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Technological Mastery in Rice Farming: A DEA-Malmquist Index Approach

Azharuddin M. Amin[1]

azharuddin@agr.uir.ac.id

Islamic University of Riau https://orcid.org/0009-0001-2349-2453

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Abstract

Technological adoption does not automatically improve farm performance; farmers must also use available technologies efficiently. This study assessed technological mastery among rice farmers in Indragiri Hilir Regency, where the cultivated rice area has declined substantially, and productivity improvement is increasingly important. A balanced panel of 59 rice-farming decision-making units was observed in 2023 and 2024, respectively. An output-oriented data envelopment analysis and Malmquist productivity index were estimated using land, labor, seed, fertilizers, pesticides, and farm equipment as inputs and rice production as the output variable. Productivity change was decomposed into technical efficiency, pure efficiency, scale efficiency, and technical changes. Technological mastery was operationally defined as a condition in which both technical efficiency change and technical change exceeded one, and technical efficiency change exceeded technical change. The average total factor productivity increased by 33.30% (TFPCH = 1.3330). This growth was driven mainly by technical change (TC = 1.3153), whereas the technical efficiency change (TEC = 1.0294) was modest with small contributions from pure efficiency change (PEC = 1.0206) and scale efficiency change (SEC = 1.0084). The sample-level technological mastery score, calculated as TEC minus TC, was − 0.2710 and was classified as not mastered. Only one farmer (1.69%) met the mastery criterion with a positive score of 0.1180. The production frontier improved faster than farmers' capacity to catch up with and effectively use the available technology. Policies should therefore move beyond technology distribution and combine practical extension, machinery service access, affordable finance, peer learning, and locally adapted input and water-management packages.

1. INTRODUCTION

Rice farming remains central to food security and rural livelihoods in the Indragiri Hilir Regency in Riau Province. The 2023 Agricultural Census recorded approximately 9,186 rice-farming households, 9,731 farmers, and 13,820.60 ha of rice fields in the region (BPS Indragiri Hilir, 2024). However, the cultivated rice area is projected to decline from 21.93 thousand hectare in 2019 to 13.82 thousand hectare in 2024, a reduction of approximately 37%. When the expansion of cultivated land is constrained, sustaining the rice supply increasingly depends on raising output relative to the combined use of land, labor, capital, and material inputs rather than relying on land productivity alone (Fuglie & Rada, 2019) (Lowder et al., 2016; Pingali, 2012; van Ittersum et al., 2013).

Agricultural technology can support this transition through mechanized land preparation and harvesting, improved seed, balanced nutrient management, reliable irrigation, integrated pest management, and more effective postharvest handling. Evidence from rice and smallholder systems shows that adoption and performance depend on education, extension, irrigation, machinery access, credit, infrastructure, and the local suitability of technology packages (Mariano et al., 2012; Mottaleb et al., 2016; Ruzzante et al., 2021). Digital and data-supported tools can further improve farm decisions, although their benefits depend on connectivity, data governance, and organizational capacity (Wolfert et al., 2017) (Abate et al., 2016; Abdul-Rahaman et al., 2021; Sheahan & Barrett, 2017; Takahashi et al., 2020; Wossen et al., 2017).

Technology adoption and technological mastery are distinct concepts. Adoption refers to the use of an innovation, whereas mastery reflects the ability to integrate technology with complementary inputs and managerial practices to improve efficiency and move toward the production frontier. This distinction is important because a technology may expand production possibilities without generating equivalent gains for farmers who lack the knowledge, finance, or risk-management capacity needed to use it effectively (Emerick et al., 2016; Mariano et al., 2012) (Bandiera & Rasul, 2006; Duflo et al., 2011; Foster & Rosenzweig, 1995; Magruder, 2018; Suri, 2011).

Technological capability can be viewed as a progression from traditional, labor-intensive production to partially mechanized, modern, and eventually data-supported farming. These stages are not determined by the ownership of a single machine; they reflect how well farmers coordinate mechanization, improved varieties, nutrient and pest management, water control, timing, and post-harvest practices. Machinery-service markets and custom hiring can broaden access for small farms, but effective use still depends on operator skills, maintenance, infrastructure, and supportive institutions (Mottaleb et al., 2016; Daum & Birner, 2020). Advanced digital agriculture adds real-time monitoring and data-supported decision-making to this capability set (Wolfert et al., 2017) (Fielke et al., 2020; Klerkx et al., 2019; Klerkx & Rose, 2020; Rotz et al., 2019).

Existing studies commonly examine either technical efficiency or total factor productivity, but relatively few translate the relationship between efficiency change and technical change into an operational diagnostic of farmer-level technological mastery. Evidence is particularly limited for Indragiri Hilir, where the declining rice area increases the urgency for sustainable intensification. Therefore, this study asks the following questions: (1) how did the productivity of rice-farming decision-making units change between 2023 and 2024; (2) which component was the main source of productivity growth; and (3) to what extent did farmers master the available technology? This study applies an output-oriented DEA–Malmquist framework to distinguish efficiency catching-up from the movement of the production frontier (Färe et al., 1994; Coelli & Rao, 2005; Emrouznejad & Yang, 2018) (O'Donnell, 2010; Pastor & Lovell, 2005).

By separating efficiency catching-up from frontier movement, this analysis provides a more actionable basis for local planning. A low rate of technical efficiency changes relative to technical change points toward capability building and management support, whereas weak technical change points toward limited innovation supply, infrastructure, or technology access. This diagnostic distinction is consistent with productivity decomposition research and evidence that technology promotion strategies must be adapted to local agricultural and institutional conditions (Coelli & Rao, 2005; Ruzzante et al., 2021) (Kassie et al., 2015; Pretty et al., 2018; Takahashi et al., 2020).

2. RESEARCH METHODS

2.1 Research Design and Study Area

This study used a quantitative panel design supported by contextual information from agricultural stakeholders. This study was conducted in Indragiri Hilir Regency, Riau Province, Indonesia, where rice production remains important, but cultivated land has been declining. Each rice farm was treated as a decision-making unit (DMU). The same 59 rice farmers were observed in 2023 and 2024, producing a balanced two-period panels. Stratified random sampling captured variations in farm size, farming experience, socioeconomic conditions, and geographical location, while interviews with agricultural experts and policymakers supported the interpretation of the quantitative findings. Panel farm data are particularly useful for examining productivity dynamics and heterogeneous technology use patterns over time (Fuglie & Rada, 2019; Mariano et al., 2012). The analytical framework is shown in Fig. 1 (Lowder et al., 2016; Tho & Umetsu, 2022).

2.2 Data and Variables

Data were collected using a structured questionnaire that addressed aspects such as farmer demographics, production methods, technology application, farm inputs, and outputs. The input vector included land size, labor, seeds, fertilizers (urea, TSP, and KCl), pesticides, and farming machinery, with rice production quantified in metric tons serving as the sole output. These variables are the key resources converted into farm output, aligning with the multi-input productivity analysis and empirical research on the adoption of modern rice technology (Coelli & Rao, 2005; Mariano et al., 2012). Additional information was sourced from government statistics and agricultural extension records, and the observations from the two periods were verified for consistency prior to estimation (Abdul-Rahaman et al., 2021; Sheahan & Barrett, 2017; Tho & Umetsu, 2022).

2.3 DEA Formulation and Distance Functions

An output-oriented data envelopment analysis was selected because rice farmers generally seek to maximize output from a given input bundle. DEA estimates a piecewise-linear best-practice frontier without imposing a parametric production function. For period t, let X and Y denote the observed input and output matrices, respectively, and let x_i and y_i denote the input and output vectors of DMU. The constant-returns-to-scale (CRS) output-oriented envelopment model is specified in Eq. (1) (Charnes et al., 1978; Emrouznejad & Yang, 2018) (Banker & Natarajan, 2008; Bravo-Ureta et al., 2007; Tone, 2001).

$$\max_{\phi,\lambda} \phi \text{s.t.} X^t\lambda \le x_i^t, Y^t\lambda \ge \phi y_i^t, \lambda \ge 0$$

1

The scalar φ measures the proportional expansion of output that is feasible while inputs remain fixed, and λ is the intensity vector that forms the reference combination of the observed farms. Because φ* is at least one in the output-oriented model, the radial technical efficiency score is reported as $TE_i = 1/\varphi^*$, with values in the interval (0, 1]. The variable-returns-to-scale model adds the convexity restriction 1'λ = 1, which separates pure managerial efficiency from scale effects (Banker et al., 1984) (Tone, 2001).

For each period, the technology set P𝒕(x) contains all output vectors that can be produced using input vector x. The output distance function measures the largest feasible radial expansion of the observed output vector relative to the period-specific frontiers. For feasible observations, 0 < D𝒐𝒕 (x, y) ≤ 1, and a value of one identifies a point on the frontier (Caves et al., 1982; Färe et al., 1994) (O'Donnell, 2010).

$$P^t(x) = \{y : x \text{ can produce } y \text{ in period } t\}$$

2

$$D_o^t(x, y) = \inf\{\theta > 0 : y/\theta \in P^t(x)\}$$

3

1. **Malmquist Productivity Index and Decomposition**

The output-oriented Malmquist productivity index compares each DMU with the production frontiers in periods t and t + 1. It is defined as the geometric mean of two adjacent-period productivity ratios based on the four required output distance functions, as shown in Eq. (4) (Caves et al., 1982; Färe et al., 1994) (O'Donnell, 2010; Pastor & Lovell, 2005).

$$M_o^{t,t+1} = \left[\frac{D_o^t\left(x^{t+1}, y^{t+1}\right)}{D_o^t\left(x^t, y^t\right)} \times \frac{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_o^{t+1}\left(x^t, y^t\right)}\right]^{1/2}$$

4

The index is decomposed into technical efficiency change (TEC), which measures movement toward or away from the frontier, and technical change (TC), which measures an outward or inward shift of the frontier, respectively. Under the standard Färe et al. decomposition, the two components are given by Equations (5) and (6), and the total factor productivity change satisfies TFPCH = M𝒐𝒕, 𝒕+𝟏 = TEC × TC (Färe et al., 1994; Coelli & Rao, 2005) (O'Donnell, 2010; Pastor & Lovell, 2005).

$$TEC = \frac{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_o^t\left(x^t, y^t\right)}$$

5

$$TC = \left[\frac{D_o^t\left(x^{t+1}, y^{t+1}\right)}{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D_o^t\left(x^t, y^t\right)}{D_o^{t+1}\left(x^t, y^t\right)}\right]^{1/2}$$

6

The technical efficiency change (TEC) under constant returns to scale can be further decomposed into pure efficiency change (PEC) and scale efficiency change (SEC). PEC is calculated from variable returns-to-scale distance functions and captures changes in managerial or operational performance. The scale

efficiency in each period is the ratio of CRS efficiency to VRS efficiency, and SEC is the change in the scale efficiency ratio between periods. Thus, TEC = PEC × SEC, as summarized in Equations (7) and (8) (Banker et al., 1984; Coelli & Rao, 2005) (Banker & Natarajan, 2008).

$$PEC = \frac{D_{o,\mathrm{VRS}}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{o,\mathrm{VRS}}^{t}\left(x^{t}, y^{t}\right)}$$

7

$$SEC = \frac{D_{o,\mathrm{CRS}}^{t+1}\left(x^{t+1}, y^{t+1}\right) / D_{o,\mathrm{VRS}}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{o,\mathrm{CRS}}^{t}\left(x^{t}, y^{t}\right) / D_{o,\mathrm{VRS}}^{t}\left(x^{t}, y^{t}\right)}$$

8

For all Malmquist components, a value greater than one indicates improvement or progress, a value equal to one indicates no change, and a value less than one indicates deterioration or technological regress. Sample summaries were calculated using geometric means because the indices are multiplicative, and the identities TFPCH = TEC × TC and TEC = PEC × SEC were used as internal consistency checks (Färe et al., 1994; Coelli & Rao, 2005) (O'Donnell, 2010).

