Fertilizers, Pesticides and Herbicides Use Efficiency of Rice Monoculture Farms at the Coastal Region in Vietnam's Mekong Delta during the Winter-Spring Crop

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DOI: https://dx.doi.org/10.47772/IJRISS.2025.906000437

Received: 16 June 2025; Accepted: 18 June 2025; Published: 22 July 2025

ABSTRACT

This study evaluates the technical efficiency and input utilization of rice monoculture farms in the coastal region of Vietnam's Mekong Delta during the Winter-Spring crop season. Using the Slack-Based Measure Data Envelopment Analysis (SBM-DEA) model, the study analyzes input redundancy and identifies inefficiencies in the use of fertilizers, pesticides, herbicides, and irrigation resources. Based on a survey of 342 farms across five provinces, results reveal that the average technical efficiency score is 0.662, with only 12.9% of farms achieving optimal efficiency. Pesticides and irrigation were the most overused inputs, with redundancy rates of 21% and 15%, respectively, while seed use showed the lowest inefficiency at 5.95%. Determinants of efficiency included gender, farm size, and irrigation systems, with male-headed farms and larger plots exhibiting higher efficiency.

Keywords: Rice monoculture farms, Slack-Based Measure DEA, Technical efficiency, Input redundancy, Mekong Delta.

INTRODUCTION

Rice production in the coastal regions of the Mekong Delta (MD) faces increasing challenges due to the impacts of climate change. According to Nguyen et al. (2020), over 50% of rice farms in coastal areas are now subject to frequent salinity intrusion and reducing productivity. Recent studies indicate that rice productivity is now approaching its optimal level, with yields averaging 7-8 tons/ha during the Winter-Spring season (CIAT 2020). However, this trend raises concerns about diminishing returns to input use, as further increases in yield may require disproportionately higher resource investments. One of the critical issues in current rice production practices in the MD is the inefficiency in input utilization. High levels of fertilizer application and suboptimal irrigation management contribute to resource wastage without commensurate increases in productivity (Huynh et al., 2019). For instance, Nguyen and Tran (2021) highlighted that up to 30% of fertilizer inputs could be reduced without impacting rice yields, suggesting significant room for optimization. These inefficiencies underline the urgent need for research on technical efficiency and input redundancy in rice production. Understanding the determinants of technical efficiency and identifying strategies to reduce excessive input use can provide a suitable solution for achieving higher efficiency levels in rice production, particularly in the challenging environments of coastal at the MD.

The CCR (Charnes, Cooper, and Rhodes, 1978) and the BCC (Banker, Charnes, and Cooper, 1984) models use the non-parameter approach in the data envelopment analysis (DEA). Both are used to evaluate the efficiency of decision-making units (DMUs), but they differ in their assumptions about returns to scale. The CCR model assumes constant returns to scale (CRS). This means that the model assumes that increasing all inputs by a certain proportion will lead to an increase in output by the same proportion. The CCR model is suitable for analyzing efficiency in cases where the scale of production does not affect efficiency, such as in industries with a perfectly competitive market structure. The BCC model assumes variable returns to scale (VRS). The BCC model allows efficiency to vary with the scale of production. This means that the model allows efficiency to increase or decrease as the scale of production changes. The BCC model is more suitable for agriculture sector, where the impact of scale of production on the efficiency of production should be examined. Regarding

