Efficiency of Input Use in Rice Production during Summer-Autumn at the Coastal Regions of Vietnamese Mekong Delta

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ABSTRACT

This study evaluates the technical efficiency (TE) and input utilization efficiency of monoculture rice farms in the coastal provinces of the Mekong Delta, Vietnam, during the Summer-Autumn crop season, using the Slack-Based Measure Data Envelopment Analysis (SBM-DEA) model. A dataset of 342 farms from five provinces was analyzed to assess the efficiency of key inputs such as irrigation, fertilizers, pesticides, labor, and land preparation. The results show that the average TE score was 0.728, with only 11.1% of farms achieving optimal efficiency (Type I). Input slack analysis revealed significant overuse of irrigation water (30.06%), pesticides (18.28%), and fertilizers (16.93%), indicating considerable inefficiencies in resource use. Conversely, seed utilization exhibited the lowest excess, at only 1.77%, reflecting better management in this area. Determinants of TE included gender, land area, irrigation systems, and crop variety changes, with male-managed farms and larger-scale farms showing higher efficiency. However, farms with complete irrigation systems had lower TE, potentially due to poor management or high maintenance costs. Recommendations to improve efficiency include optimizing resource utilization, promoting crop variety diversification, and enhancing irrigation system management to ensure sustainable rice production in saline-affected areas. The study's findings highlight significant resource-saving potential and productivity improvements through targeted interventions.

Keywords: Monoculture rice farms, technical efficiency, slack-based measure data envelopment analysis, input slack, Mekong Delta.

INTRODUCTION

Rice production in the coastal areas of the Mekong Delta (MD) is facing significant challenges due to climate change, particularly saltwater intrusion, which affects more than 50% of farms and results in declining yields (Nguyen et al., 2020). Currently, the average rice yield reaches 7–8 tons/ha during the Winter-Spring crop and 6–7 tons/ha during the Summer-Autumn crop (CIAT, 2020). However, as rice yield approaches its optimal level, further yield increases require disproportionate resource investments, raising concerns about inefficiency. Excessive fertilizer application and inefficient irrigation systems are notable issues, with studies indicating that fertilizer use could be reduced by up to 30% without affecting yield (Nguyen & Tran, 2021). These inefficiencies underscore the need to study technical efficiency (TE) and input slacks to improve resource utilization in rice production under challenging coastal conditions. The Data Envelopment Analysis (DEA) method, a non-parametric approach, is commonly used to evaluate efficiency. The CCR model (Charnes, Cooper, and Rhodes, 1978) assumes constant returns to scale (CRS) and is suitable for industries where efficiency is unaffected by scale. Conversely, the BCC model (Banker, Charnes, and Cooper, 1984) assumes variable returns to scale (VRS), making it more appropriate for agriculture, where efficiency varies with scale. DEA has been widely applied in Vietnam to assess economic efficiency and allocative efficiency in agriculture. These studies reveal that while agricultural households often exhibit high technical efficiency, allocative efficiency is hindered by poor management of labor and fertilizer use (Thong, 2012; Huynh & Nguyen, 2016; Chinh et al., 2022).

An important advancement in DEA is the Slack-Based Measure DEA (SBM-DEA) model introduced by Tone (2001), which evaluates inefficiencies by explicitly accounting for input slacks and output shortfalls. This model is particularly useful in agriculture, where inefficiencies often arise from imbalances between inputs and outputs. Studies such as Wu et al. (2018) and Thirtle et al. (2003) highlight the capability of SBM-DEA in identifying inefficiencies in the use of water, labor, and fertilizers in rice cultivation in China, Thailand, and Vietnam. The extensions by Zhu (2003, 2014) have enhanced the SBM-DEA framework by incorporating nonlinear factors and improving accuracy in slack calculations, making it suitable for complex systems. In Vietnam, studies by Huynh & Nguyen (2016) and Bui et al. (2019) applied SBM-DEA to rice farming in the MD and discovered the potential to improve efficiency by 20–30% through better resource management. Additionally, climate-smart agricultural practices such as "Three Reductions, Three Gains" and "One Must, Five Reductions" have effectively minimized inefficiencies in fertilizer and irrigation use (Chinh et al., 2022).This study utilizes the SBM-DEA model to analyze technical efficiency and input slacks in monoculture rice farms in the coastal provinces of the MD. The paper is structured into three sections: the theoretical framework of SBM-DEA, results and discussions on technical efficiency and input slacks, and finally, conclusions and recommendations to optimize resource use and enhance sustainable agricultural practices.