2.5 Estimation and Internal Consistency Checks

The CRS and VRS DEA models and the four adjacent-period distance functions were estimated for each DMU using DEAP version 2.1 (Coelli, 1996). Counts and percentages were then calculated for farmers with component indices above one, and the highest values were reported to describe the observed range rather than as population benchmarks. The output orientation was maintained throughout to ensure comparability across the TEC, PEC, SEC, TC, and TFPCH. Because DEA is deterministic and can be sensitive to outliers and measurement errors, the findings are interpreted as relative frontier estimates rather than causal effects of individual technologies (Emrouznejad & Yang, 2018; Simar & Wilson, 2007) (Banker & Natarajan, 2008; Simar & Wilson, 2011; Tone, 2001).

2.6 Operational Measure of Technological Mastery (TM)

Following the operational criterion proposed by Amin (2007), the farmer-level mastery score was calculated as the difference between the technical efficiency change and technical change. A farmer was classified as having mastered the available technology when $TEC_i > 1$, $TC_i > 1$, and $TEC_i > TC_i$. Therefore, the criterion identifies farms whose efficiency catching-up accompanies technological progress and exceeds the rate of frontier movement. A negative score indicates that the available production frontier progressed faster than the farmers' capacity to use it efficiently. This measure is study-specific and should be interpreted as a diagnostic extension of the standard TEC–TC decomposition rather than as a universally established DEA indicator (Färe et al., 1994; Coelli & Rao, 2005) (Magruder, 2018; Suri, 2011).

$$TM_i = TEC_i - TC_i$$

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics

Table 1 presents the descriptive statistics for the DEA input and output variables. Because DEA constructs a relative frontier from observed input-output combinations, the scale and dispersion of the variables are important for interpreting the efficiency and productivity estimates. The mean, standard deviation, minimum, maximum, and number of observations allow readers to assess heterogeneity in farm size, input intensity, and production performance before the DEA–Malmquist estimation (Masuda, 2019; Singh et al., 2019; Nodin et al., 2022) (Bravo-Ureta et al., 2007; Ogundari, 2014; Thiam et al., 2001; Tho & Umetsu, 2022).

Table 1
Descriptive statistics of DEA input and output variables, 2023–2024

Variable	Mean	Standard deviation	Minimum	Maximum	Observations for Two Years
Land area (ha)	0.85	0.41	0.25	2.00	59
Labor (person-days)	49.08	21.24	16.78	111.53	59
Seed (kg)	28.89	14.54	10.00	75.00	59
Urea fertilizer (kg)	150.32	100.88	10.00	449.00	59
TSP fertilizer (kg)	124.23	75.91	25.00	345.00	59
KCl fertilizer (kg)	156.51	124.68	25.00	560.00	59
Pesticide use (mL)	540.00	660.30	10.00	2,500.00	59
Equipment cost (million IDR)	1.24	0.68	0.35	6.52	59
Rice production (metric tons)	4.13	2.43	0.90	11.69	59

Across the 59 farm-year observations, the average cultivated area was 0.85 ha, ranging from 0.25 to 2.00 ha. This confirms that the sample predominantly comprised small-scale rice farms. The average labor and seed use were 49.08 person-days and 28.89 kg, respectively. Their relatively large standard deviations indicate substantial differences in production scale, cultivation intensity, and management practices across observations (Lowder et al., 2016; Tho & Umetsu, 2022).

Fertilizer application also varied considerably among the farms. The average use was 150.32 kg for urea, 124.23 kg for TSP, and 156.51 kg for KCl, with particularly wide ranges for urea and KCl. These distributions suggest that fertilizer management differed across farms because of variations in the

cultivated area, soil conditions, financial capacity, and access to inputs. Pesticide use displayed the greatest relative dispersion, averaging 540.00 mL, with a standard deviation of 660.30 mL and a range of 10.00–2,500.00 mL. The average equipment cost was IDR 1.24 million, ranging from IDR 0.35 million to IDR 6.52 million, indicating unequal access to machinery and production equipment (Duflo et al., 2011; Sheahan & Barrett, 2017).

The average rice production was 4.13 metric tons per farm-year observation, with a standard deviation of 2.43 metric tons and a range of 0.90–11.69 metric tons. The wide variation in production is consistent with the heterogeneity in farm size, input intensity, management, and technological use. The observed variation was sufficient for DEA–Malmquist estimation of efficiency, productivity, and technological mastery (Abdul-Rahaman et al., 2021; Tho & Umetsu, 2022).

3.2 DEA–Malmquist Results

The Malmquist results show that the average total factor productivity increased substantially between 2023 and 2024. The mean TFPCH was 1.3330, equivalent to a 33.30% increase, and 55 of the 59 DMUs (93.22%) recorded TFP growth. Under the standard index interpretation, this means that the sampled farms generally produced more output relative to their combined input use in 2024 than in 2023 (Färe et al., 1994; Coelli & Rao, 2005) (O'Donnell, 2010; Pastor & Lovell, 2005).

Table 2
Average DEA–Malmquist results and technological mastery, 2023–2024

Indicator	Mean index/score	Interpretation	DMUs improved
VRS technical efficiency (VRS TE)	0.9805 (2023) 0.9903 (2024)	0.0098% increase	25 (43.37%)
Technical efficiency change (TEC)	1.0294	2.94% improvement	39 (66.10%)
a) Pure efficiency change (PEC)	1.0206	2.06% improvement	41 (69.49%)
b) Scale efficiency change (SEC)	1.0084	0.84% improvement	33 (55.93%)
Technical change (TC)	1.3153	31,53% progress	53 (89.83%)
Total factor productivity change (TFPCH)	1.3330	33.30% improvement	55 (93.22%)
Technological mastery (TM = TEC − TC)	−0.2710	Not mastered	1 (1.69%) mastered

Note. An index value above 1 indicates improvement or progress. Technological mastery requires TEC > 1, TC > 1, and TEC > TC.

Table 2 summarizes the DEA–Malmquist productivity results for the 59 rice-farming decision-making units observed between 2023 and 2024. The results include changes in variable returns to scale (VRS) technical efficiency, technical efficiency change, technical change, pure efficiency change, scale

efficiency change, total factor productivity, and technological mastery. These indicators provide a comprehensive assessment of whether productivity improvement originated from farmers' movement toward the best-practice frontier, an outward shift in the production frontier, improvements in managerial performance, or adjustments toward a more efficient production scale. Decomposition is also used to determine whether the sampled farmers were able to translate technological progress into corresponding improvements in farm-level efficiency (O'Donnell, 2010).

1) Technical Efficiency Performance

The average variable returns-to-scale technical efficiency score increased from 0.98 in 2023 to 0.99 in 2024, indicating that the sampled rice farms operated in close proximity to the best-practice frontier during both periods. Nevertheless, only 28 farmers, accounting for 47.46% of the sample, enhanced their technical efficiency scores. This outcome implies that the improvement in average efficiency was modest and unevenly distributed among the decision-making units. Similar observations have been documented in rice-production studies, which demonstrate that high average efficiency can coexist with significant farm-level variation in managerial capacity, irrigation access, input allocation, and production conditions (Abdul-Rahaman et al., 2022; Salam et al., 2023; Nodin et al., 2021; Bravo-Ureta et al., 2007; Ogundari, 2014; Thiam et al., 2001; Tho & Umetsu, 2022). For Variable Returns to Scale Technical Efficiency (VRS TE) of each decision-making unit, refer to Fig. 2 below.

The findings indicate a general improvement in technical efficiency between the two observation periods. The average VRS TE score increased from 0.9805 in 2023 to 0.9903 in 2024, reflecting an average rise of 0.098 efficiency points. This progression towards the frontier suggests that, on average, farmers enhanced their ability to convert available inputs into rice output. Similar studies on rice productivity suggest that efficiency improvements may result from enhanced farm management, more effective input allocation, improved production practices, and increased access to agricultural knowledge and services (Chau & Scrimgeour, 2021; Cai et al., 2024).

The change-status indicators reveal that 25 farmers (42.37%) experienced an increase, 24 farmers (40.687%) experienced a decrease, and 10 farmers (16.95%) maintained a constant efficiency score.The predominance of increasing scores indicates that fewer than half of the farmers enhanced their relative managerial performance in 2024. However, the substantial proportion of farmers experiencing declining efficiency suggests that productivity improvements were not uniformly distributed across the sample. This heterogeneity may be attributed to variations in managerial ability, input quality, access to machinery, extension contact, credit availability, climatic exposure, and the adoption of improved rice-production practices (Sumaryanto et al., 2023; Xue et al., 2025).

The higher average efficiency observed in 2024 should not be automatically construed as technological progress. VRS TE primarily reflects farmers' relative ability to operate efficiently under existing production conditions, whereas technological change denotes a shift in the production frontier. Therefore, improvements in VRS TE are more accurately interpreted as a catch-up effect, indicating that

farmers moved closer to the best-practice frontier. DEA–Malmquist studies distinguish this efficiency catch-up component from technological change and demonstrate that total factor productivity growth may be driven by either enhanced technical efficiency, frontier-shifting innovation, or both (Gao et al., 2022; Wang et al., 2023).

