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EXPLORING THE DYNAMICS OF PADDY PRODUCTION IN NORTHERN MALAYSIA: TECHNICAL ADVANCEMENTS AND EFFICIENCY CHANGES THROUGH THE DEA-MALMQUIST INDEX

(*Meneroka Dinamik Pengeluaran Padi Malaysia Utara: Kemajuan Teknikal dan Perubahan Kecekapan Melalui APD-Indeks Malmquist*)

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ABSTRACT

Paddy production is a vital sector in Malaysia's agricultural economy, with Pertubuhan Peladang Kawasan (PPKs) under the Muda Agricultural Development Authority (MADA) playing a key role in sustaining yields and sector resilience. This study evaluates the efficiency and productivity changes of 27 PPKs over four planting seasons (Season 2, 2020 – Season 1, 2022) using output-oriented Data Envelopment Analysis (DEA) with the BCC model and the Malmquist Productivity Index (MPI). DEA results show an average efficiency score of 0.892 (89.2%), with PPK Arau and PPK Kangar achieving full efficiency consistently. However, 92.6% of the PPKs experienced inefficiency in at least one season, with the lowest score recorded in Season 2, 2020. The MPI analysis assessed productivity changes across three phases: Season 2, 2020 – Season 1, 2021; Season 1, 2021 – Season 2, 2021; and Season 2, 2021 – Season 1, 2022. The findings revealed a mixed performance trend, where several PPKs experienced productivity growth while others saw declines. Titi Haji Idris recorded the highest MPI score (2.8921), indicating strong productivity improvement overall, although a temporary drop was observed in Phase 2 (0.7787) before recovering. The lowest score was recorded by Hutan Kampung (0.6543), whereas Arau maintained an MPI score close to 1.000 across all three phases, indicating stable productivity performance. These findings highlight the need for targeted interventions, efficient resource allocation, and the adoption of technology. Benchmarking against high-performing PPKs can support strategic planning and strengthen the sustainability of national paddy production.

Keywords: efficiency; DEA; productivity; paddy; Malquist Productivity Index

ABSTRAK

Pengeluaran padi merupakan sektor penting dalam ekonomi pertanian Malaysia, dengan Pertubuhan Peladang Kawasan (PPK) di bawah Lembaga Kemajuan Pertanian Muda (MADA) memainkan peranan utama dalam mengekalkan hasil dan kelestarian sektor ini. Kajian ini menilai kecekapan dan perubahan produktiviti 27 PPK sepanjang empat musim penanaman (Musim 2, 2020 – Musim 1, 2022) menggunakan Analisis Penyampulan Data (APD) berorientasikan output dengan model BCC serta Indeks Produktiviti Malmquist (MPI). Dapatan APD menunjukkan purata skor kecekapan sebanyak 0.892 (89.2%), dengan PPK Arau dan Kangar mencapai kecekapan penuh secara konsisten. Namun, 92.6% daripada PPK mencatatkan ketidakefisienan sekurang-kurangnya dalam satu musim, dengan skor terendah direkodkan pada Musim 2, 2020. Analisis MPI pula menilai perubahan produktiviti merentasi tiga fasa: Musim 2 2020 – Musim 1 2021, Musim 1 2021 – Musim 2 2021, dan Musim 2 2021 – Musim 1 2022. Hasil menunjukkan corak prestasi yang bercampur, dengan beberapa PPK menunjukkan peningkatan produktiviti manakala yang lain mengalami penurunan. Titi Haji Idris mencatatkan skor MPI tertinggi (2.8921), namun mengalami penurunan dalam Fasa 2 (0.7787) sebelum meningkat semula. Skor terendah direkodkan oleh Hutan Kampung (0.6543), manakala Arau mengekalkan skor sekitar 1.000 dalam ketiga-tiga fasa, menunjukkan kestabilan prestasi. Dapatan ini menekankan keperluan kepada intervensi bersasar, pengagihan sumber secara efisien dan penggunaan teknologi. Penandaarasan terhadap PPK berprestasi tinggi boleh menyokong perancangan strategik dan memperkukuh kelestarian pengeluaran padi negara.

Kata kunci: kecekapan; APD; produktiviti; padi, Indeks Produktiviti Malmquist

1. Introduction

Paddy is a strategic and culturally significant crop in Malaysia, serving as the staple food for the majority of the population. Ensuring the sustainability and productivity of the paddy sector is critical not only for national food security but also for safeguarding the livelihoods of hundreds of thousands of farmers. The Malaysian government has consistently prioritized rice self-sufficiency, as reflected in successive policy frameworks such as the National Agro-Food Policy (2011–2020), the Eleventh Malaysia Plan (2016–2020), and most recently, the National Agro-Food Policy 2.0 (NAFP 2021–2030). These policies aim to enhance paddy production, modernize the agricultural sector, and reduce reliance on rice imports.

Despite various efforts, Malaysia's paddy production continues to face persistent structural challenges. These include fragmented land ownership, limited mechanization in certain regions, and an aging farming population. Climate-related factors have also become a growing concern. In a recent study, Firdaus *et al*. (2020) highlighted that climate variability particularly fluctuations in rainfall and temperature has significantly affected paddy yields in Peninsular Malaysia. Similar concerns have been documented across Southeast Asia, where Waqas *et al*. (2024) emphasized that climate change remains a major threat to agricultural productivity, especially for water-intensive crops such as paddy.

The Muda Agricultural Development Authority (MADA) man ages one of the largest rice granary areas in Northern Malaysia and plays a crucial role in ensuring consistent production levels. In MADA, each Paddy Collection Center is operated by its respective Pertubuhan Peladang Kawasan (PPKs), a farmer organization that manages services at the local level. However, differences in productivity and operational efficiency among PPKs suggest that not all are utilizing their resources optimally or adopting modern technologies effectively (Zaibidi *et al*. 2016). Furthermore, while certain PPKs have started exploring precision farming technologies, widespread adoption remains limited. As noted by Hashim *et al*. (2024), smart farming approaches in Malaysian paddy fields are still at an early stage, facing constraints in infrastructure, awareness, and technical expertise.

Paddy consumption in Malaysia has steadily increased over the last two decades due to population growth and changing dietary patterns. Between 2010 and 2020, domestic demand for rice rose from 2.69 million metric tons to 2.80 million metric tons, while paddy production remained relatively stagnant (Nixon 2024). This gap between demand and domestic production has resulted in increased dependence on imported rice to meet national consumption needs (Makhtar *et al*. 2022). Addressing inefficiencies in local paddy production, especially within high-impact areas such as MADA, is essential to reduce this dependency and strengthen national food security.

Efficiency analysis in agriculture offers a way to assess the performance of production units relative to their peers. Data Envelopment Analysis (DEA) is a widely used non-parametric method for evaluating the relative efficiency of Decision-Making Units (DMUs) based on multiple inputs and outputs (Charnes *et al*. 1978). In the context of paddy production, DEA allows for the assessment of farm-level efficiency by comparing inputs such as land area, fertilizers, labor, and machinery against the paddy yield (Nandy & Singh 2021). The method helps identify underperforming units and provides benchmarks for improvement.

Beyond static efficiency, understanding how productivity evolves over time is essential. The Malmquist Productivity Index (MPI) enables the decomposition of total productivity change into two components: Efficiency Change (EC) and Technological Change (TC). This approach is particularly useful in agricultural studies where productivity is influenced by seasonal changes, policy interventions, and environmental factors (Al-Refaie *et al*. 2015; Liu *et al*. 2024). For example, Liu *et al*. (2024) highlighted how input quality, institutional settings, and environmental changes significantly affect total factor productivity in food crop systems in China, which supports the relevance of MPI-based evaluations.

DEA-MPI integration provides a dynamic view of performance that goes beyond a single-point analysis. Previous studies in the Malaysian context have employed DEA and related methods to evaluate rice farm performance. Kalimuthu and Applanaidu (2024) analyzed the key determinants of paddy productivity in the MADA region, while Mailena *et al.* (2014) used a two-stage DEA approach with bootstrapping and Tobit regression. Zaibidi *et al*. (2018) compared SFA and DEA to assess environmental awareness among farmers. Nodin *et al*. (2021) applied DEA to compare efficiency in granary versus non-granary areas. However, these studies largely focus on single-season efficiency or cross-sectional analysis. Empirical applications of DEA combined with MPI to analyze productivity trends across multiple planting seasons, particularly at the PPK level within MADA, are still limited.

This study seeks to fill that gap by evaluating the technical efficiency and productivity trends of 27 PPKs under MADA over four consecutive planting seasons (Season 2, 2020 – Season 1, 2022). The findings will offer insights into whether these PPKs are improving or declining in performance over time and identify best practices that can be replicated to enhance rice production efficiency in Malaysia. Through this analysis, the study aims to support evidence based policymaking and contribute to long-term strategies that enhance food security and agricultural sustainability. The remainder of the paper continues as follows: the data is outlined in Section 2, as well as the elaboration of the methodology. Section 3 provides the empirical findings and discussions, and lastly, Section 4 sums up the whole paper with conclusions and suggested future work.

