investigating the effectiveness of these technologies in improving efficiency will be an important avenue for future research.

External factors, including climatic conditions, market fluctuations, and pest outbreaks, have also been shown to influence production outcomes despite improvements in technical efficiency. Future studies should examine the role of these external variables in shaping efficiency and develop models that account for both internal inefficiencies and external challenges. Longitudinal studies that track changes in technical efficiency over an extended period taking into consideration factors such as climate change, agricultural policy shifts, and the adoption of sustainable farming practices could offer valuable insights for policymakers.

Finally, expanding the scope of future research to include other agricultural sectors or comparing paddy farming with other staple crops could yield lessons on the most effective strategies for improving agricultural productivity. By addressing both internal inefficiencies and external constraints, Malaysia can work towards achieving greater sustainability in paddy production and overall agricultural development.

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