Despite the overall improvement, most farmers remained below the efficiency frontier, suggesting that further productivity gains could be achieved through better utilization of existing resources. Recent evidence indicates that agricultural extension, advisory services, and access to specialized production services can enhance rice-farm efficiency by strengthening farmers' knowledge, managerial capacity, input decisions, and adoption of modern production practices (Alam et al., 2024; Cai et al., 2024; Owusu et al., 2025). Consequently, targeted support should prioritize farmers whose efficiency declined, particularly through field-specific extension, improved seed access, appropriate mechanization, production financing, and farmer-group-based knowledge sharing.

2) Technical Efficiency Catching-Up

The average technical efficiency changes of 1.0294 indicates that the average farm moved approximately 2.70% closer to the best practice frontier. A total of 39 farmers, representing 66.10% of the sample, recorded an improvement in technical efficiency improvement. Although this result is positive, its magnitude is substantially smaller than the technical change of 29.80%. This implies that farmers improved their resource-use efficiency, but their progress was insufficient to keep pace with the rapid shift in the available production technology (O’Donnell, 2010).

The gap between technical change and efficiency change may occur when technologies become available without sufficient training, access to credit, maintenance services, complementary inputs or continuous extension assistance. Yitayew et al. (2023) found that advisory services and effective technology channeling mechanisms can improve technical efficiency by strengthening farmers’ ability to apply innovations. Similarly, Nodin et al. (2022) emphasized that agricultural modernization should be supported by efficient input use, irrigation management, and farmer capacity development programs (Davis et al., 2012; Ragasa & Mazunda, 2018; Takahashi et al., 2020; Wossen et al., 2017). Technical Efficiency Change (TEC) for each DMUs see Fig. 3 below.

The average TEC value was 1.0294, indicating an average improvement in technical efficiency of approximately 2.94% from 2023 to 2024. This result suggests that, collectively, the sampled rice farmers improved their ability to convert the available production inputs into output relative to the observed efficiency frontier. In practical terms, the positive average TEC indicates better use of the existing production technology, potentially through improved input allocation, production planning, timing of farming operations, and managerial decision-making. Recent DEA–Malmquist studies similarly show that efficiency gains can contribute substantially to agricultural productivity growth, although the relative contribution of efficiency change and technological progress differs across production systems and regions (Mobarok et al., 2021) (Liu et al., 2024).

At the farm level, 35 farmers (59.32%) recorded TEC values greater than 1 and were therefore classified as experiencing an increase in technical efficiency. Conversely, 20 farmers (33.90%) had TEC values below 1, indicating a decrease, while four farmers (6.78%) recorded TEC values equal to 1 and maintained a constant level of technical efficiency. The predominance of farms with TEC values above 1 confirms that the overall positive average was supported by improvements across a majority of the sample rather than by only a small number of exceptionally high-performing farms.

Nevertheless, the farm-level results reveal considerable heterogeneity. The highest TEC value was 1.182, recorded by DMU 2 and DMU 7, corresponding to an efficiency improvement of approximately 18.2%. In contrast, DMU 40 recorded the lowest TEC value of 0.884, indicating an efficiency decline of approximately 11.6%. Such variation implies that farmers differed substantially in their ability to adapt production practices and manage available inputs between the two periods. Similar farm-productivity research has linked differences in efficiency change to managerial capacity, access to training, financial services, production infrastructure, farm organization, and the adoption of suitable agricultural technologies (Hoi et al., 2022) (He et al., 2021).

The findings also indicate that the adoption of production technology alone may not guarantee higher farm efficiency. Evidence from rice farming shows that improved varieties or other technologies may fail to generate superior productivity when farmers lack the managerial skills required to use them effectively. Consequently, narrowing the efficiency gap may require strengthening farmers' technical knowledge and management practices alongside technology dissemination (Chau & Scrimgeour, 2021). Recent studies also suggest that agricultural production and advisory services can enhance grain-production efficiency, particularly when services are adapted to farm size, farmer capability, and local production constraints (Liu et al., 2025).

From a policy perspective, the positive average TEC indicates that rice farming in the study area experienced an overall managerial catch-up between 2023 and 2024. However, the presence of 20 farms with declining efficiency demonstrates that the improvement was not uniform. Extension programs should therefore prioritize farms with TEC values below 1 through farm-specific diagnostics, improved input-management guidance, machinery-access support, production training, and stronger farmer-group learning mechanisms. Agricultural training and access to financial institutions have been associated with higher probabilities of farm productivity growth and technological upgrading, while infrastructure, mechanization, information access, and the capacity to absorb innovation may also support efficiency improvement (Hoi et al., 2022) (He et al., 2021) (Shah et al., 2024).

Overall, the TEC results demonstrate a favorable improvement in the relative technical efficiency of rice farming, with an average increase of 2.94% and nearly three-fifths of farmers moving closer to the efficiency frontier. However, the coexistence of substantial efficiency gains and declines across farms highlights the need for differentiated interventions. Policies should not focus solely on introducing new technologies but should also strengthen farmers' ability to manage, adapt, and use existing technologies efficiently.

3) Technical Efficiency Change Decomposition

The decomposition of the technical efficiency change (TEC) into pure efficiency change (PEC) and scale efficiency change (SEC) to depict of management aspect. The small PEC and SEC gains indicate that improvements in day-to-day input management and movement toward the most productive operating scale contributed less than the frontier shift. This interpretation follows the distinction between VRS managerial efficiency and CRS scale efficiency in DEA (Banker et al., 1984; Coelli & Rao, 2005) (Banker & Natarajan, 2008; O'Donnell, 2010). Pure Efficiency Change (TEC) and Scale Efficiency Change (SEC) for each DMUs see Fig. 4 below.

1. **Pure Efficiency Change**

The average pure efficiency change index was 1.0206, indicating a 2.06% improvement in managerial and operational efficiencies. The pure efficiency improved for 41 farmers, representing 69.49% of the sample. This result suggests that some farmers improved their day-to-day management of land, labor, seed, fertilizers, pesticides, water, and farm equipment, independently of changes in the production scale.

Nevertheless, the relatively small increase in pure efficiency indicates that weaknesses may remain in terms of input timing, fertilizer dosage, irrigation scheduling, pest management, labor organization, and the integration of complementary practices. Evidence shows that irrigation management, advisory support, farmer organizations, and resource allocation influence the efficiency of smallholder farms (Abdul-Rahaman & Abdulai, 2018; Nodin et al., 2022; Salam et al., 2023) (Davis et al., 2012; Ragasa & Mazunda, 2018; Wossen et al., 2017). This interpretation follows the distinction between VRS managerial efficiency and CRS scale efficiency in DEA (Banker et al., 1984; Coelli & Rao, 2005) (Banker and Natarajan (2008) and O'Donnell (2010).

Overall, Fig. 4 demonstrates that rice farmers achieved a meaningful improvement in average managerial efficiency from 2023 to 2024, although the coexistence of increasing and decreasing farm-level scores highlights persistent differences in production capability. Policies should therefore combine broad productivity-enhancing interventions with targeted assistance for inefficient farms, while the Malmquist decomposition should be used to determine whether the observed productivity change originated from technical-efficiency improvement, technological progress, or scale-efficiency change.

1. **Scale Efficiency Change**

The average scale efficiency change index was 1.0084, indicating an improvement of only 0.84%. Scale efficiency improved for 33 farmers, or 55.93% of the sample. The smaller scale-efficiency improvement relative to pure efficiency suggests that productivity gains were driven more by better farm management than by a movement toward the most productive scale of operation.

Limited scale adjustment is common in smallholder rice farming because farmers frequently face fragmented landholdings, limited capital, seasonal labor shortages, and restricted access to machinery.

These constraints may prevent farms from expanding or reorganizing their production activities, even when improved technologies are available. Paudel et al. (2019) showed that scale-appropriate mechanization can improve smallholder productivity, but its effectiveness depends on affordable hiring services, financing, equipment maintenance, and institutional coordination (Lowder et al., 2016; Tho & Umetsu, 2022).

4) Technological Progress

The high average technical change or technological progress index suggests that the factors affecting the best-practice frontier changed considerably during the observation period. Plausible mechanisms include greater use of mechanized operations, improved varieties, better input availability, irrigation improvements, and learning through extension and farmer networks. However, the DEA–Malmquist method identifies the net frontier shift and does not attribute it to a single intervention. Therefore, the results should be interpreted as evidence of improved production possibilities, not as proof that every farmer adopted the same technology (Mariano et al., 2012; Mottaleb et al., 2016; Wolfert et al., 2017) (Fielke et al., 2020; Grassini et al., 2013; Pingali, 2012; van Ittersum et al., 2013).

Figure 5 presents the technological change (TC) index of 59 rice farmers in Indragiri Hilir Regency during the 2023–2024 production period. Within the DEA–Malmquist productivity index framework, the technological change component measures shifts in the production frontier over time and reflects technological innovation rather than improvements in managerial efficiency (Färe et al., 1994). The TC value greater than 1.00 indicates technological progress, suggesting that farmers operated under a more advanced production frontier during the subsequent period, whereas TC values below 1.00 indicate technological regress, and TC equal to 1.00 implies no technological change (Wan & Zhou, 2021; Liu et al., 2024).

The average TC of 1.3153 indicates technological progress of 31.53%, confirming that frontier expansion was the primary driver of productivity growth from 2023 to 2024. This finding demonstrates that productivity improvement among rice farmers was primarily driven by shifts in production technology rather than solely by improvements in technical efficiency. The increase in TC may reflect wider adoption of improved rice varieties, mechanization, better irrigation management, precision fertilizer application, and more effective cultivation practices. Similar evidence has been reported by Wan and Zhou (2021), who concluded that technological progress is one of the principal contributors to agricultural productivity growth under the Malmquist productivity framework. Likewise, Liu et al. (2024) found that technological change contributed more substantially than efficiency change to long-term agricultural productivity growth in China's food production sector.

At the individual farm level, 53 farmers (89.83%) recorded TC values greater than or equal to one, indicating technological progress, whereas only six farmers (10.17%) experienced technological regress (TC < 1.00). The predominance of farms with positive technological change suggests that technological innovations were widely adopted throughout the study area. These findings imply that most farmers

successfully benefited from technological improvements that shifted the production frontier upward rather than merely improving the efficiency with which existing technologies were utilized. Similar conclusions were reported by Zhang et al. (2023), who observed that technological innovation constituted the dominant source of agricultural productivity growth across several production regions. Technical Change (TC) for each DMUs see Fig. 5 below.