2. Materials and Methods

2.1. *Data*

The following section provides a detailed explanation of the dataset used in this study. The research aims to evaluate and interpret the productivity of paddy production in the northern region of Malaysia, specifically within areas managed by the Muda Agricultural Development Authority (MADA). MADA is a federal agency responsible for managing irrigation infrastructure and paddy cultivation systems in the Muda region. The administrative and operational structure of MADA, including the distribution of Pertubuhan Peladang Kawasan (PPK) across its four main regions, is summarized in Table 1.

This study focuses on four key regions under MADA's supervision. Each of these regions consists of several PPK, 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.

In total, 27 PPKs operate under MADA's administration to facilitate the smooth governance and management of the paddy farming sector in the states of Kedah and Perlis as shown in Table 1.

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 Semut)	B-IV	Pengkalan Kundur	
	C-IV	Kangkong	
	D-IV	Permatang Buluh	7
	E-IV	Bukit Besar	
	F-IV	Sungai Limau	
	G-IV	Guar Chempedak	

To ensure efficient oversight, MADA has divided these areas into four main regions:

- Region I – Kangar (State of Perlis)
- Region II – Jitra (State of Kedah)
- Region III – Pendang (State of Kedah)
- Region IV – Kota Sarang Semut (State of Kedah)

This regional division allows for a more systematic and comprehensive monitoring of paddy farming activities in these areas. Additionally, this organizational structure helps optimize agricultural resources and enhances the effectiveness of strategies aimed at improving paddy yields within MADA's jurisdiction.

2.2. *Input and output variables*

In efficiency analysis using DEA, the selection of appropriate input and output variables is crucial to ensure accurate and meaningful assessment of performance. In this study, the output-oriented BCC model (Banker *et al*. 1984) is applied in the first stage to evaluate the efficiency scores of PPKs involved in paddy cultivation. A total of seven input variables and one output variable are considered, as summarized in Table 2.

Table 2 presents the selected inputs and output for this study, along with their respective units. The output is the average yield, calculated by dividing the total paddy yield by the land area under cultivation. A higher average yield signifies better efficiency in paddy production. The first input is the number of farmers represents the labor force available for farming activities, including land preparation, planting, maintenance, and harvesting. The second input is land area. This input represents the amount of land allocated for growing paddy and plays a crucial role in determining overall production. A larger land area can potentially yield more output.Third input is fertilizer (compound). It is used to enhance soil fertility and promote healthy paddy growth. The effectiveness of compound fertilizer depends on its proper application, ensuring balanced nutrient supply to improve crop yield and overall farming efficiency. The fouth input is Urea. It is widely used in paddy farming to promote healthy leaf and stem development, which is crucial for higher crop yields. Urea is highly soluble in water and must be applied correctly to prevent nutrient loss due to evaporation or leaching. Proper usage helps improve soil fertility and enhances the efficiency of paddy production. The fifth input, NPK fertilizer, is commonly used in paddy farming to ensure balanced nutrient supply, leading to improved productivity and efficiency in paddy cultivation.

The sixth input is plowing costs, which include labor, machinery (such as tractors or plows), and fuel. Proper plowing helps improve soil aeration, water retention, and nutrient absorption, which are essential for healthy paddy growth and higher yields. Efficient management of plowing costs can contribute to better overall farm productivity. The last input is pesticide cost. This cost includes the price of chemical or biological pesticides, labor for application, and equipment used for spraying. Proper pesticide management is essential to prevent crop damage, ensure healthy plant growth, and maximize yield while minimizing environmental impact and unnecessary costs.

Table 2: Description input output selected

	Variable	Units	Description
Output	Average yield	Kg/Hektar	Average yield refers to the average amount of paddy harvested per season.
Inputs	No of farmer	Farmers	Number of farmers refers to the total count of farmers involved in paddy cultivation within a specific area or organization.
	Land area	Hektar (Ha)	Land area refers to the total size of the farmland used for paddy cultivation, usually measured in hectares.
	Fertilizer (Compound)	No. of Bags	Fertilizer (Compound) refers to a type of fertilizer that contains a mix of essential nutrients, such as Nitrogen (N), Phosphorus (P), and Potassium (K), in a single formulation.
	Urea	No. of Bags	Urea is a type of nitrogen-based fertilizer that provides an essential nutrient for plant growth.
	NPK	No. of Bags	NPK fertilizer refers to a type of fertilizer that contains three primary nutrients essential for plant growth: Nitrogen (N); Phosphorus (P) and Potassium (K).
	Plowing cost	RM	Plowing cost refers to the expenses incurred for land preparation before planting, including activities such as soil tilling, leveling, and breaking up hard soil.
	Pesticide cost	RM	Pesticide cost refers to the expenses associated with purchasing and applying pesticides to protect paddy crops from pests, diseases, and weeds.

The selection of input and output variables in this study is grounded in both theoretical relevance and empirical support from prior studies. Inputs such as labor (represented by the number of farmers), land, and fertilizer types are commonly identified as critical factors in agricultural efficiency analyses (Coelli *et al*. 2005; Mailena *et al*. 2014; Kalimuthu &

Applanaidu 2024). Additionally, cost-related inputs such as plowing and pesticide expenditure reflect operational investment and are often used in DEA studies to capture the resource intensity of crop production. The output variable, average yield per season serves as a standardized indicator of productive performance and is consistent with prior applications in paddy efficiency evaluations. While correlation analysis was not conducted, the inclusion of these variables was guided by their consistent appearance in literature and practical significance in the context of paddy production under MADA.

2.3. *Methodology*

This study employs a two stage approach. The first stage focuses on the estimation of technical efficiency using DEA method. The second stage deals with the estimation of paddy productivity for three seasonal pair using MPI based on the estimated efficiency obtained in stage 1. Figure 1 presents the research methodology of this study.

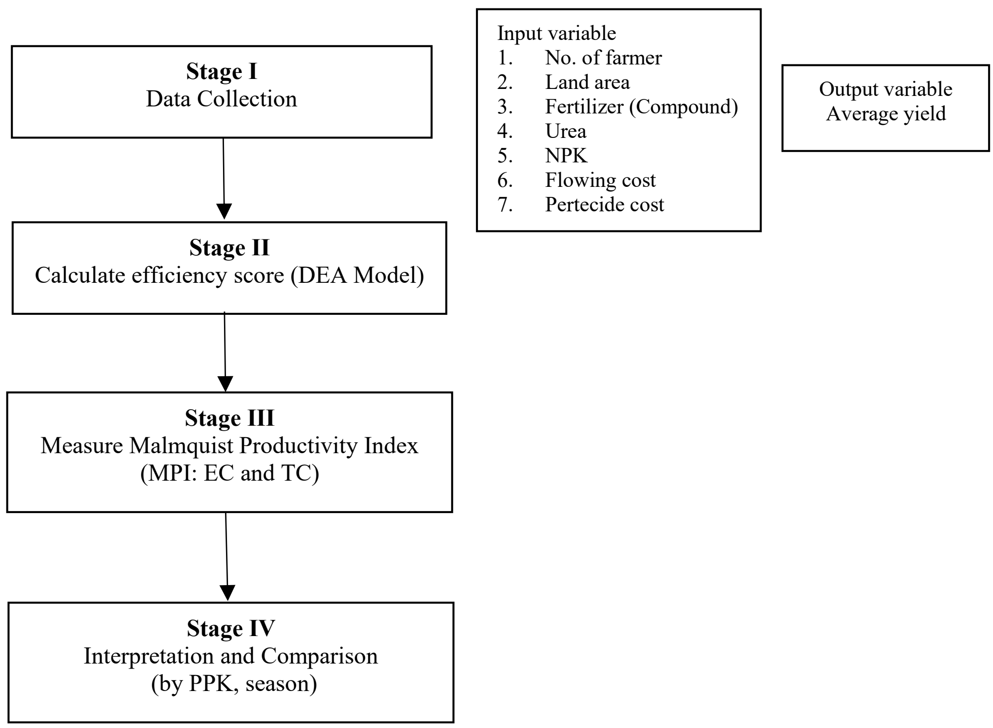

Figure 1: Process flow of the research methodology

The DEA model is first employed to calculate the technical efficiency of each PPK across four consecutive planting seasons. These seasonal efficiency scores are then utilized to compute the MPI, which captures productivity changes between seasons. This sequential application ensures a cohesive framework where DEA provides the efficiency baseline, and MPI reveals the dynamics over time. The findings are interpreted jointly to assess both static and dynamic performance of the paddy-producing PPKs.