THEORETICAL FRAMEWORK

Description of SBM-DEA Models

Data Envelopment Analysis (DEA) is a non-parametric method used to evaluate the efficiency of Decision-Making Units (DMUs). Unlike the Stochastic Frontier Analysis (SFA) model, DEA does not require assumptions about the functional form of the production function. Instead, it uses linear programming to construct an efficiency frontier based on the most efficient DMUs in the dataset. DMUs located on the frontier are considered efficient, while those below it are deemed inefficient. The model also identifies the sources of inefficiency by pinpointing misused inputs or outputs. DEA offers significant advantages, such as handling multiple inputs and outputs, not requiring explicit specification of the production function, and quantifying inefficiency sources for each DMU. However, it also has limitations: the results are sensitive to the choice of inputs and outputs; high efficiency scores may arise from favorable input/output combinations rather than true efficiency; the number of efficient DMUs increases with the number of variables; and efficiency scores may depend on non-unique weight combinations.

The two main DEA models are the CCR and BCC models. The CCR model (Charnes, Cooper, and Rhodes, 1978) assumes constant returns to scale (CRS), meaning proportional increases in inputs result in proportional increases in outputs. This model is suitable when production scale does not affect efficiency. In contrast, the BCC model (Banker, Charnes, and Cooper, 1984) assumes variable returns to scale (VRS), allowing efficiency to vary with production scale, making it more suitable for agriculture, where scale influences efficiency. DEA models can also be classified as input-oriented or output-oriented. An input-oriented model measures the extent to which inputs can be minimized without affecting outputs, while an output-oriented model evaluates the extent to which outputs can be maximized without changing inputs. This study applies the input-oriented BCC model (or input-oriented VRS DEA model) for two main reasons: first, it aligns with rice production in the Mekong Delta (MD), where farm sizes vary significantly; and second, rice farmers in the MD focus more on optimizing input use rather than maximizing output due to output prices being influenced by domestic and international market fluctuations. This study includes one output, rice yield (kg/ha), and seven inputs: land preparation costs (thousand VND/ha), irrigation costs (thousand VND/ha), seed quantity (kg/ha), fertilizer quantity (kg/ha), labor (workdays/ha), pesticide costs (thousand VND/ha), and herbicide costs (thousand VND/ha). This analytical framework helps assess the technical efficiency of rice farms and identifies inefficiencies in input usage.

The Slack-Based Measure DEA (SBM-DEA) model, introduced by Tone (2001), is an extension of the basic DEA model designed to address inefficiencies related to input slacks (excess usage) and output slacks (shortfalls). Unlike basic DEA models that only provide efficiency scores, the SBM-DEA model integrates slack values directly into the efficiency measurement, making it more robust in identifying and quantifying inefficiencies in DMUs. Given a set of nnn DMUs, each with mmm inputs and sss outputs, the SBM-DEA model evaluates the efficiency of each DMU based on the following optimization:

Minimize: $\rho = \dfrac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{r0}}}$

Subject to:

$X\lambda + s^- = x_0, \quad Y\lambda - s^+ = y_0, \quad \lambda \geq 0, \; s^- \geq 0, \; s^+ \geq 0$

where:

s^-: input slack (excess inputs)

s^+: output slack (shortfalls in outputs)

λ: the intensity variable

x_0, y_0: the input and output vectors for the DMU under evaluation.