Despite the encouraging overall performance, the existence of several farms experiencing technological regress indicates that technology adoption remains heterogeneous among producers. Differences in farmers' access to agricultural machinery, improved seed varieties, extension services, production capital, irrigation infrastructure, and technical knowledge may explain these disparities. Recent studies have emphasized that technological innovation generates significant productivity gains only when farmers possess sufficient managerial capability and institutional support to effectively utilize new technologies (Hoi et al., 2022; Shah et al., 2024). Consequently, technological advancement should be accompanied by continuous farmer training, extension programs, and improved access to agricultural support services.

From a policy perspective, the relatively high average TC demonstrates that technological innovation has become the principal engine of productivity growth in rice farming within the study area. Therefore, agricultural development policies should continue promoting technological diffusion through improved seed distribution, precision agriculture, farm mechanization, digital extension services, climate-smart farming practices, and stronger research–extension linkages. Furthermore, targeted assistance should be directed toward farmers exhibiting technological regress to reduce disparities in technology adoption and sustain future productivity growth. These recommendations are consistent with recent empirical evidence showing that technological innovation and agricultural support services significantly improve long-term agricultural productivity (Liu et al., 2025; Shah et al., 2024).

Overall, Fig. 4 demonstrates that technological progress was widespread among rice farmers during the 2023–2024 production period. Indicates that shifts in production technology constituted the major source of productivity improvement. Nevertheless, continued investment in agricultural innovation, extension services, and technology dissemination remains necessary to ensure that all farmers can benefit equally from technological advancement.

5) Total Factor Productivity Growth

The average total factor productivity change index was 1.3330, indicating that the total factor productivity increased by 33.30% between 2023 and 2024. A total of 55 farmers, or 93.22% of the decision-making units, recorded a productivity growth. This finding indicates that most of the sampled farms improved their ability to generate rice output from the combined use of land, labor, seeds, fertilizers, pesticides, and farm equipment. Nevertheless, the Malmquist productivity index measures changes in multi-input productivity rather than simple yield growth because it incorporates both efficiency change and movement of the production frontier (Färe et al., 1994; Coelli & Rao, 2005)

(O'Donnell, 2010; Pastor & Lovell, 2005). Total factor productivity change (TFPCH) for each DMUs see Fig. 6 below.

As shown in Fig. 6, the average TFPCH was 1.3330, indicating that rice farming productivity increased by approximately 33.30% during the observation period. This result demonstrates that, on average, rice farmers experienced a substantial improvement in total factor productivity, reflecting better utilization of production resources and/or technological progress. According to Färe et al. (1994), a TFPCH value exceeding unity signifies positive productivity growth because the production frontier shifts upward, efficiency improves, or both occur simultaneously.

The distribution of productivity performance further confirms this positive trend. Of the 59 decision-making units (DMUs), 55 farmers (93.22%) recorded TFPCH values greater than 1.00, indicating productivity growth, whereas only 4 farmers (6.78%) experienced productivity decline (TFPCH < 1.00). None of the farmers recorded a value exactly equal to 1.00, suggesting that nearly all farms experienced measurable changes in productivity during the study period. The dominance of productivity growth indicates that technological improvements and managerial adaptation were widely adopted among rice farmers.

The line graph also reveals that although productivity generally increased across most DMUs, the magnitude of improvement varied considerably. Several farmers achieved TFPCH values exceeding 1.50, indicating substantial productivity gains, whereas a small number of DMUs remained below the benchmark, reflecting productivity deterioration. Such variation is common in agricultural production because farmers differ in their capacity to adopt improved cultivation techniques, production technologies, input combinations, and management practices (Coelli et al., 2005). Farmers who rapidly adopt improved seed varieties, better water management, mechanization, and appropriate fertilizer application tend to experience higher productivity growth than those relying on conventional production methods.

The predominance of TFPCH values above unity suggests that improvements in productivity were not merely the result of increased input use but also reflected enhanced production performance. Since the Malmquist index measures productivity independently of price effects, productivity growth indicates that farms generated greater output relative to the quantity of inputs employed (Färe et al., 1994). This finding implies that rice farming in Indragiri Hilir Regency became more productive over time through improved efficiency, technological advancement, or the interaction of both components.

Overall, Fig. 6 demonstrates that the rice farming sector exhibited a strong positive productivity trajectory during 2023–2024. The average TFPCH greater than one and the high proportion of farmers experiencing productivity growth indicate that technological innovation and efficiency improvements contributed significantly to enhancing agricultural productivity. These findings support previous studies showing that sustained productivity growth is primarily driven by simultaneous improvements in production efficiency and technological progress (Färe et al., 1994; Coelli et al., 2005; Thanassoulis et al., 2020).

6) Sources of Growth

Productivity decomposition shows that technical change is the main source of total factor productivity growth. The average technical change index was 1.3153, representing a technological progress of 29.80%, and 53 farmers, or 89.83% of the sample, experienced an outward shift in the production frontier. In contrast, the average technical efficiency change index was 1.0294, indicating an efficiency-catching-up improvement of 2.70%. The substantial difference between TC and TEC demonstrates that production possibilities improved more rapidly than farmers' ability to use the available technologies efficiently (Grassini et al., 2013; O'Donnell 2010).

The relatively high technical change may reflect improvements in seed varieties, mechanized land preparation and harvesting, irrigation services, production inputs and access to agronomic information. Mechanization may increase operational timeliness, reduce labor constraints, and expand production possibilities when the machinery is appropriate for local farm conditions (Paudel et al., 2019). Improved irrigation, seed quality, fertilizer management, and crop protection practices may also contribute to the outward movement of the production frontier (Silva et al., 2022; Salam et al., 2023). However, the DEA–Malmquist analysis does not directly establish which intervention caused the technical change; therefore, these factors should be interpreted as possible explanatory mechanisms (Abdul-Rahaman et al., 2021; Pretty et al., 2018; Sheahan & Barrett, 2017).

As presented in Fig. 7, the majority of rice farmers **(**33 DMUs or 55.93%**)** experienced productivity growth resulting from the combined contribution of Technical Efficiency Change (TEC) and Technical Change (TC). This finding suggests that productivity gains resulted from improvements in both farm management and technological progress. Simultaneous improvements in efficiency and technology are generally regarded as the most desirable source of productivity growth because they reflect farmers' ability to adopt innovations while simultaneously utilizing available resources more efficiently (Färe et al., 1994).

A further 20 farmers (33.90%) achieved productivity growth primarily through Technical Change (TC) alone. This result suggests that technological innovation, such as the adoption of improved rice varieties, mechanization, improved cultivation practices, irrigation management, or other technological advancements, played a dominant role in enhancing productivity for approximately one-third of the sampled farmers. According to Coelli et al. (2005), technological progress shifts the production frontier upward, allowing farmers to produce higher output from the same quantity of inputs even when managerial efficiency remains unchanged.

Only 6 farmers (10.17%) exhibited productivity growth that was attributable solely to Technical Efficiency Change (TEC). These farmers improved productivity primarily through better management practices, improved allocation of production inputs, and enhanced operational efficiency without substantial technological innovation. Such improvements typically arise from farmers learning to optimize existing technologies and production processes rather than introducing new technologies (Thanassoulis et al., 2020).

Interestingly, no farmer (0.00%) was classified in the no growth category, indicating that every decision-making unit (DMU) experienced productivity growth driven by at least one component of the Malmquist index. This finding suggests that rice farming systems in Indragiri Hilir Regency underwent measurable changes during the study period, either through efficiency improvement, technological advancement, or the interaction between the two.

The graphical distribution also demonstrates that farmers whose productivity growth originated from both TEC and TC consistently recorded higher Malmquist Index values than those whose growth depended on only one component. This observation supports the theoretical framework of the Malmquist Productivity Index, which emphasizes that sustainable productivity growth is strongest when improvements in managerial efficiency occur simultaneously with technological progress (Färe et al., 1994). Consequently, policies aimed at improving rice productivity should not focus solely on technological dissemination but should also strengthen farmers' managerial capabilities through training, extension services, and efficient resource management.

Overall, the results indicate that technological progress and efficiency improvement jointly constituted the principal driver of productivity growth among rice farmers in Indragiri Hilir Regency during 2023–2024. The predominance of farmers whose productivity growth was supported by both TEC and TC demonstrates that the agricultural sector has begun to integrate improved production technologies with better farm management practices. This combination provides a stronger foundation for sustainable productivity improvement than reliance on only one source of growth.

7) Technological Mastery

The average technological mastery score was − 0.2710, calculated as the difference between the average technical efficiency change of 1.0294, and the average technical change of 1.3153. A negative score indicates that technological progress occurred more rapidly than farmers' efficiency-catching-up. Under the operational criterion applied in this study, TEC greater than one, TC greater than one, and TEC greater than TC, only one farmer, representing 1.69% of the sample, was classified as having mastered the available technology.

This does not imply that the remaining farmers did not use modern agricultural technologies. This indicates that most farmers were unable to convert technological progress into efficiency improvements of equal or greater magnitude. Farmers may use improved seeds, fertilizers, machinery, or irrigation but still obtain limited efficiency gains because of inappropriate timing, unsuitable dosage, inadequate equipment maintenance, or insufficient technical knowledge. Yitayew et al. (2023) emphasized that the benefits of agricultural technology are stronger when farmers receive effective advisory support, while Abdul-Rahaman and Abdulai (2018) found that farmer organizations can facilitate technology utilization through collective learning and improved institutional access (Abdul-Rahaman et al., 2021; Duflo et al., 2011; Magruder, 2018; Suri, 2011).

As shown in Fig. 8, the average Technological Mastery (TM) score was − 0.2710, indicating that the overall level of technological mastery among rice farmers remained relatively low during the study period. The predominance of negative TM values suggests that most farmers had not yet fully mastered the technologies required to achieve substantial improvements in production performance. According to Rogers (2003), technology adoption is a gradual process in which farmers move through several stages from awareness and evaluation to implementation and confirmation before technology can be fully integrated into routine farming practices.

The classification results further demonstrate the limited level of technological mastery. Of the 59 decision-making units (DMUs), only one farmer (1.69%), namely DMU 5, was classified as Mastering, with a TM value of 0.1180. In contrast, the remaining 58 farmers (98.31%) were categorized as Not Proficient. This distribution indicates that technological capability remains concentrated in only a very small proportion of farmers, while the vast majority still experience limitations in effectively utilizing available production technologies.