2.3.1 Data Envelopment Analysis (DEA)

The DEA method, originally introduced by Farrell (1957), is a non-parametric linear programming technique designed to evaluate the efficiency performance of firms or organizations, commonly referred to as DMUs in DEA literature. The methodology was later extended by Charnes *et al*. (1978), who proposed an input-oriented model known as the Charnes, Cooper, and Rhodes (CCR) model. DEA has gained renewed attention in recent empirical research, particularly in agricultural and environmental efficiency assessments (Ben Mabrouk *et al*. 2022; Sanyaolu & Sadowski 2024).

The CCR model assumes Constant Returns to Scale (CRS), implying that increases or reductions in inputs lead to proportional changes in outputs. Under this assumption, all DMUs are evaluated based on a common production frontier, and the resulting score reflects General Technical Efficiency (GTE) (Nunamaker 1985). While the CCR model provides a foundational framework, it may not fully capture operational realities when scale efficiency varies. To address this, Banker *et al*. (1984) introduced the BCC model, which relaxes the CRS assumption to accommodate Variable Returns to Scale (VRS). The BCC model allows for distinguishing whether a DMU operates under increasing, constant, or decreasing returns to scale, making it more suitable for assessing efficiency across heterogeneous units with diverse operational capacities.

In this study, each DMU represents a Pertubuhan Peladang Kawasan (PPK). Each PPK utilizes multiple agricultural inputs, including the number of farmers, land area, fertilizer application (compound, urea, and NPK), plowing cost, and pesticide cost to produce a single output, namely the average paddy yield per season. The output-oriented BCC model is employed to assess how efficiently each PPK transforms inputs into output relative to a benchmark frontier formed by the most efficient units. This approach evaluates the maximum feasible output expansion each PPK could achieve while holding input levels constant. The following linear programming formulation is used to estimate the relative efficiency score:

$$\max \phi$$

subject to:

$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{io}\ ;\ \ \forall_i = 1,.......,m \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge \phi y_{ro}\ ;\ \ \forall_r = 1,.....,s \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0,\ \ \forall_j = 1,..........,n
\end{aligned} \qquad (1)$$

where:

x_{ij} : Input i used by PPK j. Examples of inputs include the number of farmers, land area, fertilizers (compound, urea, NPK), plowing cost, and pesticide cost.

y_{rj} : Output r produced by PPK j. In this study, the output refers to the average paddy yield per season.

x_{io} : Value of input i for the PPK being evaluated (target PPK).

y_{ro} : Value of output r for the PPK being evaluated (target PPK).

λ_j : Weight assigned to PPK j in forming the reference set for the target PPK's efficiency evaluation.

n : Total number of PPKs evaluated.

m : Number of inputs used in the model.

s : Number of outputs used in the model.

The variable ϕ shows how much a PPK's output can be increased using the same amount of input in order to become efficient. The best value, ϕ, tells us the maximum increase possible. In simple terms, it reflects how many times the current output can be boosted to reach the level of the most efficient PPKs. To measure this, an output-oriented BCC model is used, which compares each PPK to the top-performing ones, known as the efficiency frontier. The Eq. (1) calculates ϕ, which indicates the additional output a PPK needs to produce to become efficient. A higher ϕ value means the PPK is further behind. However, to make the results easier to interpret, the efficiency score is normalized into a value between 0 and 1, denoted as θ. This normalized score provides a clearer picture of efficiency:

- A score of 1 means the PPK is fully efficient.
- A score closer to 0 means there is still a lot of room for improvement.

This method helps us easily identify which PPKs are performing well and which ones need to improve their output using the same level of input.

2.3.2 Malmquest Productivity Index (MPI)

The MPI is used to assess productivity changes in paddy production from one planting season to the next. In the context of paddy farming, this includes the adoption of high-quality seed varieties, mechanization of land preparation and harvesting, use of modern irrigation systems, and improved agronomic practices. This is known as the "frontier shift," where technology enhances the maximum achievable output, even when input levels remain unchanged. By combining these two components, the MPI helps determine whether productivity improvements are due to better efficiency in managing available resources, technological progress, or both. Although the MPI is calculated using mathematical distance functions, the core idea is simple: it compares the actual paddy output to the potential output under optimal conditions and tracks changes in productivity across seasons whether from internal improvements by farmers or external advancements in agricultural technology (Coelli *et al*. 2005). To evaluate changes in productivity across paddy farming seasons, this study applies the MPI framework. As detailed in Section 2.3.1, efficiency scores for each PPK were derived using DEA model. The MPI captures productivity change by comparing distance functions (DEA efficiency scores) across two adjacent time periods using two alternative reference technologies. These comparisons are based on the following two approaches:

Approach 1: Reference Technology from Season t (Past Technology)-This method measures productivity change based on the DEA frontier from the initial season t:

$$\mathrm{MPI}^{(1)}_{t\to t+1} = \frac{D_t^t\left(x_{t+1}, y_{t+1}\right)}{D_t^t\left(x_t, y_t\right)} \tag{2}$$

where:

$D_t^t(x_t, y_t)$ is the DEA score of the PPK in season t, evaluated using the technology available in season t.

$D_t^t(x_{t+1}, y_{t+1})$ is the DEA score of the same PPK in season $t+1$, evaluated using the same (past) technology from season t.

Approach 2: Technology from Season $t+1$ (Future Technology Reference)-Eq.(3) uses the DEA frontier from the subsequent season:

$$\mathrm{M}_{t \to t+1}^{(2)} = \frac{D_{t+1}^{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}^{t+1}(x_t, y_t)} \tag{3}$$

where

$D_{t+1}^{t+1}(x_t, y_t)$ is the the DEA score of the PPK in season t, evaluated using the future technology frontier (season $t+1$).

$D_{t+1}^{t+1}(x_{t+1}, y_{t+1})$ is the the DEA score of the PPK in season $t+1$, evaluated using the current technology frontier.

Combined Approach-MPI (Geometric Mean): Eq. (2) and (3) represent two distinct perspectives for measuring productivity change between two time periods (seasons). Eq. (2) evaluates performance using the production technology from season t as the reference, while Eq. (3) uses the technology from season $t+1$. Each perspective reflects how a production unit performs relative to the respective period's frontier. To provide a more balanced and comprehensive assessment of productivity change, both perspectives are combined using a geometric mean, as proposed by Färe *et al*. (1994). This leads to the formulation of the MPI, as shown in Eq. (4):

$$\mathrm{MPI}_{t \to t+1} = \left[\left(\frac{D_t^t(x_{t+1}, y_{t+1})}{D_t^t(x_t, y_t)} \right) \left(\frac{D_{t+1}^{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}^{t+1}(x_t, y_t)} \right) \right]^{1/2} \tag{4}$$

Eq. (4) captures the overall productivity change across two periods, but it does not indicate whether the change is driven by improvements in efficiency or shifts in technology. To address this, the MPI can be further decomposed into two components: EC and TC. This decomposition provides deeper insight into the sources of productivity growth. The relationship is shown in Eq. (5):

$$\mathrm{MPI} = \mathrm{EC} \times \mathrm{TC} \tag{5}$$

The EC component reflects the ability of a production unit, such as a paddy-producing entity, to catch up to the best practice frontier over time. It compares how efficiently inputs are used to produce outputs across two periods (seasons) and is calculated as:

$$\mathrm{EC} = \frac{D_{t+1}^{t+1}(x_{x+1}, y_{x+1})}{D_t^t(x_t, y_t)} \tag{6}$$

The TC component captures shifts in the production frontier itself, which represent technological advancements or innovations in farming practices. It is measured as the geometric mean of the relative shifts in distance functions across periods, as shown in below:

$$\mathrm{TC} = \left[\left(\frac{D_t^{t+1}\left(x_{t+1}, y_{t+1}\right)}{D_{t+1}^{t+1}\left(x_{t+1}, y_{t+1}\right)} \right) \left(\frac{D_t^t\left(x_t, y_t\right)}{D_{t+1}^{t+1}\left(x_t, y_t\right)} \right) \right]^{1/2} \tag{7}$$

Through this decomposition, it becomes easier to understand whether the observed improvements in paddy productivity are due to farmers becoming more efficient in using available inputs such as land, fertilizers, seeds, and labor or due to the adoption of better agricultural technologies, such as improved seed varieties, mechanization, or more effective irrigation systems. According to Färe *et al*. (1994), the MPI offers several advantages over other productivity measurement approaches. First, it only requires quantity data on inputs and outputs, without the need for price information, which is often unavailable, especially in agricultural settings. Second, since MPI is based on linear programming, it does not require any assumption about the underlying production function, and therefore avoids the complications related to error terms in statistical models. Third, it does not assume that producers are always optimizing their behavior, such as maximizing output or profit. Most importantly, the MPI allows us to break down productivity change into two meaningful components efficiency change and technical change, giving valuable insight into both the internal improvements made by farmers and the external shifts in technology over time.