According to the model, the slack incorporation allows to integrate slacks directly into the efficiency calculation by providing a more detail analysis of inefficiency sources. That is, the efficiency score is invariant to the units of measurement so that making it versatile across different datasets. Another advantage is the capacity to handle non-proportional adjustments where inefficiencies stem from both proportional and non-proportional changes in inputs and outputs. In addition, the SBM-DEA model is able to handle multiple inputs and outputs studies. It also has effective in distinguishing between efficient and inefficient DMUs. Figure 1 describes both input slack and output slack in the SBM-DEA model. The input slack presents the gap between the actual input level of the inefficient DMU and the efficient input level required to reach the efficiency frontier. The output slack shows the gap between the actual output level of the inefficient DMU and the output level required to reach the efficiency frontier.

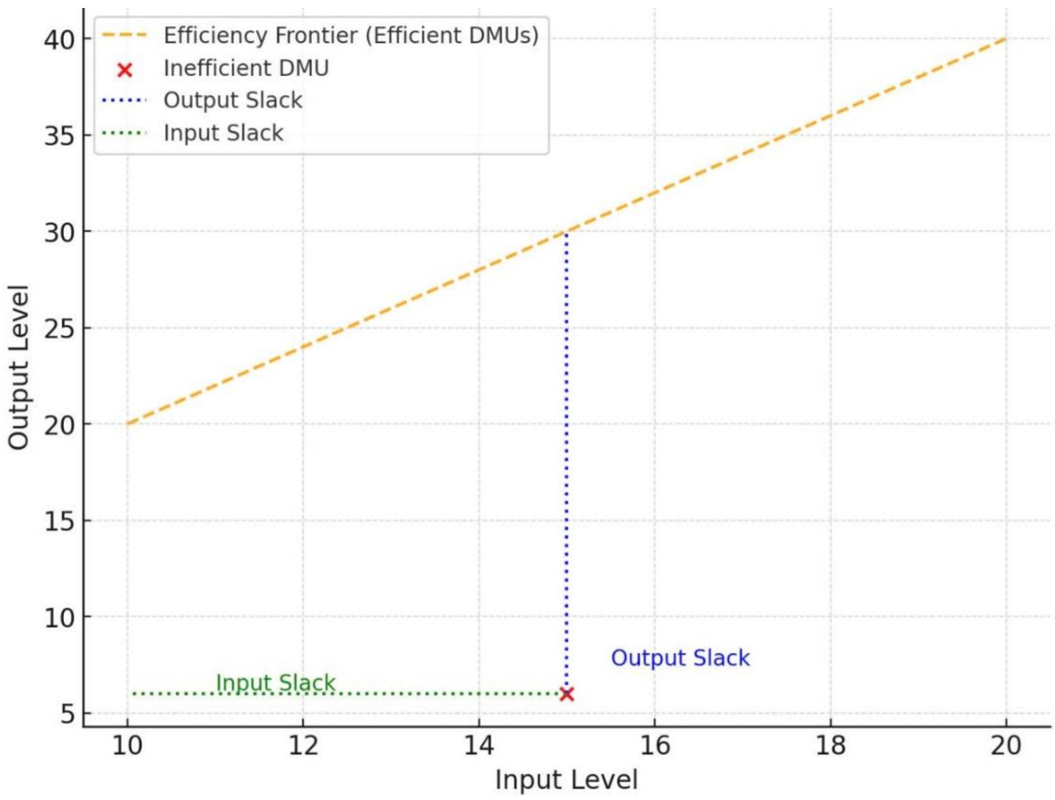

Figure 1: Input slack and output slack in the SBM-DEA model

In this study the rDEA function in the R software is applied to estimate technical efficiency scores, perform descriptive statistical analyses and group farms by efficiency levels.