The graphical distribution of TM values also reveals considerable variation among individual farmers. Although several DMUs recorded values close to the zero-reference line, most observations remained below zero, reflecting insufficient technological capability. The existence of only one mastering farmer suggests that technological innovations introduced into rice farming have not yet been uniformly internalized by producers. Such variation is commonly observed in agricultural systems where differences in education, farming experience, access to extension services, financial resources, and information availability influence farmers' capacity to adopt and master new technologies (Feder et al., 1985; Rogers, 2003).

Low technological mastery may reduce farmers' ability to translate technological innovations into productivity gains. Even when improved technologies are available, productivity improvements depend on farmers' competence in operating, adapting, and integrating these technologies into existing production systems (Coelli et al., 2005). Consequently, technological progress alone may not automatically generate productivity growth unless accompanied by sufficient technological capability at the farm level.

These findings imply that strengthening farmers' technological capability should become a priority in agricultural development programs. Continuous extension services, field demonstrations, farmer training, digital agricultural education, and closer collaboration between research institutions and farmers may accelerate technology mastery and improve the effectiveness of innovation diffusion. Previous studies have consistently shown that human capital development and continuous learning substantially enhance farmers' ability to adopt technology and improve agricultural productivity (Feder et al., 1985; Rogers, 2003).

Overall, Fig. 8 indicates that technological mastery among rice farmers in Indragiri Hilir Regency remains limited, despite the productivity improvements observed in previous analyses. The finding that only 1.69% of farmers were classified as mastering technology suggests that future productivity growth will

depend not only on technological innovation itself but also on farmers' capacity to absorb, understand, and effectively utilize those innovations. Therefore, improving technological capability through education, extension, and capacity-building programs is essential for sustaining long-term productivity growth.

Technology adoption and mastery represent different stages of agricultural development. Adoption refers to farmers' access to or initial use of an innovation, whereas mastery represents their ability to combine technology with appropriate management practices and complementary production inputs. A farmer may adopt machinery or improved seed without achieving technological mastery when the technology is not applied efficiently (Bandiera & Rasul, 2006; Foster & Rosenzweig, 1995; Suri, 2011).

The relatively low technological mastery identified in this study highlights the importance of farmer capability rather than technology availability alone. Technological interventions should be accompanied by practical knowledge, financial access, maintenance services, input coordination, and locally adapted recommendations to be effective. This distinction is particularly relevant for smallholder systems, where institutional and resource constraints may limit the effective application of otherwise productive innovations (Nodin et al., 2022; Yitayew et al., 2023) (Abate et al., 2016; Magruder, 2018; Takahashi et al., 2020).

1. **Policy Recommendations**
2. **Extension and Capacity-Building Implications**

Extension programs should move beyond one-time demonstrations and provide repeated field-based coaching on seed selection, fertilizer application, irrigation scheduling, pest management, machinery operation, and post-harvest handling. Continuous advisory support can strengthen managerial capabilities and help farmers translate technological availability into sustained efficiency gains. Yitayew et al. (2023) demonstrated that effective advisory services can improve both farm productivity and technical efficiency by increasing farmers' capacity to correctly implement production technologies correctly (Davis et al., 2012; Ragasa & Mazunda, 2018; Takahashi et al., 2020; Wossen et al., 2017).

Peer-learning plots and demonstration farms may also help farmers observe locally successful combinations of inputs and production practices in the field. These approaches can reduce the uncertainty surrounding new technologies and allow farmers to adapt innovations to local soil, water, labor, and climatic conditions. Farmer groups can support this process by organizing training, disseminating information, and coordinating knowledge exchange among their members (Abdul-Rahaman & Abdulai, 2018) (Bandiera & Rasul, 2006; Foster & Rosenzweig, 1995).

2) Machinery and Financial Support

Machinery service units and custom-hiring arrangements should be strengthened so that small farms can access equipment without bearing the full fixed cost of ownership. Timely access to machinery can reduce labor bottlenecks, improve the timing of land preparation and harvesting, and reduce production

loss. Paudel et al. (2019) found that scale-appropriate mechanization can improve productivity among smallholder rice farmers when machinery services are affordable and suited to local production conditions (Klerkx & Rose 2020; Tho & Umetsu 2022).

Access to seasonal credit is also important because farmers require sufficient funds to purchase seeds, fertilizers, pesticides, and machinery services at the appropriate stage of production. Inadequate or delayed financing may force farmers to reduce input quantities or apply inputs after the optimal period has passed. Therefore, financial programs should be linked with technical guidance to ensure that credit is used for productive and complementary input combinations (Abate et al., 2016; Duflo et al., 2011; Magruder, 2018).

3) Farmer-Group and Institutional Support

Farmer groups can function as platforms for collective input purchasing, machinery scheduling, peer learning, credit access, and market coordination. Collective action may reduce transaction costs and improve farmers' bargaining positions when purchasing inputs or hiring machinery. Abdul-Rahaman and Abdulai (2018) found that farmer group participation positively affects farm yield and technical efficiency by improving access to extension, inputs, information, finance, and output markets (Bandiera & Rasul, 2006; Wossen et al., 2017).

Institutional support should also include reliable machinery maintenance, input quality control, irrigation coordination, and follow-up extension services. Providing technology without these supporting services may result in nominal adoption but limited efficiency improvements. The difference between TC and TEC in this study indicates that institutional capacity should be strengthened so that technological progress can be translated into broad-based farm-level performance (Fielke et al., 2020; Klerkx et al., 2019; Rotz et al., 2019).

4) Irrigation and Integrated Input Management

Irrigation interventions should be integrated with seed, fertilizer, pest management, and crop management programs. The productivity effects of irrigation depend not only on water availability but also on irrigation timing, soil characteristics, seed quality, fertilizer use, and farmers' operational skills. Salam et al. (2023) showed that irrigation sources and water management practices significantly influenced rice productivity and technical efficiency (Kassie et al., 2015; Pretty et al., 2018; van Ittersum et al., 2013).

Therefore, locally adapted technology packages are likely to be more effective than isolated input-support programs. Such packages should combine suitable seed varieties, balanced fertilizer application, reliable water management, integrated pest control, machinery services, and post-harvest handling practices. Silva et al. (2022) emphasized that closing rice yield gaps requires coordinated

improvements in crop management and resource allocation rather than dependence on a single technological intervention (Kassie et al., 2015; Pingali, 2012; Pretty et al., 2018).

The findings indicate that the distribution of technology is unlikely to be sufficient. A strong rise in TC can reflect the broader availability of improved seeds, machinery, water-control infrastructure, production information, or other innovations; however, low mastery means that most farmers did not convert these opportunities into equally strong efficiency gains. Agricultural innovations often generate their largest benefits when they are combined with complementary inputs, knowledge, finance, and risk-management practices, rather than being adopted in isolation (Emerick et al., 2016; Ruzzante et al., 2021) (Abdul-Rahaman et al., 2021; Magruder, 2018; Suri, 2011).

5) Integrated Support Strategy

Therefore, a more integrated support strategy is required. Extension should emphasize repeated field-based coaching rather than one-off demonstrations, while machinery service units and farmer groups can reduce equipment costs and improve timely access for small farms. Affordable seasonal credit can help farmers purchase quality inputs at the correct time, and peer learning plots can demonstrate locally successful combinations of seed, fertilizer, water, and pest management. Evidence from agricultural technology diffusion shows that extension, social learning, infrastructure, and service markets work best as complementary mechanisms (Conley & Udry, 2010; Krishnan & Patnam, 2014; Mottaleb et al., 2016; Daum & Birner, 2020) (Fielke et al., 2020; Ragasa & Mazunda, 2018; Takahashi et al., 2020; Wossen et al., 2017).

6) Institutional Interpretation

The gap between TC and TEC also has an institutional dimension to it. Small farmers may gain nominal access to machinery or inputs but still face delays, weak maintenance services, unsuitable financing terms, and insufficient guidance on complementary practices. Extension programs may introduce a technology without the follow-up required to solve operational problems, whereas farmer groups can coordinate machinery schedules, purchase inputs collectively, and spread field-level knowledge among farmers. Cross-country evidence confirms that education, extension, credit, organization membership, infrastructure, and context-specific adaptation influence whether farmers adopt and effectively use agricultural technology (Krishnan & Patnam, 2014; Mottaleb et al., 2016; Ruzzante et al., 2021) (Abate et al., 2016; Magruder, 2018; Rotz et al., 2019; Suri, 2011).

7) Methodological Limitations

The findings should be interpreted with caution because conventional DEA is deterministic and attributes all deviations from the production frontier to inefficiencies. It does not directly distinguish technical inefficiency from measurement errors, weather variability, pest outbreaks, flooding, or other random

shocks. Consequently, some changes in efficiency or productivity may reflect factors beyond farmers' managerial control (Emrouznejad & Yang, 2018; Simar & Wilson, 2007) (Banker & Natarajan, 2008; Bravo-Ureta et al., 2007; Simar & Wilson, 2011; Tone, 2001).

The analysis covers only 59 farms over two production periods; therefore, the estimated frontier may be sensitive to influential observations and year-specific conditions. The design also does not estimate the causal effects of individual technologies, and the technological mastery criterion is an operational diagnostic that requires validation in other settings. Longer panels, alternative input-output specifications, bootstrap inference, and comparisons with stochastic frontier models would strengthen the robustness and external validity of the findings (Ogundari, 2014; Thiam et al., 2001).

8) Future Research

Future studies should apply bootstrap DEA to correct potential biases and construct confidence intervals for efficiency estimates. Nodin et al. (2022) used a non-parametric bootstrap DEA approach in rice production analysis to improve the reliability of efficiency estimates and policy interpretations. Sensitivity analysis should also be conducted by removing extreme observations and testing alternative assumptions regarding returns to scale (Banker & Natarajan, 2008; Pastor & Lovell, 2005; Simar & Wilson, 2011).

Stochastic frontier analysis may be used as a complementary method because it separates statistical noise from technical inefficiency (TIF). Longer panel data would also allow researchers to assess whether technological progress and efficiency-catching-up are sustained over time. Further analysis should identify which specific technologies, institutional services, and farmer characteristics contribute most strongly to technical change and technological mastery (O'Donnell, 2010; Pastor & Lovell, 2005).