3. Results and Discussions

3.1. *Efficiency analysis*

Based on the DEA-BCC results shown in Table 3, PPKs with a score of 1.0000 are considered fully efficient, while those with scores below 1.0000 are classified as inefficient. The analysis of 27 PPKs across four seasons; Season 2 (2020), Season 1 (2021), Season 2 (2021), and Season 1 (2022) reveals an overall average efficiency score of 0.892 (or 89.2%). This indicates a relatively high level of efficiency, though there remains room for improvement in several PPKs. Among the most efficient PPKs, Arau and Kangar from Region I consistently achieved a perfect score of 1.0000 in all seasons, demonstrating sustained operational excellence. These two PPKs can serve as benchmarks for other PPKs aiming to enhance their efficiency. However, 92.6% (25 out of 27 PPKs) exhibited inefficiency in at least one season, underscoring the widespread need for performance optimization in resource management and operational practices.

Examining efficiency trends across seasons, Season 2 (2020) recorded the lowest efficiency levels, with many PPKs scoring below 0.90. A slight improvement was observed in Season 1 (2021), reflecting adjustments and enhancements in agricultural practices. In Season 2 (2021), efficiency remained relatively stable, with some PPKs showing minor improvements. In Season 1 (2022), several PPKs demonstrated significant efficiency gains, yet disparities between highly efficient and inefficient units persisted. In Region IV, Pengkalan Kundur maintained full efficiency for three consecutive seasons (2 (2020), 1 (2021), and 2 (2021)) but experienced a slight decline to 0.9390 in 1 (2022). Similarly, Kangkong and Bukit Besar exhibited steady improvements, reaching full efficiency in the final season.

Conversely, some PPKs consistently struggled with inefficiency. Titi Haji Idris (Region III) had the lowest efficiency scores, ranging from 0.5173 in Season 2 (2020) to 0.6601 in Season 1 (2022), showing minimal improvement. Alor Senibong in the same region remained inefficient, with scores fluctuating between 0.6974 and 0.8190. Likewise, Guar Chempedak (Region IV) consistently scored below 0.88, indicating ongoing inefficiencies, while Tunjang (Region II) failed to surpass 0.90, suggesting persistent operational challenges. Despite these inefficiencies, several PPKs demonstrated positive efficiency trends. Kayang (Region I) improved significantly from 0.8453 in Season 2 (2021) to 0.9881 in Season 1 (2022), nearing full efficiency. In Region II, Kerpan performed consistently well, reaching 0.9794 in the final season. A similar trend was observed in Region IV, where Kangkong and Bukit Besar achieved full efficiency in Season 1 (2022) following steady progress.

Table 3: Efficiency score for season from Season 2 (2020) to Season 1 (2022)

Region	Pertubuhan Peladang Kawasan (PPK)		Season			
			2 (2020)	1 (2021)	2 (2021)	1(2022)
Region I (Perlis)	A-I	Arau	1.0000	1.0000	1.0000	1.0000
	B-I	Kayang	0.8636	0.8749	0.8453	0.9881
	C-I	Kangar	1.0000	1.0000	1.0000	1.0000
	D-I	Tambun Tulang	0.9083	0.8889	0.9042	0.9311
	E-I	Simpang Empat	0.8000	0.9346	0.9025	0.9208
Region II (Jitra)	A-II	Kodiang	0.9042	0.8547	0.8865	0.8857
	B-II	Sanglang	0.7981	0.8375	0.9001	0.8787
	C-II	Kerpan	0.9066	0.9718	0.9217	0.9794
	D-II	Tunjang	0.7680	0.8354	0.8482	0.8961
	E-II	Kubang Sepat	1.0000	0.9542	0.8703	0.9662
	F-II	Jerlun	0.9814	0.9588	0.8969	0.9533
	G-II	Jitra	0.7937	0.7734	0.9107	0.8039
	H-II	Kepala Batas	0.8913	0.8757	0.8518	0.8688
	I-II	Kuala Sungai	0.8467	0.9398	0.9225	0.9050
Region III (Pendang)	A-III	Hutan Kampong	0.8058	0.9542	0.9294	0.7843
	B-III	Alor Senibong	0.6974	0.8123	0.8190	0.7435
	C-III	Tajar	0.7968	0.9794	0.8905	0.9166
	D-III	Titi Haji Idris	0.5173	0.7911	0.7158	0.6601
	E-III	Kobah	0.7148	0.8562	0.8347	0.9099
	F-III	Pendang	0.8985	0.9653	0.9083	0.9107
Region IV (Kota Sarang Semut)	A-IV	Batas Paip	0.8842	0.9033	0.8865	0.9579
	B-IV	Pengkalan Kundur	1.0000	1.0000	1.0000	0.9390
	C-IV	Kangkong	0.8757	0.9320	0.9066	1.0000
	D-IV	Permatang Buluh	0.8511	0.9234	0.8658	0.9066
	E-IV	Bukit Besar	0.9107	0.9506	0.9124	1.0000
	F-IV	Sungai Limau	0.8163	0.9756	0.9328	0.9634
	G-IV	Guar Chempedak	0.7800	0.8787	0.8688	0.8628

Overall, Region I recorded the highest proportion of efficient PPKs, with Arau and Kangar maintaining full efficiency throughout the study period. Regions II, III, and IV exhibited mixed performances, with persistent inefficiencies in several PPKs. Notably, underperforming PPKs such as Titi Haji Idris, Alor Senibong, and Guar Chempedak require targeted interventions to enhance efficiency.

Meanwhile, high-performing PPKs like Arau, Kangar, and Pengkalan Kundur can serve as benchmarks for best practices, offering valuable insights into strategies for improving efficiency among underperforming units. While the overall efficiency of PPKs remains relatively high, the substantial performance gap between the most and least efficient PPKs highlights the need for technological adoption, improved resource management, and tailored strategic interventions to achieve a more balanced and efficient agricultural sector.

Figure 2 illustrates the efficiency score trends of selected PPKs (Titi Haji Idris, Arau, Jitra, Alor Senibong, and Kobah) across four consecutive planting seasons. Among these, Arau consistently recorded a perfect efficiency score (1.0000), making it a potential benchmark for best practices in resource utilization and operational management. In contrast, PPKs like Titi Haji Idris and Alor Senibong showed lower efficiency levels, although both exhibited improvements over time. The widening gap between top-performing and less efficient PPKs underscores the need for enhanced technological adoption, targeted interventions, and capacity building to ensure more balanced performance across the MADA region.

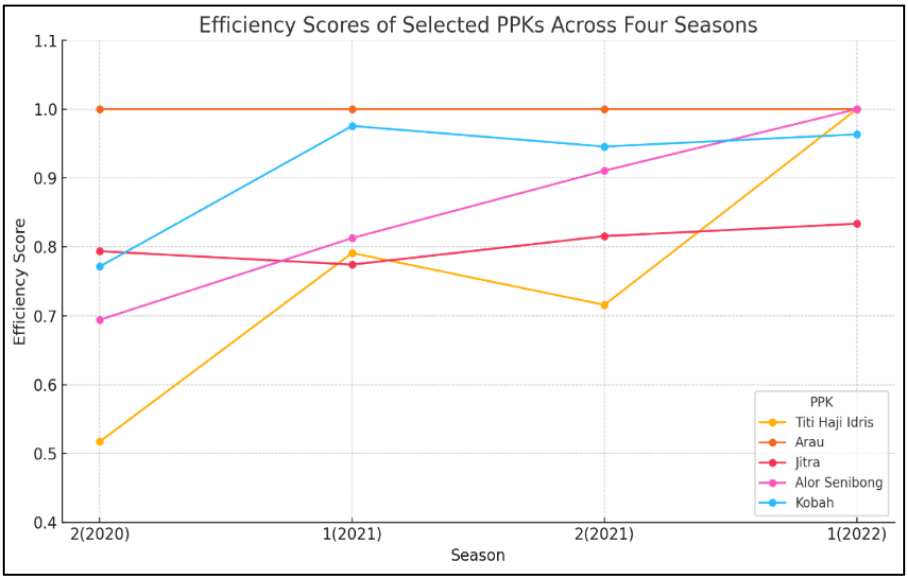

Figure 2: Temporal changes in efficiency scores among selected PPKs across 4 season

3.2. *Productivity analysis*

The MPI is a method used to measure changes in productivity over time, particularly in the context of production or efficiency. In this case, it is applied to evaluate the productivity performance of PPK from one season to the next. The first seasonal pair covers the period from Season 2 (2020) to Season 1 (2021) (MPI_1); Season 1 (2021) to Season 2 (2021) (MPI_2); and the third period periods from Season 2 (2021) to Season 1 (2022).

Three MPIs for each PPK have been calculated, providing insights into productivity changes for each PPK. The overall MPI value reflects total productivity changes, where productivity increases or decreases result from a combination of Efficiency Change (EC) and Technological Change (TC). Table 4 presents the analysis of the MPI by comparing relative efficiency in seasonal pairs. The MPI values shown illustrate productivity changes between two consecutive seasons, specifically from Season 2 (2020) to Season 1 (2021).