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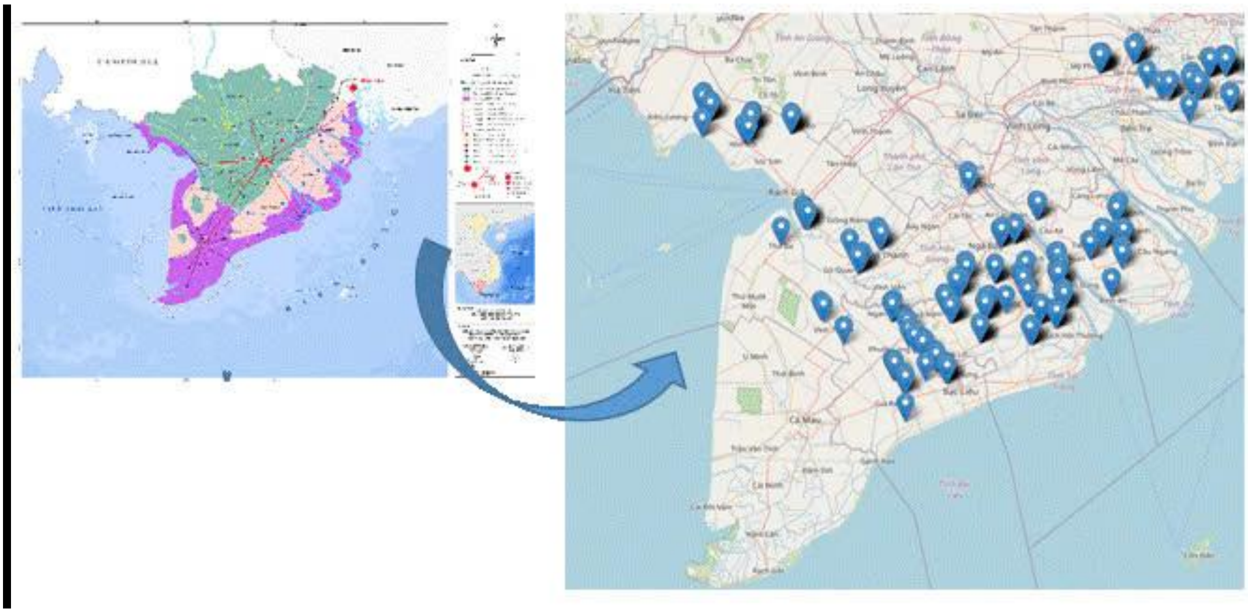
Scope and Sampling Methodology

This study focuses on analyzing the technical efficiency of annual monoculture rice farms during the Summer-Autumn crop season, surveyed in 2020 in the coastal provinces of the Mekong Delta (MD). Among the seven coastal provinces, the study area includes five provinces: Tien Giang, Tra Vinh, Soc Trang, Bac Lieu, and Kien Giang. This selection excludes Ben Tre, which has rapidly transitioned to other agricultural activities, and Ca Mau, which predominantly practices the rice-shrimp farming model, beyond the scope of this study. A multi-stage random sampling method was employed, as outlined below: Initial Survey, a preliminary survey identified 57 districts affected by saltwater intrusion across the five coastal provinces of the MD. This step was based on the 2016 saltwater intrusion map by the Southern Institute of Water Resources Research and consultations with experts and provincial agricultural departments. Random Selection of Hamlets, from the identified districts, 100 hamlets were randomly selected. Farmer Selection, within each hamlet, eight rice farming households were chosen, resulting in an initial sample of 800 households. Refined Sample, the study narrowed its focus to households cultivating the Summer-Autumn crop in 2020 within the five target provinces. This refined sample forms the basis for evaluating the technical efficiency of monoculture rice farms.