4. CONCLUSION

Rice-farm productivity in Indragiri Hilir improved between 2023 and 2024, with the average total factor productivity rising by 33.30%. The improvement was driven predominantly by technical change of 29.80%, while technical efficiency improved by only 2.70%; pure efficiency and scale efficiency increased by 1.90% and 0.80%, respectively. Consequently, the average technological mastery score was − 0.2710, and only one of the 59 farmers met the study's mastery criterion, with a positive score of 0.1180. The central policy implication is that frontier-level technological progress must be accompanied by practical extension, machinery services, finance, peer learning, and locally adapted input and water-management packages so that farmers can convert new production possibilities into broad-based efficiency gains (Coelli & Rao, 2005; Ruzzante et al., 2021; Daum & Birner, 2020) (Abdul-Rahaman et al., 2021; Pretty et al., 2018; Takahashi et al., 2020).

Declarations

Ethics Approval and Informed Consent: This study was reviewed and approved by the **[full name of the ethics committee or approving institution]** under approval number **[approval number]**. Before data collection, all participating rice farmers and key informants were informed of the study's objectives, procedures, voluntary nature, confidentiality safeguards, and their right to withdraw at any time without consequence. **Written informed consent** was obtained from all participants before the questionnaires and interviews were conducted, and all collected data were anonymized and used solely for research purposes.

Conflict of Interest:

The authors declare that they have no known financial or non-financial competing interests, personal relationships, institutional affiliations, or other circumstances that could have influenced the design, implementation, analysis, interpretation, or reporting of this study.

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Author contributions:

Azharuddin M. Amin: conceptualization, methodology, formal analysis, supervision, writing the original draft, and writing the review and editing. Juliani Sati Handayani: Investigation, data curation, validation, writing, review, and editing. All the authors have read and approved the final manuscript.

Data availability:

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to participant confidentiality and institutional requirements.

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Figures

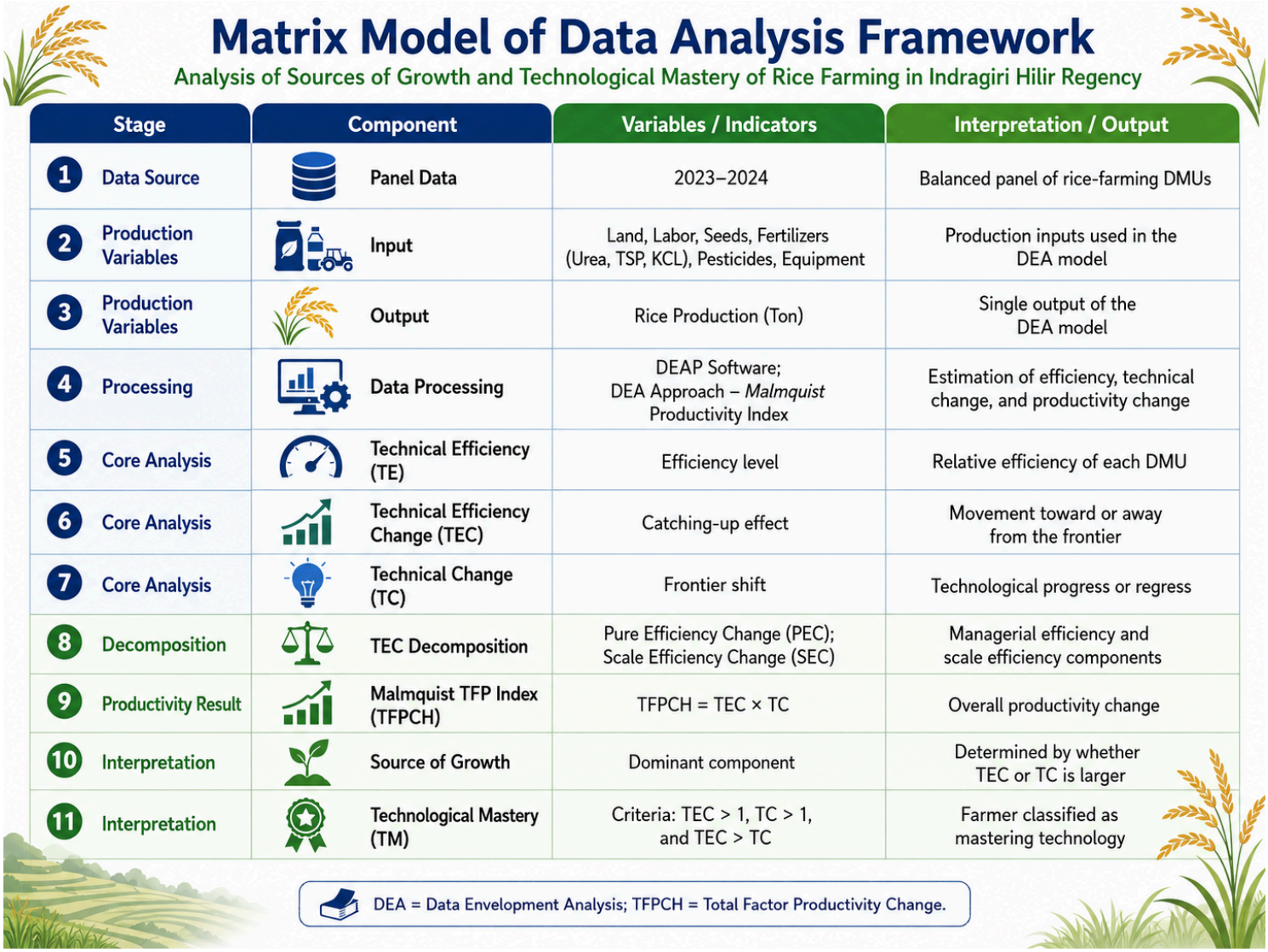


Figure 1

Matrix Model and Data Analysis Frameworks



Figure 2. VRS technical efficiency of 59 rice farmers in 2023 and 2024 and changes from 2023 to 2024.
The blue and red lines represent VRS technical efficiency in 2023 and 2024, respectively.
The green line shows the change in VRS technical efficiency (2024 minus 2023) and corresponds to the right axis.
The dashed line (TE = 1.00) indicates the efficiency frontier.
Symbols below the x-axis show the direction of change from 2023 to 2024 for each Decision Making Unit (DMU): Increase (I), Decrease (D), or Constant (C).

Figure 2

VRS Technical Efficiency

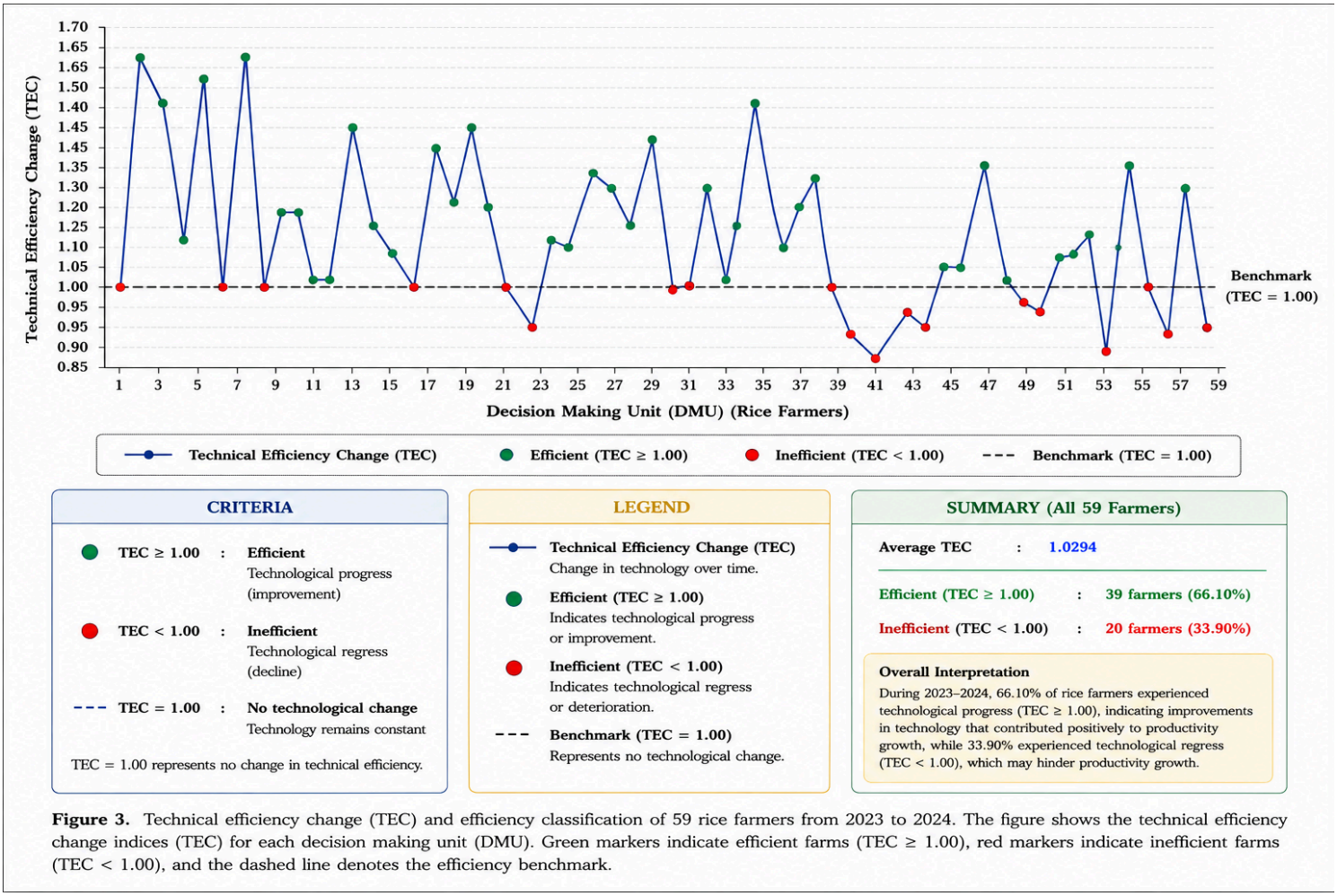


Figure 3. Technical efficiency change (TEC) and efficiency classification of 59 rice farmers from 2023 to 2024. The figure shows the technical efficiency change indices (TEC) for each decision making unit (DMU). Green markers indicate efficient farms (TEC ≥ 1.00), red markers indicate inefficient farms (TEC < 1.00), and the dashed line denotes the efficiency benchmark.