An MPI value greater than 1 indicates an increase in productivity, while a value less than 1 reflects a decline. For Region I (Perlis), PPK Kayang recorded an MPI of 1.0331, indicating a 3.31% productivity increase, while PPK Simpang Empat showed an MPI of 1.4751, reflecting a 47.51% increase, the highest in the region. Conversely, PPK Tambun Tulang experienced a productivity decline with an MPI of 0.9475, representing a 5.25% decrease. Both PPK Arau and PPK Kangar maintained an MPI of 1.0000, indicating no change in productivity.

In Region II (Jitra), PPK Sanglang recorded an MPI of 1.1282, reflecting a 12.82% productivity increase, while PPKs Kerpan and Tunjang showed improvements of 18.96% and 23.39%, respectively. The highest increase was observed in PPK Kuala Sungai, with an MPI of 1.2980, marking a 29.80% productivity improvement. However, several PPKs experienced productivity declines. PPK Kodiang recorded an MPI of 0.8688, indicating a 13.12% decline, while Kubang Sepat had an MPI of 0.8894, showing an 11.06% decrease. Other PPKs, such as Jerlun (MPI: 0.9435), Jitra (MPI: 0.9374), and Kepala Batas (MPI: 0.9568), also showed productivity declines of 5.65%, 6.26%, and 4.32%, respectively.

Table 4: Malmquist Index Analysis from Season 2 (2020) to Season 1 (2021)

Region	Pertubuhan Peladang Kawasan (PPK)		Change		Malmquist Index	Productivity Interpretation
			Efficiency	Technological		
Region I (Perlis)	A-I	Arau	1.0000	1.0000	1.0000	No Change
	B-I	Kayang	1.0131	1.0197	1.0331	Increasing
	C-I	Kangar	1.0000	1.0000	1.0000	No Change
	D-I	Tambun Tulang	0.9787	0.9682	0.9475	Decreasing
	E-I	Simpang Empat	1.1682	1.2627	1.4751	Increasing
Region II (Jitra)	A-II	Kodiang	0.9453	0.9191	0.8688	Decreasing
	B-II	Sanglang	1.0494	1.0750	1.1282	Increasing
	C-II	Kerpan	1.0719	1.1098	1.1896	Increasing
	D-II	Tunjang	1.0877	1.1344	1.2339	Increasing
	E-II	Kubang Sepat	0.9542	0.9321	0.8894	Decreasing
	F-II	Jerlun	0.9770	0.9657	0.9435	Decreasing
	G-II	Jitra	0.9745	0.9620	0.9374	Decreasing
	H-II	Kepala Batas	0.9825	0.9738	0.9568	Decreasing
	I-II	Kuala Sungai	1.1100	1.1694	1.2980	Increasing
Region III (Pendang)	A-III	Hutan Kampong	1.1842	1.2886	1.5259	Increasing
	B-III	Alor Senibong	1.1649	1.2573	1.4646	Increasing
	C-III	Tajar	1.2292	1.3628	1.6751	Increasing
	D-III	Titi Haji Idris	1.5293	1.8912	2.8921	Increasing
	E-III	Kobah	1.1978	1.3109	1.5701	Increasing
	F-III	Pendang	1.0743	1.1135	1.1963	Increasing
Region IV (Kota Sarang Semut)	A-IV	Batas Paip	1.0217	1.0327	1.0551	Increasing
	B-IV	Pengkalan Kundur	1.0000	1.0000	1.0000	No Change
	C-IV	Kangkong	1.0643	1.0980	1.1686	Increasing
	D-IV	Permatang Buluh	1.0849	1.1301	1.2261	Increasing
	E-IV	Bukit Besar	1.0437	1.0663	1.1129	Increasing
	F-IV	Sungai Limau	1.1951	1.3065	1.5615	Increasing
	G-IV	Guar Chempedak	1.1265	1.1957	1.3470	Increasing

Region III (Pendang) demonstrated significant productivity improvements across all PPKs. PPK Titi Haji Idris recorded the highest increase in the entire dataset, with an MPI of 2.8921, reflecting a 189.21% productivity surge. Other PPKs, such as Hutan Kampong (52.59%), Alor Senibong (46.46%), Tajar (67.51%), and Kobah (57.01%), also recorded substantial increases. PPK Pendang showed a more moderate improvement, with an MPI of 1.1963, indicating a 19.63% increase. In Region IV (Kota Sarang Semut), several PPKs demonstrated productivity gains. PPK Sungai Limau recorded an MPI of 1.5615, reflecting a 56.15% improvement, followed by Guar Chempedak (MPI: 1.3470) with a 34.70% increase. Other PPKs, such as Permatang Buluh (22.61%) and Bukit Besar (11.29%), also experienced productivity growth. However, PPK Pengkalan Kundur recorded an MPI of 1.0000, indicating no change in productivity.

EC measures relative efficiency changes of a unit (PPK) from one season to the next, without accounting for technological advancements. An EC value greater than 1.0 signifies improved efficiency, while a value below 1.0 suggests efficiency declines. PPK Simpang Empat (EC: 1.1682) in Region I and PPKs Kuala Sungai (EC: 1.1100) and Tunjang (EC: 1.0877) in Region II demonstrated improved efficiency. In Region III, PPK Titi Haji Idris exhibited the highest efficiency increase (EC: 1.5293), while PPKs Sungai Limau (EC: 1.1951) and Guar Chempedak (EC: 1.1265) led efficiency improvements in Region IV. Conversely, PPK Tambun Tulang (EC: 0.9787) and Kubang Sepat (EC: 0.9542) showed declining efficiency, suggesting input optimization challenges. TC measures advancements in production techniques. TC values above 1.0 indicate technological progress, while values below 1.0 signal technological regression. In Region I, PPK Simpang Empat (TC: 1.2627) recorded notable technological improvements, while PPK Tambun Tulang (TC: 0.9682) lagged. In Region II, PPK Kuala Sungai (TC: 1.1694) and Tunjang (TC: 1.1344) demonstrated significant technological advancements. Region III recorded the highest technological progress, particularly in PPK Titi Haji Idris (TC: 1.8912), while in Region IV, PPK Sungai Limau (TC: 1.3065) and Guar Chempedak (TC: 1.1957) showed considerable advancements. Overall, Regions III and IV demonstrated the most substantial productivity improvements, largely attributed to efficiency gains and technological progress. Conversely, productivity declines in Region II highlight challenges that require strategic interventions, such as improved management practices and technology adoption, to enhance overall performance.

Table 5 shows the analysis of MPI from Season 1 (2021) to Season 2 (2021). In Region I (Perlis), PPK Tambun Tulang recorded a productivity increase with an MPI value of 1.0435. Tambun Tulang's showed an increase of 4.35% in productivity. On the other hand, PPK Simpang Empat and PPK Kayang both showed slight declines with MPI values of 0.9165 and 0.9176, respectively. PPK Arau and PPK Kangar showed no change in productivity, with MPI values remaining at 1.0000, indicating stable productivity during this period. In Region II (Jitra), several PPKs experienced significant productivity increases. PPK Jitra achieved the highest growth in the region, with an MPI of 1.5048, representing a 50.48% productivity increase. PPK Sanglang followed closely with an MPI of 1.1974, indicating a 19.74% increase. PPK Kodiang and PPK Tunjang also showed improvements, with MPIs of 1.0957 (9.57%) and 1.0386 (3.86%), respectively. Conversely, some PPKs in Region II saw declining productivity. PPK Kubang Sepat recorded an MPI of 0.7945, indicating a 20.55% decline, the most significant drop in the region. PPK Jerlun followed with an MPI of 0.8463, reflecting a 15.37% decrease. Other PPKs experiencing declines included PPK Kerpan (MPI of 0.8759, -12.41%), PPK Kepala Batas (MPI of 0.9332, -6.68%), and PPK Kuala Sungai (MPI of 0.9545, -4.55%).

In Region III (Pendang), productivity declines were observed in most PPKs. PPK Titi Haji Idris recorded the steepest drop with an MPI of 0.7787, reflecting a 22.13% decrease. PPK Tajar followed with an MPI of 0.7882, showing a 21.18% decline. PPK Pendang (MPI of 0.8589, -14.11%), PPK Hutan Kampong (MPI of 0.9362, -6.38%), PPK Kobah (MPI of 0.9386, -6.14%), and PPK Alor Senibong (MPI of 1.0206, +2.06%) demonstrated small to moderate productivity changes. In Region IV (Kota Sarang Semut), productivity declines were also prevalent. PPK Permatang Buluh recorded an MPI of 0.8514, indicating a 14.86% productivity decrease. PPK Bukit Besar (MPI of 0.9026, -9.74%), PPK Sungai Limau (MPI of 0.8940, -10.60%), and PPK Kangkong (MPI of 0.9334, -6.66%) all showed notable declines. PPK Pengkalan Kundur, representing Region IV, recorded an MPI of 1.0000, reflecting no change in productivity. EC for PPK Jitra (EC of 1.1776) and PPK Sanglang (EC of 1.0747) showed the highest efficiency improvements, indicating better resource optimization. However, PPKs such as Kubang Sepat (EC of 0.9121) and Titi Haji Idris (EC of 0.9048) experienced significant efficiency declines, suggesting input mismanagement. TC assesses advancements in farming techniques and production methods. PPK Jitra recorded the highest TC value of 1.2779, reflecting strong technological improvements. However, PPKs such as Kubang Sepat (TC of 0.8711) and Titi Haji Idris (TC of 0.8606) experienced technological regressions, indicating a lag in adopting modern agricultural practices. Overall, while some PPKs demonstrated productivity growth, others faced efficiency and technological challenges that require strategic intervention. Targeted investments in technology, training programs, and resource management strategies could help mitigate these declines and improve overall productivity in the underperforming regions.