(a) Agro-regions in the Mekong Delta (b) Sample selection

Figure 2: Study site and sample selection of the study

Source: CIAT (2020)

RESULTS AND DISCUSSION

Sample Characteristics

A survey of 342 monoculture rice farms revealed that 90% of household heads were male, with an average age of 53 years. The majority of farmers (80%) were of the Kinh ethnic group, and the average household size ranged from 3 to 4 members. Regarding farm production conditions, 63% of farms had complete in-field irrigation systems, and 55% of these farms had saline intrusion prevention gates to protect against saltwater intrusion. Despite these measures, 80% of farms still faced risks of saltwater intrusion, and 53% of the surveyed farms were located in areas at high risk of salinity. In terms of farming practices, 67% of farms purchased agricultural inputs on credit. The average rice cultivation area was approximately 2.3 hectares, with the largest area being 38 hectares and the smallest 0.15 hectares. During the Summer-Autumn crop season, the average rice yield reached 6.2 tons/ha. Input Variables in DEA and SBM-DEA Models The input variables used in the DEA and SBM-DEA models included irrigation costs, land preparation costs, seeds, herbicides, fertilizers, pesticides, and labor. For the Summer-Autumn crop season: The average irrigation cost was 389 thousand VND/ha. Land preparation costs remained similar, at 1,411 thousand VND/ha. Seed usage slightly increased to 153 kg/ha. The average costs of herbicides and fertilizers were 591 thousand VND/ha and 255 thousand VND/ha, respectively. Pesticide costs remained high at 3,784 thousand VND/ha. Labor input decreased to 13 workdays/ha.

Table 1: Descriptive Statistics of Key Variables in the SBM-DEA Model

Variable	Variable description	N	Min	Max	Mean	Std. Dev.
Yield_ht	Yield (kg/ha)	342	2,466	11,834	6,212	1,284
Irri_ha_ht	Irrigation cost (thousand VND/ha)	342	0	6,500	389	629
Land_power _ha_ht	Land preparation cost (thousand VND/ha)	342	0	3,000	1,411	488
Seed_volume _ha_ht	Seed (kg/ha)	342	48	433	153	41
Herb_ha_ht	Herbal cost (thousand VND)	342	0	4,166	591	635
Fert_ht_ha	Fertilizer cost (kg/ha)	342	0	835	255	122
Pest_ha_ht	Pest cost (thousand VND/ha)	342	0	16,483	3,784	3,100
Labor_ha_ht	Labor (days/ha)	342	1	45	13	7

Technical Efficiency Scores

Figure 3 illustrates the VRSTE values (Variable Returns to Scale Technical Efficiency) of farms across the provinces during the Summer-Autumn crop season. The average VRSTE, or technical efficiency (TE), for the Summer-Autumn season was 0.728. Regarding provincial technical efficiency, the results show that Soc Trang and Kien Giang had the highest TE scores, at 0.766 and 0.760, respectively, while Bac Lieu had the lowest TE score, at 0.640. The disparity in TE among the coastal provinces was relatively small during the Summer-Autumn season.