Figure 3

Technical Efficiency Change (TEC)

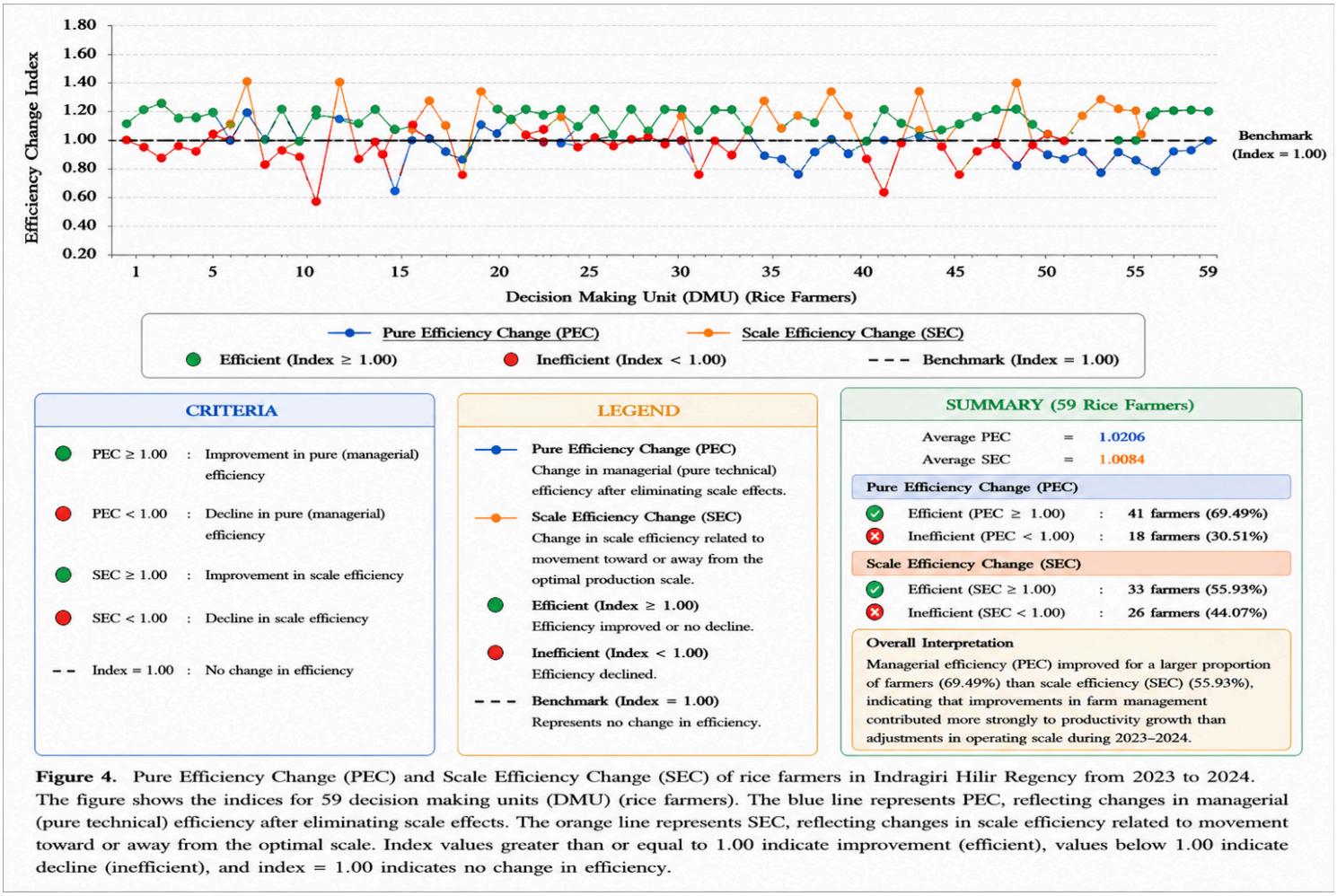


Figure 4. Pure Efficiency Change (PEC) and Scale Efficiency Change (SEC) of rice farmers in Indragiri Hilir Regency from 2023 to 2024. The figure shows the indices for 59 decision making units (DMU) (rice farmers). The blue line represents PEC, reflecting changes in managerial (pure technical) efficiency after eliminating scale effects. The orange line represents SEC, reflecting changes in scale efficiency related to movement toward or away from the optimal scale. Index values greater than or equal to 1.00 indicate improvement (efficient), values below 1.00 indicate decline (inefficient), and index = 1.00 indicates no change in efficiency.

Figure 4

PEC and SEC

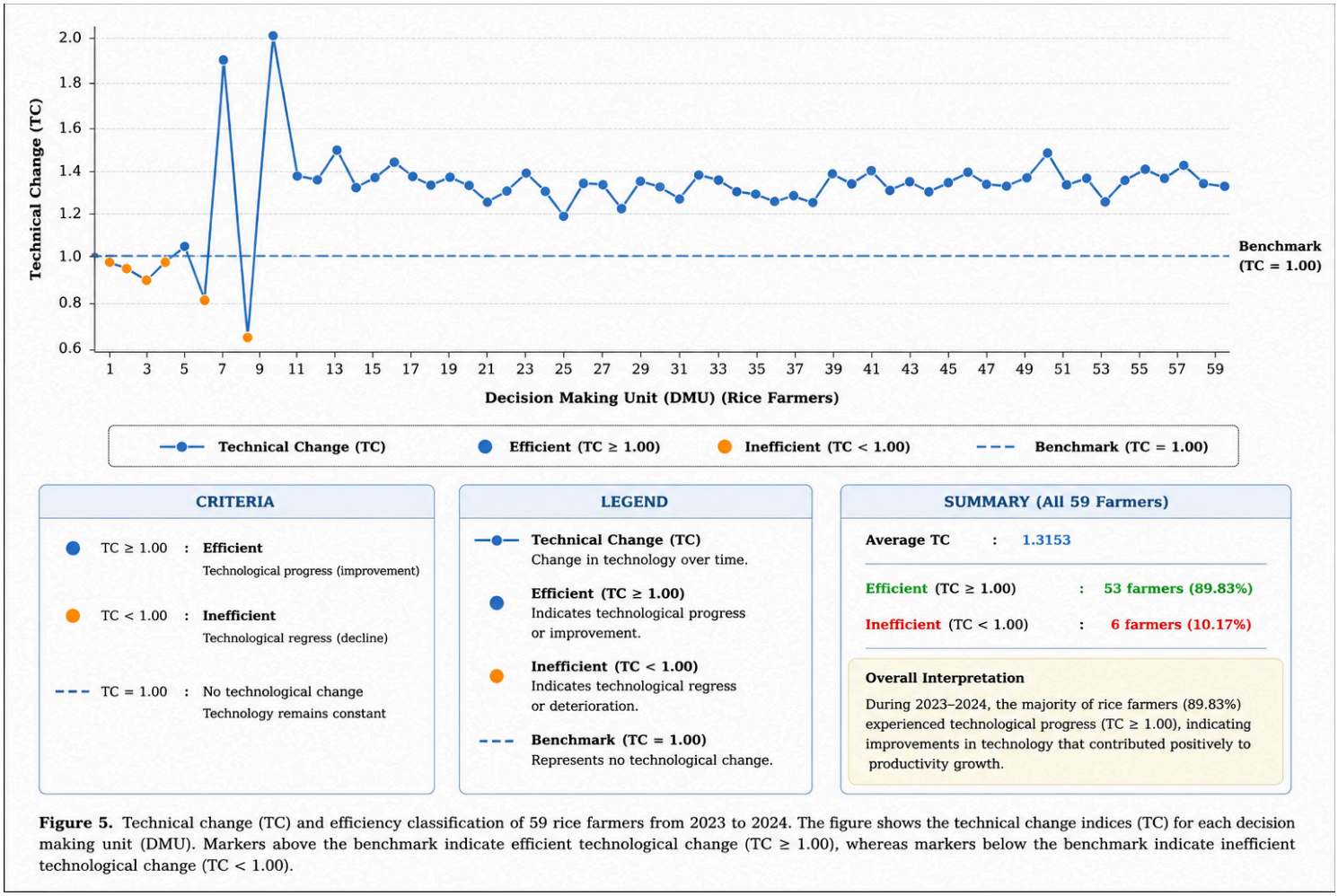


Figure 5. Technical change (TC) and efficiency classification of 59 rice farmers from 2023 to 2024. The figure shows the technical change indices (TC) for each decision making unit (DMU). Markers above the benchmark indicate efficient technological change (TC ≥ 1.00), whereas markers below the benchmark indicate inefficient technological change (TC < 1.00).

Figure 5

Technical Change (TC)