Table 5: Malmquist Index Analysis from Season 1 (2021) to Season 2 (2021)

Region	Pertubuhan Peladang Kawasan (PPK)		Change		Malmquist Index	Productivity Interpretation
			Efficiency	Technological		
Region I	A-I	Arau	1.0000	1.0000	1.0000	No Change
(Perlis)	B-I	Kayang	0.9662	0.9497	0.9176	Decreasing
	C-I	Kangar	1.0000	1.0000	1.0000	No Change
	D-I	Tambun Tulang	1.0172	1.0259	1.0435	Increasing
	E-I	Simpang Empat	0.9657	0.9490	0.9165	Decreasing
Region II	A-II	Kodiang	1.0372	1.0564	1.0957	Increasing
(Jitra)	B-II	Sanglang	1.0747	1.1141	1.1974	Increasing
	C-II	Kerpan	0.9484	0.9236	0.8759	Decreasing
	D-II	Tunjang	1.0153	1.0230	1.0386	Increasing
	E-II	Kubang Sepat	0.9121	0.8711	0.7945	Decreasing
	F-II	Jerlun	0.9354	0.9047	0.8463	Decreasing
	G-II	Jitra	1.1776	1.2779	1.5048	Increasing
	H-II	Kepala Batas	0.9727	0.9594	0.9332	Decreasing
	I-II	Kuala Sungai	0.9815	0.9725	0.9545	Decreasing
Region III	A-III	Hutan Kampong	0.9740	0.9612	0.9362	Decreasing
(Pendang)	B-III	Alor Senibong	1.0082	1.0123	1.0206	Increasing
	C-III	Tajar	0.9092	0.8669	0.7882	Decreasing
	D-III	Titi Haji Idris	0.9048	0.8606	0.7787	Decreasing
	E-III	Kobah	0.9750	0.9627	0.9386	Decreasing
	F-III	Pendang	0.9410	0.9128	0.8589	Decreasing
Region IV	A-IV	Batas Paip	0.9814	0.9722	0.9541	Decreasing
(Kota Sarang	B-IV	Pengkalan Kundur	1.0000	1.0000	1.0000	No Change
Semut)	C-IV	Kangkong	0.9728	0.9595	0.9334	Decreasing
	D-IV	Permatang Buluh	0.9377	0.9080	0.8514	Decreasing
	E-IV	Bukit Besar	0.9599	0.9404	0.9026	Decreasing
	F-IV	Sungai Limau	0.9562	0.9350	0.8940	Decreasing
	G-IV	Guar Chempedak	0.9887	0.9831	0.9720	Decreasing

The Malmquist Index values presented in Table 6 illustrate productivity changes between Season 2_2021 and Season 1_2022. For Region I (Perlis), PPK Tambun Tulang recorded an MPI of 1.0762, indicating a 7.62% productivity increase. Meanwhile, Simpang Empat showed a slight improvement, with an MPI of 1.0514. Kayang recorded a substantial productivity gain, with an MPI of 1.4774. PPK Arau and Kangar showed no change, both with an MPI of 1.0000.

In Region II (Jitra), Kubang Sepat recorded an MPI of 1.298, indicating a 29.85% increase, the highest in the region. Kepala Batas also showed increases, with MPIs of 1.0507, Kerpan with MPI 1.1642 and Jerlun 1.1648 respectively, followed by Tunjang 1.1472. However, other PPKs experienced declines. PPK Kodiang recorded an MPI of 0.9978, reflecting a significant productivity drop. Jitra showed the most substantial decline with an MPI of 0.7319, indicating a 26.81% productivity decrease. Other PPKs, including Sanglang (0.9417) and Kuala Sungai (0.9532) also experienced reductions.

In Region III (Pendang), PPK Tajar recorded an MPI of 1.0749, reflecting a slight increasing, Kobah (1.2406) and Pendang (1.0068). PPK Hutan Kampong had the steepest decline in the region, with an MPI of 0.6543 (-34.57%). Other PPKs, such as Alor Senibong (0.7852) and Titi Haji Idris (0.8165), also exhibited productivity losses.

In Region IV (Kota Sarang Semut), some PPKs showed positive changes. PPK Batas Paip recorded the highest increase in productivity, with an MPI of 1.2134, marking a 21.34% improvement. Kangkong also experienced a strong increase, with an MPI of 1.2777. Bukit Besar (1.2576), Permatang Buluh (1.221) and Sungai Limau (1.0839) also increase. Guar Chempedak recorded an MPI of 0.9828, reflecting a slight decrease in productivity. Pengkalan Kundur losses productivity with MPI , 0.8543.

Table 6: Malmquist Index Analysis from Season 2 (2021) to Season 1 (2022)

Region	Pertubuhan Peladang Kawasan (PPK)		Change		Malmquist Index	Productivity Interpretation
			Efficiency	Technological		
Region I (Perlis)	A-I	Arau	1.0000	1.0000	1.0000	No Change
	B-I	Kayang	1.1690	1.2639	1.4774	Increasing
	C-I	Kangar	1.0000	1.0000	1.0000	No Change
	D-I	Tambun Tulang	1.0298	1.0450	1.0762	Increasing
	E-I	Simpang Empat	1.0203	1.0305	1.0514	Increasing
Region II (Jitra)	A-II	Kodiang	0.9991	0.9987	0.9978	Decreasing
	B-II	Sanglang	0.9763	0.9646	0.9417	Decreasing
	C-II	Kerpan	1.0627	1.0955	1.1642	Increasing
	D-II	Tunjang	1.0565	1.0859	1.1472	Increasing
	E-II	Kubang Sepat	1.1101	1.1697	1.2985	Increasing
	F-II	Jerlun	1.0629	1.0958	1.1648	Increasing
	G-II	Jitra	0.8826	0.8292	0.7319	Decreasing
	H-II	Kepala Batas	1.0200	1.0301	1.0507	Increasing
	I-II	Kuala Sungai	0.9810	0.9716	0.9532	Decreasing
Region III (Pendang)	A-III	Hutan Kampong	0.8439	0.7753	0.6543	Decreasing
	B-III	Alor Senibong	0.9078	0.8649	0.7852	Decreasing
	C-III	Tajar	1.0293	1.0443	1.0749	Increasing
	D-III	Titi Haji Idris	0.9221	0.8855	0.8165	Decreasing
	E-III	Kobah	1.0901	1.1381	1.2406	Increasing
	F-III	Pendang	1.0027	1.0041	1.0068	Increasing
Region IV (Kota Sarang Semut)	A-IV	Batas Paip	1.0805	1.1231	1.2134	Increasing
	B-IV	Pengkalan Kundur	0.9390	0.9099	0.8543	Decreasing
	C-IV	Kangkong	1.1030	1.1584	1.2777	Increasing
	D-IV	Permatang Buluh	1.0471	1.0715	1.1221	Increasing
	E-IV	Bukit Besar	1.0960	1.1474	1.2576	Increasing
	F-IV	Sungai Limau	1.0328	1.0495	1.0839	Increasing
	G-IV	Guar Chempedak	0.9931	0.9897	0.9828	Decreasing

PPKs with EC values greater than 1 improved efficiency, while values below 1 indicate declines. For example, Tunjang (1.0565) and Kayang (1.1690) showed increased efficiency, while Jitra (0.8826) and Hutan Kampong (0.8439) faced efficiency drops. TC reflects advancements in production techniques. PPKs such as Kubang Sepat (1.1697) and Kangkong (1.1584) showed strong technological improvements. However, Jitra (0.8292) and Hutan Kampong (0.7753) faced technological regressions, indicating a lag in adopting modern agricultural methods. The overall analysis shows that certain PPKs, particularly in Regions II and III, need to focus on improving both efficiency and technological adoption. While Batas Paip and Kangkong demonstrated notable productivity increases, PPKs like Jitra and Hutan Kampong require targeted interventions to address efficiency losses and outdated farming techniques.