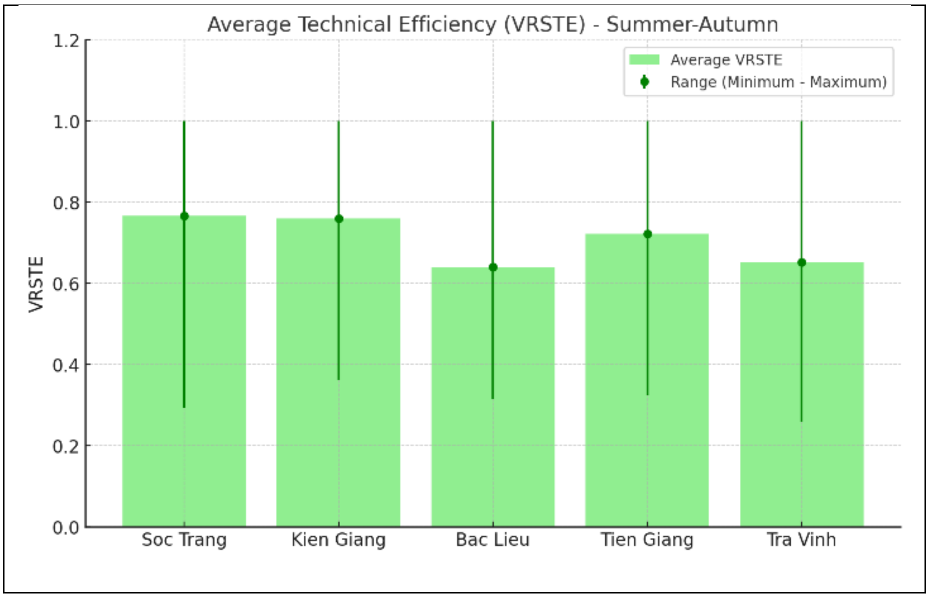


Figure 3: Statistics of Technical Efficiency Scores for Monoculture Rice Farms

The proportion of farms is grouped by their TE scores in the Summer-Autumn crop. The largest group of farms (22.81%) falls within the efficiency range of 0.4 to 0.5, followed by 19.15% of farms with scores between 0.3 and 0.4. Farms scoring between 0.5 and 0.6 account for 16.37%, while those in the 0.6 to 0.7 range make up 10.67%. Farms with very low efficiency (0.1 to 0.2) are only 0.29%, while farms scoring 0.2 to 0.3 account for 7.60%. On the highest TE score of 1.0, 7.46% of farms belong to this category, and 4.09% of farms have scores between 0.9 and 1.0. The results indicate that the majority of farms operate below optimal efficiency levels, with only a small proportion achieving the highest score of 1.0. Based on the calculation results of technical efficiency types CRSTE, VRSTE, and scale efficiency (SE), rice farming households are classified into three types of farms to assess differences in production efficiency. In this paper, Type I represents the most efficient farms, followed by Type II, and Type III is considered the least efficient. Conceptually, Type I includes farms with CRSTE = 1, VRSTE = 1, and SE = 1; Type II consists of farms with VRSTE = 1, while CRSTE < 1 and SE < 1. Type III comprises farms with CRSTE < 1, VRSTE < 1, and SE < 1. In the Summer-Autumn crop, 11.1% (38 farms) were classified as Type I, while the share of Type II farms increased to 21.1% (72 farms). Type III farms accounted for 67.8% (232 farms), indicating a slight improvement as some farms transitioned from Type III to Type II. These results highlight that most farms remain in the lowest efficiency group, with relatively few achieving higher efficiency levels. Overall, the Summer-Autumn crop shows fewer farms in the least efficient category (Type III) compared to previous trends.

Table 2: Classification on technical efficiency of rice monoculture farms

Type of farm	N	%
Type I	38	11.1
Type II	72	21.1
Type III	232	67.8
Total	***342***	***100.0***

Table 3 describes the proportion of types of farms corresponding to their technical efficiencies in the Summer-Autumn crop. In the Summer-Autumn crop, the results show that 67.84% of farms are classified as Type III, while 11.11% are Type I farms. The calculation results also indicate that the proportion of farms operating under Increasing Returns to Scale (IRS) is 58.19%. A deeper analysis shows that 68.34% of Type III farms operate under IRS. These findings suggest that rice production in the Summer-Autumn season achieves notable technical efficiency improvements, but the majority of farms still fall within the least efficient category.

Table 3: Type of technical efficiency corresponding to the economies of scale

Type of farm	N	Mean			Number of farms with …			
		CRSTE	VRSTE	SE	CRS	DRS	IRS	
Type I	38	1.000	1.000	1.000	38	0	0	
Type II	72	0.741	1.000	0.741	0	9	63	0
Type III	232	0.503	0.621	0.810	92	4	136	63
Total	***342***				***130***	***13***	***199***	136

Note: CRS, DRS, IRS: constant return to scale (super optimal), decreasing return to scale (sub optimal, increasing return to scale, respectively.

CRSTE, VRSTE, SE: constant return to scale technical efficiency, variable return to scale technical efficiency, scale efficiency, respectively.