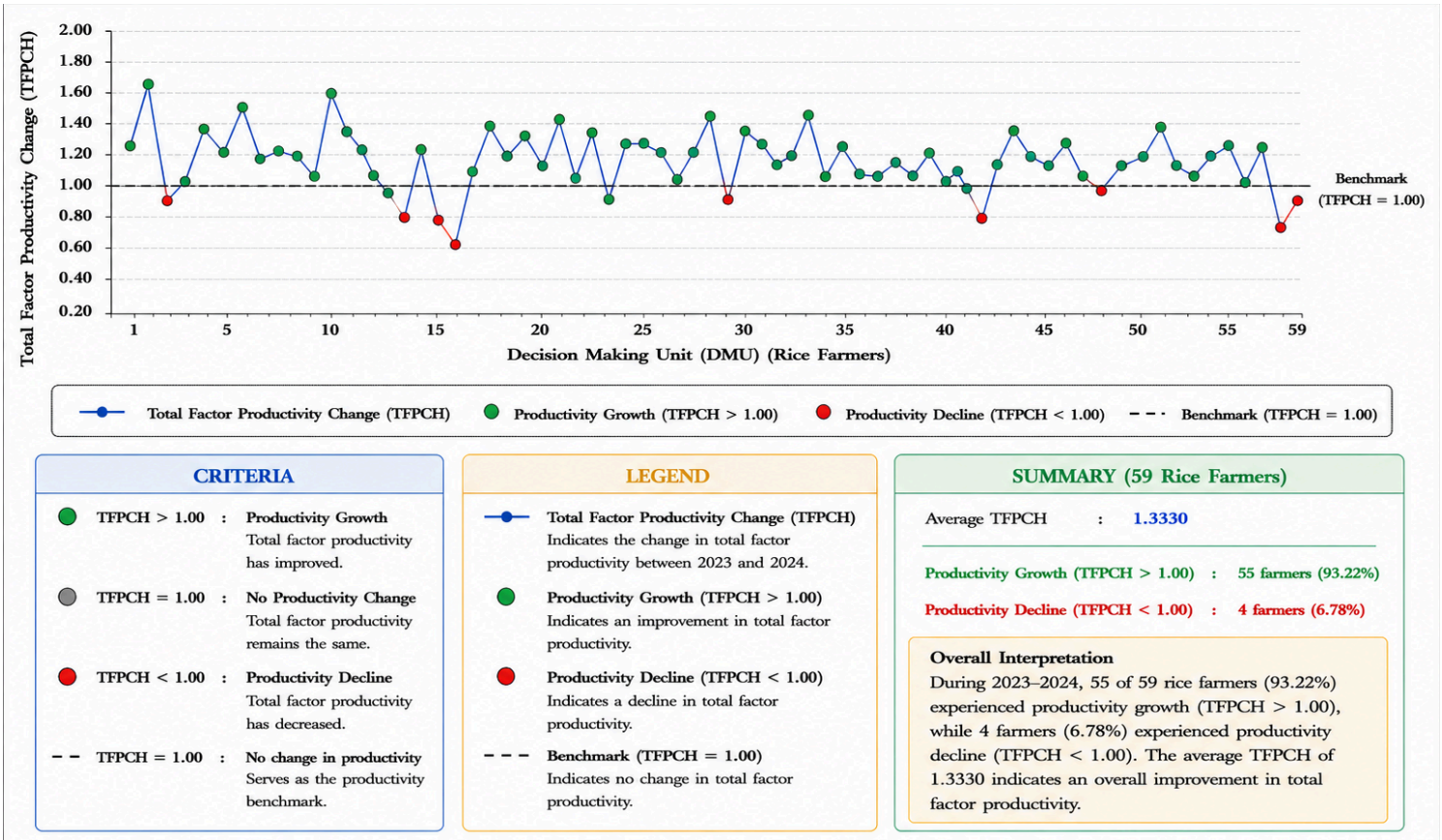


Figure 6. Total Factor Productivity Change (TFPCH) and productivity classification of 59 rice farmers from 2023 to 2024. The figure shows the TFPCH indices for each decision making unit (DMU). Green markers indicate productivity growth (TFPCH > 1.00), red markers indicate productivity decline (TFPCH < 1.00), grey markers (if any) indicate no productivity change (TFPCH = 1.00), and the dashed line denotes the productivity benchmark (TFPCH = 1.00).

Figure 6

TFPCH

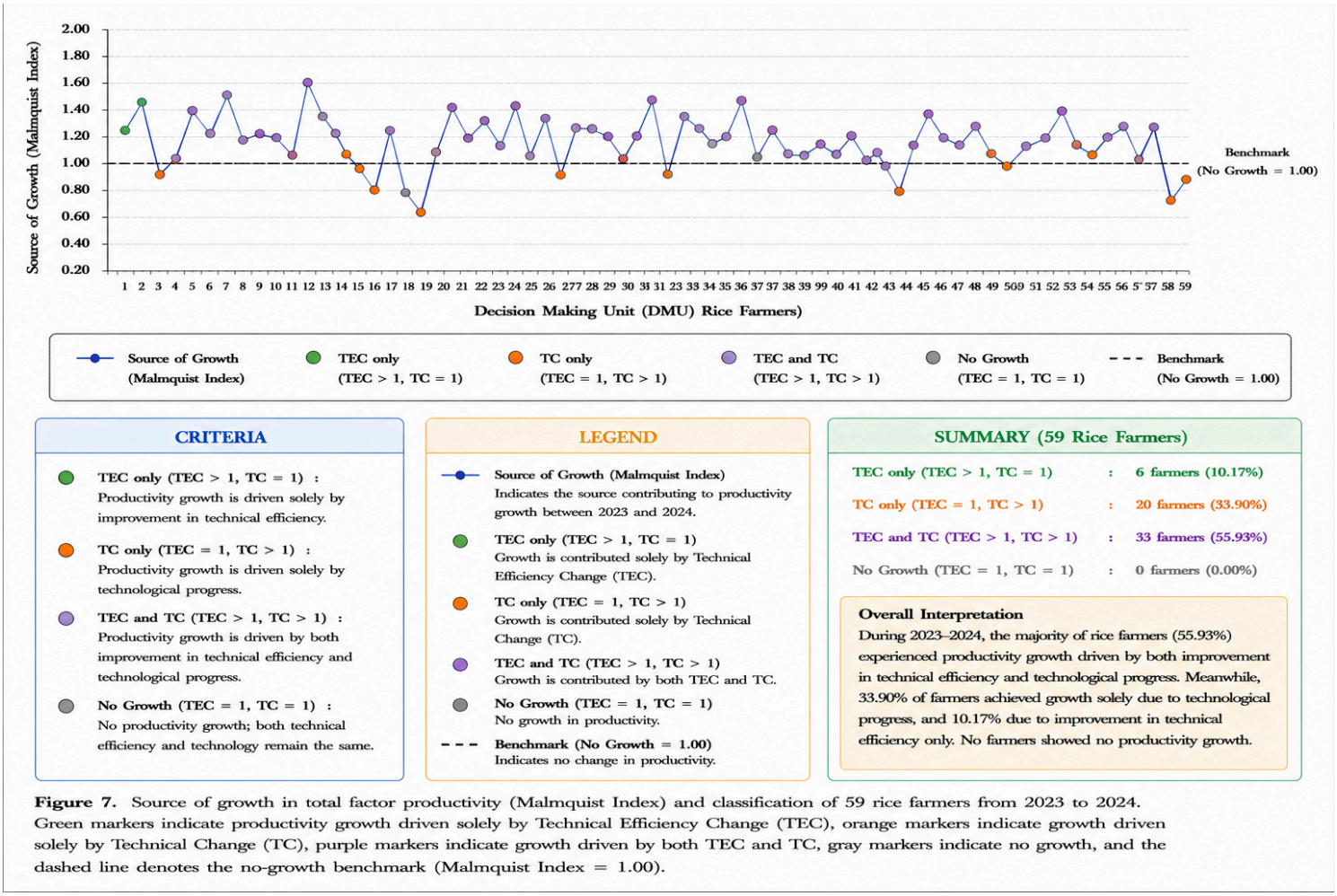


Figure 7. Source of growth in total factor productivity (Malmquist Index) and classification of 59 rice farmers from 2023 to 2024. Green markers indicate productivity growth driven solely by Technical Efficiency Change (TEC), orange markers indicate growth driven solely by Technical Change (TC), purple markers indicate growth driven by both TEC and TC, gray markers indicate no growth, and the dashed line denotes the no-growth benchmark (Malmquist Index = 1.00).

Figure 7

Source of Growth

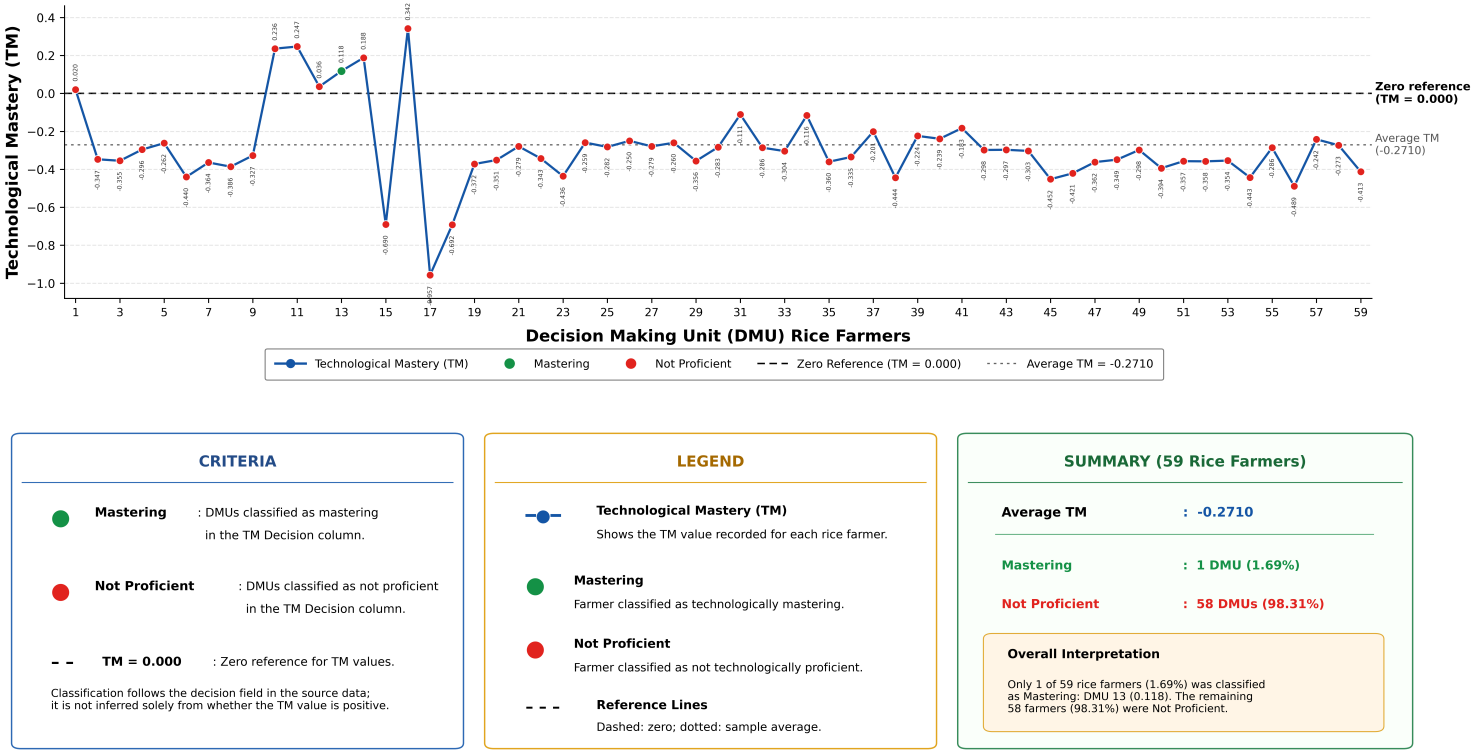


Figure 8. Technological Mastery (TM), classification, and individual values of 59 rice farmers during 2023–2024.

Each point is labelled with its corresponding TM value. Green and red markers identify the Mastering and Not Proficient classifications recorded in the source dataset, respectively.

Figure 8

Technological Mastery

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Table1and2.docx
- Table1and2.docx