To enhance the understanding of the MPI results presented earlier, Figure 3 visualizes the MPI trends of six selected PPKs across the three phases. This line chart provides a clear view of temporal changes in productivity performance over time. An MPI value greater than 1 indicates an increase in productivity, a value less than 1 reflects a decline, and a value equal to 1 denotes no change in productivity. This interpretation helps contextualize the trends observed in Figure 3. Notably, Titi Haji Idris exhibited a very high MPI value in Phase 1 (MPI_1) (2.8921) but experienced a significant decline in the following phases. In contrast, Arau maintained a stable MPI of 1.0000 across all phases, indicating consistent productivity. Other PPKs, such as Kerpan and Simpang Empat, showed moderate fluctuations over the period.The line chart improves the readability of MPI dynamics compared to dense tabular presentation.

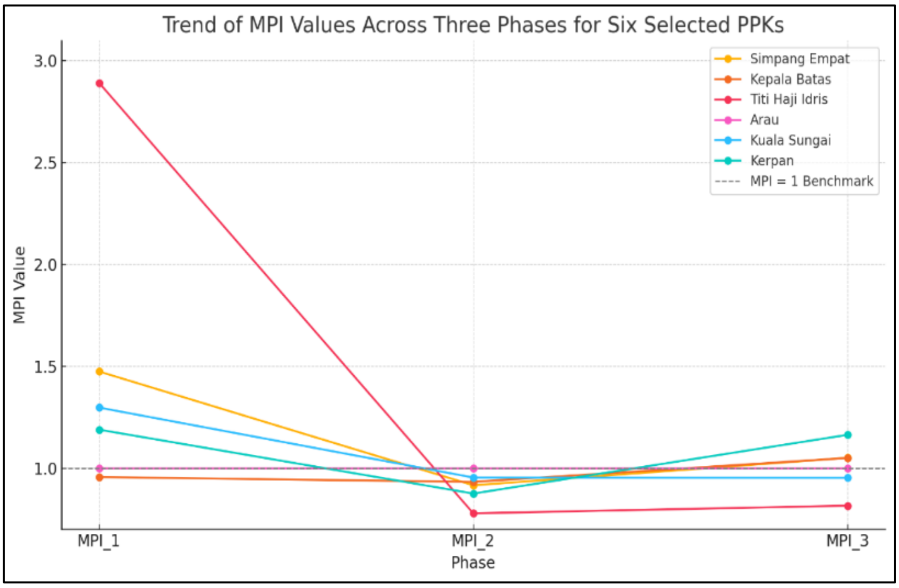

Figure 3: Trend of MPI values across three phases for six selected PPKs

3.3. *Discussion of results*

In the context of MADA, paddy production follows a structured biannual planting cycle: Season 1 typically runs from March to July (the drier season), while Season 2 spans from August to February (the wetter or monsoon-influenced season). This seasonal distinction is crucial when interpreting MPI results, as climatic variability particularly heavy rainfall and flooding during Season 2 can significantly affect planting schedules, productivity, and technological adoption. MPI Phase 1 (Season 2, 2020 – Season 1, 2021) revealed mixed performance across PPKs, likely influenced by the monsoon season which often disrupts the planting and harvesting cycles. Several PPKs experienced notable declines in productivity, presumably due to delays in replanting and adverse weather conditions. For instance, PPK Tambun Tulang recorded an MPI of 0.9475, indicating an overall decline in productivity, primarily driven by a decrease in technological change (TC = 0.9682). Other PPKs, such as Kodiang, Kubang Sepat, and Jerlun, also recorded MPI values below 1, reflecting similar downward trends. These findings support the argument that agricultural efficiency is highly sensitive to seasonal variations and external shocks (Arslan *et al*. 2017).

From a technological change (TC) perspective, the MPI Phase 1 results indicate that many PPKs experienced only marginal improvements or even declines in TC values. This suggests that productivity changes during this period were not predominantly driven by technological advancements, but rather influenced by changes in efficiency or external operational constraints. On average, TC values for most PPKs hovered around or fell below 1.000, reflecting either technological stagnation or regression. This pattern points to a limited adoption of new innovations or a lack of significant technological upgrading in paddy farming practices between Season 2, 2020 and Season 1, 2021. Notably, this period coincided with the onset of the COVID-19 pandemic, which plausibly disrupted the supply chain for modern agricultural inputs, limited access to machinery, and restricted the availability of extension and advisory services. As a result, the low TC values observed may reflect a critical juncture where technological progress was significantly constrained, despite the strategic importance of innovation in driving long-term productivity improvements.

In addition to weather-related disruptions, it is important to acknowledge the potential impact of the COVID-19 pandemic during MPI Phase 1 (2020–2021). Although paddy farming was classified as an essential activity, the implementation of movement control orders (MCOs) and associated restrictions may have affected key aspects of rice production. These include labor availability, timeliness of input supply (such as fertilizers and pesticides), machinery operations, and field supervision. Such disruptions could have contributed to delays in replanting and inconsistent management practices across some PPKs, especially those with limited operational flexibility. Government interventions, including exemptions for agriculture and financial support schemes, helped mitigate severe impacts, but localized inefficiencies may still have emerged as a result of pandemic-induced constraints. Therefore, the decline in productivity observed in certain PPKs during this phase may not only be attributed to weather, but also to the indirect effects of the pandemic.

Nonetheless, this phase also saw notable improvements among certain PPKs, particularly those that likely had better access to technology and infrastructure. For example, PPK Simpang Empat recorded a high MPI of 1.4751 with a TC of 1.2627, suggesting a significant productivity gain due to the implementation of new technologies. Similarly, PPK Titi Haji Idris experienced a substantial surge in productivity (MPI = 2.8921), most likely attributed to a major influx of technology or the adoption of new mechanization methods in paddy production management. According to Waqas *et al*. (2024), productivity growth is often driven by advancements in technology, especially in sectors reliant on natural conditions such as agriculture.

MPI Phase 2 (Season 1, 2021 – Season 2, 2021), a majority of PPKs showed drop in productivity, indicating that the implementation of modern agricultural technologies was either not effectively sustained or faced challenges during adoption, possibly due to limited technical capacity, insufficient support systems, or unfavorable weather conditions affecting field operations. Among the PPKs recorded declining performance in this phase were Kayang (MPI = 0.9176, TC = 0.9497), Simpang Empat (MPI = 0.9165, TC = 0.9490), Kobah (MPI = 0.9386, TC = 0.9627), and Hutan Kampong (MPI = 0.9362, TC=0.9612). This suggests the presence of a capability gap among PPKs in effectively adopting and applying technology, possibly due to differences in financial resources, technical skills, or management capacity (Latruffe *et al*. 2012). Tambun Tulang (MPI = 1.0435, TC = 1.0259), Kodiang (MPI = 1.0957, TC = 1.0564), Sanglang (MPI = 1.1974, TC = 1.1141), Tunjang (MPI = 1.0386, TC = 1.0230), Jitra (MPI = 1.5048, TC = 1.2779), and Alor Senibong (MPI = 1.0206, TC = 1.0123) recorded notable improvements in performance. The surge in their TC values suggests that these PPKs had actively adopted mechanization, precision fertilization, and more efficient crop monitoring systems. As noted by Sanyaolu and Sadowski (2024), the use of precision agriculture tools can significantly boost technical efficiency and support sustainable productivity growth. Although Season 1 typically offers drier conditions, MPI Phase 2 results suggest that internal factors such as technology fatigue and insufficient adoption mechanisms played a more dominant role in the observed declines. Conversely, in Season 2 of 2021, weather volatility may have again posed challenges, although selected PPKs demonstrated resilience through adaptive practices.

MPI Phase 3 (Season 2, 2021 – Season 1, 2022) served as a critical phase for evaluating the sustainability of the productivity gains achieved in the previous phase. Overall, this phase witnessed a slight recovery in productivity levels among most PPKs. For instance, PPK Kayang recorded a significant improvement in MPI 3 (1.4774) compared to its earlier decline to 0.9176 in MPI 2. Similar increase were also observed for PPK Jerlun (from 0.8463 to 1.1648) and Kubang Sepat (from 0.7945 to 1.2985). There were PPKs such as Tambun Tulang that showed continuous improvement from MPI 1 to MPI 3, suggesting that consistent management efforts and gradual technological adoption had a lasting positive impact (Mehboob & Harris 2023).

From a longitudinal perspective, productivity trends across the MPI phases varied significantly among the PPKs. For example, PPK Kayang experienced a notable decline during the second phase, followed by a recovery in the third phase, an indication of possible inconsistencies in investment or an unsustainable technology implementation strategy. In contrast, PPK Tambun Tulang exhibited steady recovery and continuous improvement across all phases, likely attributable to strengthened management and systematic technological adoption. PPK Kerpan, meanwhile, displayed fluctuating performance, with gains in the first and third phases but a decline in the second, suggesting challenges in maintaining consistent best practices.When contextualized within the national scenario, the observed trends among the PPKs align with Malaysia's fluctuating paddy production over the study period. According to Department of Statistics Malaysia (DOSM), annual paddy production showed marginal increases in 2020, followed by a slight dip in 2021, largely due to climate variability, disruptions from the COVID-19 pandemic, and rising input costs. These macro-level challenges parallel the decline in productivity observed among many PPKs in MPI Phase 2, where operational inefficiencies, limited labor mobility, and delayed input distribution were reported.