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Input Use Improvement

Radial and slack analyses in the DEA model provide a more detailed assessment of efficiency in using input factors. Definitively, total efficiency of a DMU is the sum of radial efficiency and slack movement. Table 4 presents the results of the radial and slack analyses of input use for the inefficient farms (Type III) in the Summer-Autumn crop. In the Summer-Autumn season, the radial inefficiencies dominate for most inputs, especially land preparation and seeds, while slack inefficiencies are more pronounced for irrigation, pesticides, and fertilizers. The slack analysis shows that all input factors are being used excessively beyond necessary levels, with high redundant uses, subsequently, herbicides, labor, fertilizers, pesticides, seeds, land preparation, and irrigation costs. Specifically, irrigation costs, pesticides, and fertilizers are identified as the most overused inputs, while land preparation is the least overused. These analyses suggest the possibility of reducing input uses while maintaining the same level of productivity and efficiency. In the Summer-Autumn crop, seed is the least overused input. However, fertilizer shows significant excess use, highlighting inefficiency in its utilization. Additionally, pesticide is consistently identified as an overused input, emphasizing persistent inefficiencies in its use across farms.

Table 4: Radial and slack analyses of input use for the lowest inefficiency farms (Type III)

Input	Parameter	Irri.	Land. Prep	Seed	Pest.	Fert.	Herb.	Labor
Actual use		742	2,404	3,313	1,335	8,452	5,961	4,517
Redundancy								
Movement (thousand VND)	Radial	296	2,255	3,195	847	5,590	4,235	3,132
	Slack	223	75	59	244	1,431	863	692
	Total	519	2,330	3,254	1,091	7,021	5,098	3,824
Movement (%)	Radial	39.87	93.80	96.45	63.44	66.14	71.05	69.35
	Slack	30.06	3.10	1.77	18.28	16.93	14.48	15.33
	Total	69.94	96.90	98.23	81.72	83.07	85.52	84.67

Input use efficiency of Summer-Autumn seasons

Regarding the rank of overused inputs in rice production, the results show that in the Summer-Autumn crop, irrigation is the most redundant input, followed by pesticides, while seed use has the lowest redundancy. Thus, irrigation costs and pesticides are the most overused inputs, while land preparation costs and seed are the least overused. Irrigation shows a higher redundancy in Summer-Autumn (30.06%), highlighting significant inefficiency. Land preparation and seed inputs have significantly lower redundancy in Summer-Autumn, reflecting better efficiency. Fertilizer redundancy decreases to 7.85%, and pesticide input shows minor improvement with a redundancy rate of 18.28%. Herbicides and labor inputs remain relatively stable with minimal variations. Overall, farms in the Summer-Autumn season demonstrate greater efficiency in most inputs, particularly seed, land preparation, and fertilizers, though irrigation inefficiency remains a major challenge. These insights suggest opportunities for further optimization of input uses in rice production during the Summer-Autumn crop.

Table 5: Redundant rates of input use of Summer-Autumn seasons

Season	Irri.	Land. Prep	Seed	Pest.	Fert.	Herb.	Labor
Summer-Autumn	30.06	3.10	1.77	18.28	7.85	14.48	15.33

Determinants of technical efficiency

The estimation of ordinal logistic regressions in the Summer-Autumn crop shows that gender, plot area, irrigation system, change of variety between crops, and location are the determinants of the TE of rice monoculture farms in the coastal region of the MD. Statistically, male-headed farms exhibit higher technical efficiency, reinforcing the positive association between gender and TE. Plot area has a strong impact, underlining the importance of scale in this season. Conversely, farms with complete irrigation systems tend to have lower TE, potentially due to inefficiencies in managing these systems or high maintenance costs. Importantly, changing rice varieties between crops positively influences TE, highlighting the benefits of adaptability and diversification in rice production. Location effects remain notable, with Bac Lieu and Tra Vinh provinces showing lower efficiency compared to Kien Giang province, indicating persistent location disparities. Overall, factors such as gender, plot area, and location significantly affect TE in the Summer-Autumn season, while irrigation systems and crop variety changes play prominent roles in influencing efficiency.