Moreover, the contrasting performance among PPKs can also be attributed to localized differences in agro-ecological conditions, infrastructure, and institutional support. PPKs that consistently improved, such as Tambun Tulang and Alor Senibong, may have benefited from more reliable irrigation infrastructure, stronger leadership, or better access to mechanization. Conversely, PPKs with declining or inconsistent performance, such as Kerpan or Simpang Empat, may have faced periodic flooding, pest outbreaks, or delays in technology adoption. These findings underscore the importance of customizing support mechanisms to address both national and local-level production constraints. These findings highlight the critical need for PPK management to engage in continuous and strategically planned investments in agricultural technology to ensure long-term productivity gains. Such investments should be aligned with each PPK's operational capacity and tailored to address specific inefficiencies identified through performance monitoring. In addition to financial investment, robust training and capacity-building initiatives are essential to equip management and field personnel with the skills required to implement, monitor, and adapt technological solutions effectively.

Equally important is the role of supportive agricultural policy. Policymakers should develop frameworks that offer targeted incentives, such as performance-based grants, access to low-interest financing, and technical advisory services, to reward PPKs demonstrating consistent progress. These mechanisms would not only encourage sustained improvements but also promote a culture of innovation and accountability within the sector. Ultimately, a coordinated approach involving strategic investment, human capital development, and policy support is vital for strengthening the resilience, efficiency, and sustainability of Malaysia’s paddy production system. Similar policy recommendations have been proposed by Mehboob and Harris (2023), emphasizing that tailored incentive schemes and extension services are pivotal in sustaining technology-driven gains in agricultural systems.

Overall, the integration of DEA-based efficiency scores (EC) and the Malmquist Index framework (MPI and TC) provides a more nuanced understanding of productivity dynamics among the PPKs. The results suggest that in some cases, better management and more efficient use of existing resources contributed more to productivity improvements than technological advancement. Conversely, when technological change was evident but not matched with efficiency gains, it highlights the importance of effective implementation at the field level. This interaction reinforces the need to not only introduce innovation but also ensure its proper absorption and utilization by on-ground management.

4. Conclusion and Future Work

This study applied DEA alongside the Malmquist Index (MPI) to evaluate the productivity performance of PPKs across multiple planting seasons. The findings revealed substantial variations in efficiency and technological progress, with some PPKs achieving notable productivity improvements while others remained stagnant. The decomposition of MPI into efficiency and technological change provided critical insights into the drivers of productivity, highlighting the importance of both resource utilization and technological advancement.

While the DEA-MPI framework effectively captured temporal shifts in productivity, future studies should consider integrating Stochastic Frontier Analysis (SFA) to enhance the robustness of efficiency measurement by accounting for statistical noise and external shocks. SFA enables a clearer distinction between inefficiency and random fluctuations caused by factors such as climate variability, policy shifts, and market conditions, leading to a more accurate estimation of the true production frontier. Moreover, incorporating copula-based modeling can offer a deeper understanding of the dependence structure between efficiency scores, technological change, and external risk factors. By modeling their joint distribution, copulas can reveal nonlinear dependencies often overlooked by traditional methods. This is particularly valuable in analyzing the compounded effects of risks such as fertilizer price volatility, labor shortages, and adverse weather on PPK performance.

Future research should conduct comparative analyses between DEA-MPI and SFA outcomes to better understand the underlying drivers of productivity variations. Copula-based approaches may also help assess how different PPKs respond to correlated economic and environmental shocks, supporting more resilient and targeted policy interventions. Lastly, expanding the dataset to encompass multiple years and integrating machine learning techniques within the DEA-SFA-Copula framework may enhance predictive accuracy. Investigating the impact of digital agriculture and precision farming technologies is also crucial to understanding their role in boosting productivity. These advanced approaches can provide policymakers with strategic insights for optimizing Malaysia’s paddy production, contributing to sustainable growth and national food security.

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References

Al-Refaie A., Al-Tahat M.D. & Najdawi R. 2015. Using Malmquist index approach to measure productivity change of a Jordanian company for plastic industries. *American Journal of Operations Research* **5**(5): 384–400.

Arslan A., Belotti F. & Lipper L. 2017. Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. *Food Policy* **69**: 68–81.

Banker R.D., Charnes A. & Cooper W.W. 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* **30**(9): 1078–1092.

Ben Mabrouk M., Elmsalmi M., Aljuaid A.M., Hachicha W. & Hammami S. 2022. Joined efficiency and productivity evaluation of Tunisian commercial seaports using DEA-based approaches. *Journal of Marine Science and Engineering* **10**(5): 626.

Charnes A., Cooper W.W. & Rhodes E. 1978. Measuring the efficiency of decision making units. *European Journal of Operational Research* **2**(6): 429–444.

Coelli T.J., Rao D.S.P., O'Donnell, C.J. & Battese G.E. 2005. *An Introduction to Efficiency and Productivity Analysis*. 2nd Ed. New York: Springer Science & Business Media.

Färe R., Grosskopf S., Norris M. & Zhang Z. 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review* **84**(1): 66–83.

Farrell M.J. 1957. The measurement of productive efficiency. *Journal of the Royal Statistical Society Series A: Statistics in Society* **120**(3): 253–281.

Firdaus R.B.R., Leong Tan M., Rahmat S.R. & Senevi Gunaratne M. 2020. Paddy, rice and food security in Malaysia: A review of climate change impacts. *Cogent Social Sciences* **6**(1): 1818373.

Hashim N., Ali M.M., Mahadi M.R., Abdullah A.F., Wayayok A., Kassim M.S.M. & Jamaluddin A. 2024. Smart farming for sustainable rice production: an insight into application, challenge, and future prospect. *Rice Science* **31**(1): 47–61.

Kalimuthu K. & Applanaidu S.D. 2024. Factors effecting paddy productivity in the Mada regions, Malaysia. *Malaysian Management Journal* **28**: 145–172.

Latruffe L., Fogarasi J. & Desjeux Y. 2012. Efficiency, productivity and technology comparison for farms in Central and Western Europe: The case of field crop and dairy farming in Hungary and France. *Economic Systems* **36**(2): 264–278.

Liu J., Li X., Li Y., Sirisrisakulchai J., Kang X. & Cui J. 2024. Decomposition and driving factors of total factor productivity of food crops in the Yellow River Basin, China. *Agriculture* **14**(4): 547.

Mailena L., Shamsudin M.N., Radam A. & Latief I. 2014. Rice farms efficiency and factors affecting the efficiency in MADA, Malaysia. *Journal of Applied Sciences* **14**(18): 2177–2182.

Makhtar S., Abidin I.S.Z. & Islam R. 2022. The impact of rice productivity in Malaysia: Econometric analysis. *International Journal of Business and Economy* **4**(3): 21–32.

Mehboob F. & Jawad A. 2023. Technology adoption in small and medium enterprises: An integrated framework for success. *Management Science Research Archives* **1**(2): 70–80.

Nandy A. & Singh P.K. 2021. Application of fuzzy DEA and machine learning algorithms in efficiency estimation of paddy producers of rural Eastern India. *Benchmarking: An International Journal* **28**(1): 229–248.

Nixon S. 2024. Of rice and men: Rice consumption-based estimates of undocumented persons in Malaysia. *International Migration Review* **58**(1): 5–36.

Nodin M.N., Mustafa Z. & Hussain S.I. 2021. Assessing rice production efficiency of the granary and non-granary areas in Malaysia using data envelopment analysis approach. *Journal of Physics: Conference Series* **1988**(1): 012110.

Nunamaker T.R. 1985. Using data envelopment analysis to measure the efficiency of non-profit organizations: A critical evaluation. *Managerial and Decision Economics* **6**(1): 50–58.

Sanyaolu M. & Sadowski A. 2024. The role of precision agriculture technologies in enhancing sustainable agriculture. *Sustainability* **16**(15): 6668.

Waqas M., Naseem A., Humphries U.W., Hlaing P.T., Shoaib M. & Hashim S. 2025. A comprehensive review of the impacts of climate change on agriculture in Thailand. *Farming System* **3**(1): 100114.

Zaibidi N.Z., Baten M.A., Ramli R. & Kasim M.M. 2018. Efficiency and environmental awareness of paddy farmers: Stochastic frontier analysis vs data envelopment analysis. *International Journal of Supply Chain Management* **7**(1): 170–176.

Zaibidi N.Z, Baten M.A., Kasim M.M. & Ramli R. 2016. Non-parametric approach to measure efficiency level of paddy farmers in Kedah. *Journal of Telecommunication, Electronic and Computer Engineering* **8**(8): 155–159.

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