Table 6: Results of ordinal logistic regression model

Variable	Description of variable	Coefficient
age	Head's age (years)	0.002 (0.914)
gender	Dummy variable: (1: male, 0: female)	0.835^{**} (0.339)
d_edu	Dummy education variable (1: higher primary, 0: others)	-0.463 (0.848)
number_family_member	Household size (persons)	0.006 (0.095)
plot_area	Rice cultivation area (m^2)	0.147^{**} (0.068)
number_plot	Number of rice plot	-0.135 (0.177)
trade_credit	Dummy variable: Purchase of agricultural inputs on credit (1: yes; 0: no)	0.259 (0.219)
time_living	Residence duration at locality (years)	-0.008 (0.012)

irri_system	Dummy variable: Irrigation system (1: complete; 0: incompleted)	-0.487* (0.253)
gate_protection	Dummy variable: Internal saline gate (1: yes; 0: no)	0.201 (0.227)
d_type_ variety	Dummy variable: Rice type (1: specialty; 0: high-yield)	-0.426 (0.274)
variety_change	Dummy variable: Change of rice variety between 2 crops annually (1: yes; 0: no)	0.080* (0.204)
d_TienGiang	Dummy province variable (1: Tien Giang, 0: others)	-0.089 (0.405)
d_TraVinh	Dummy province variable (1: Tra Vinh, 0: others)	-0.893* (0.507)
d_SocTrang	Dummy province variable (1: Soc Trang, 0: others)	-0.091 (0.387)
d_BacLieu	Dummy province variable (1: Bac Lieu, 0: others)	-0.868** (0.423)
Chi square		62139.222***

Note: ***, **, *: statistically significant at 1%, 5%, 10% respectively.

Numbers in () are standard errors.

CONCLUSIONS AND RECOMMENDATIONS

This study highlights significant inefficiencies in resource use among rice monoculture farms in the coastal provinces of Vietnam’s Mekong Delta. The analysis of TE using the SBM-DEA model reveals that most farms operate below optimal efficiency. In the Summer-Autumn season, the TE score mean is 0.728, yet only 11.1% of farms reached Type I efficiency (CRSTE = 1, VRSTE = 1, SE = 1). The majority of farms (67.8%) belong to Type III, characterized by low efficiency. Input redundancy analysis shows significant overuse of key resources. In the Summer-Autumn crop, irrigation is the most overused input (30.06%), followed by pesticides (18.28%) and fertilizers (16.93%). Conversely, seed use exhibits the lowest redundancy in the Summer-Autumn season, at 1.77%, indicating better efficiency in this input. Determinants of TE include gender, farm size, irrigation systems, and crop variety changes. The results show that male-headed farms and those with larger cultivation areas have higher TE, particularly in the Summer-Autumn season, where plot size showed a stronger positive effect. In contrast, farms equipped with complete irrigation systems paradoxically exhibit lower TE, possibly due to poor management or high maintenance costs. Additionally, location disparities significantly impact TE, with farms in Bac Lieu and Tra Vinh consistently showing lower efficiency compared to those in Kien Giang. To improve TE among rice monoculture farmers, the following recommendations are proposed. Firstly, cost reduction through resource optimization could allow farms to achieve higher TE. For instance, farmers could achieve up to an 18.28% reduction in pesticide use and a reduction in fertilizer use by 16.93% in the Summer-Autumn season without affecting TE. Second, enhanced irrigation management should be prioritized. Investments in efficient irrigation systems and better training for farmers in their operation and maintenance are essential. Addressing irrigation inefficiencies, which accounted for a redundancy rate of 30.06% in the Summer-Autumn season, could substantially enhance productivity. Thirdly, promoting the use of salt-tolerant rice varieties and encouraging crop variety changes between seasons could improve resilience in salinity-prone areas where 80% of farms currently face salinity risks. Lastly, encouraging land consolidation or cooperative farming models could capitalize on the positive correlation between larger plots and higher TE in the Summer-Autumn season. By addressing these inefficiencies, rice production in the coastal region of the MD can achieve greater sustainability and resilience against climate change challenges.

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