DEA studies, since its inception, numerous studies in agriculture have been implemented. In Vietnam, many studies have applied the DEA method to evaluate economic efficiency in general and allocation efficiency in agriculture. These studies indicate that agricultural households generally exhibit high technical efficiency but low allocation efficiency due to poor management of labor and fertilizers (Thong, 2012; Tuan & Nhan, 2017; Nam & Dung, 2018; Cong & Man, 2019; Nhut, 2007; Nhut & Hiền, 2014; Nhut, 2008, 2009; Nhan & Xe, 2016; Huynh and Nguyen, 2016; Ha, 2021; Chinh et al., 2022). Regarding the assessment of the inefficiency in input use, the Slack-Based Measure DEA model (SBM-DEA) has been a significant extension of the traditional DEA model via allowing for a deep evaluation of inefficiencies in resource utilization. Initially developed by Charnes, Cooper, and Rhodes (1978), DEA provided a method to measure efficiency by comparing decision-making units (DMUs) against an efficient frontier. The SBM model initiated by Tone (2001) to explicitly account for input excesses and output shortfalls, referred to as slacks, making it particularly valuable for identifying inefficiencies that traditional DEA models might overlook. In agriculture, the SBM-DEA model has been instrumental in optimizing resource use. For instance, Wu et al., (2018) used SBM-DEA to identify inefficiencies in water and fertilizer use in Chinese farms and highlighted areas for significant cost reductions without compromising output. Thirtle et al., (2003) applied the SBM-DEA model to rice production in Thailand and Vietnam revealing substantial slack in input use, particularly in water and labor. Zhu's (2003, 2014) extended the SBM-DEA framework by integrating nonlinear factors and improving computational techniques, making the model more robust for applications in diverse fields, including public services and finance. These enhancements are particularly relevant for agricultural settings, where input-output relationships can be highly variable and nonlinear. Studies by Huynh and Nguyen (2016) and Bui et al., (2019) used SBM-DEA to identify excessive labor and water use among rice farmers in the Mekong Delta, suggesting that efficiency gains of up to 20-30% were achievable through resource optimization. Additionally, Chinh et al. (2022) found that climate-smart agricultural practices, such as "Three reductions, Three gains" and "One must, Five reductions," effectively minimized slack, particularly in fertilizer and irrigation use. In summary, the SBM DEA model provides a robust framework for evaluating and improving resource efficiency and makes it a valuable tool for guiding sustainable agricultural practices and policy development as well. This paper aims to analyze the technical efficiency (TE) of rice production and identify opportunities to minimize redundant input usage in order to enhance rice productivity in the coastal provinces of the MD. The paper is presented into three sections. The first section describes the theoretical framework of SBM-DEA model consisting of its mathematical formulation, slack analyses, sampling, and scope of the study. The second section shows the results and discussions of TE and input slack of rice monoculture farms. The third section presents the conclusion and recommendation.

THEORETICAL FRAMEWORK

Description of SBM-DEA models

The DEA model is a non-parametric method used to evaluate the efficiency of decision-making units (DMUs). Unlike parametric method in Stochastic Frontier Analysis (SFA model), the DEA model does not require any assumptions about the 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 on the efficiency frontier are considered efficient, while DMUs below the frontier are deemed inefficient. The distance from an inefficient DMU to the efficiency frontier is a measure of the DMU's inefficiency. DEA can also identify the sources of inefficiency by determining the specific inputs or outputs that the DMU is utilizing inefficiently. The DEA model has advantages of not need to explicitly specify the mathematical form of the production function, handling multiple inputs and outputs effectively, and analyzing and quantifies the sources of inefficiency for each DMU. However, it also has disadvantages of that results are sensitive to the choice of inputs and outputs, high efficiency scores may result from actual efficiency or an appropriate combination of inputs/outputs, the number of efficient DMUs on the frontier increases with the number of input and output variables, and efficiency scores of DMUs can be obtained using non-unique weight combinations on input and/or output factors. There are two main DEA models. CCR model (or CRS DEA model) assumes the constant returns to scale (CRS) that increasing all inputs by a certain proportion will lead to a proportional increase in outputs. The CCR model is suitable for analyzing efficiency in cases where production scale does not affect efficiency. Meanwhile, the BCC model (or VRS DEA model) assumes variable returns to scale (VRS) that allows

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

efficiency to vary with production scale. In other words, the BCC model allows efficiency to increase or decrease as the production scale changes. Besides, the distinguish between input-oriented model vs. output-oriented model needs to justified in DEA measures. The measure of TE using the input-oriented model allows to answer the question of how much can inputs be proportionally reduced without changing the output quantity. On the other hand, in the output-oriented model, the measure of TE is measured by answering that how much output(s) can be increased without altering the amount of inputs used. In this paper, the input-oriented BCC model (or input-oriented VRS DEA model) is chosen because of two reasons that in the MD firstly it is more suitable for the rice production conditions, where farms' scale is quite different and secondly rice farms are typically more concerned with efficiently using inputs rather than seeking benefits from the output market, which is highly dependent on the uncertainties of domestic and international rice markets. Finally, there are one output and seven inputs used in the study; that is, rice yield (kg/ha), land preparation costs (thousand VND/ha), irrigation costs (thousand VND/ha), seed quantity (kg/ha), fertilizer quantity (kg/ha), labor (person-days/ha), pesticide costs (thousand VND/ha), herbicide costs (thousand VND/ha).

The SBM-DEA model, introduced by Tone (2001), is an extension of basic DEA model designed to address inefficiencies related to input excesses (slack) and output shortfalls (slack). Unlike the basic DEA models, which only provide an efficiency score, the SBM-DEA model allows to incorporate slacks directly into the efficiency measurement, making it particularly robust for identifying and quantifying inefficiencies in decision-making units (DMUs). Given a set of *n* DMUs, each with *m* inputs and *s* outputs, the SBM-DEA model evaluates the efficiency of each DMU based on the following optimization:

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

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.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

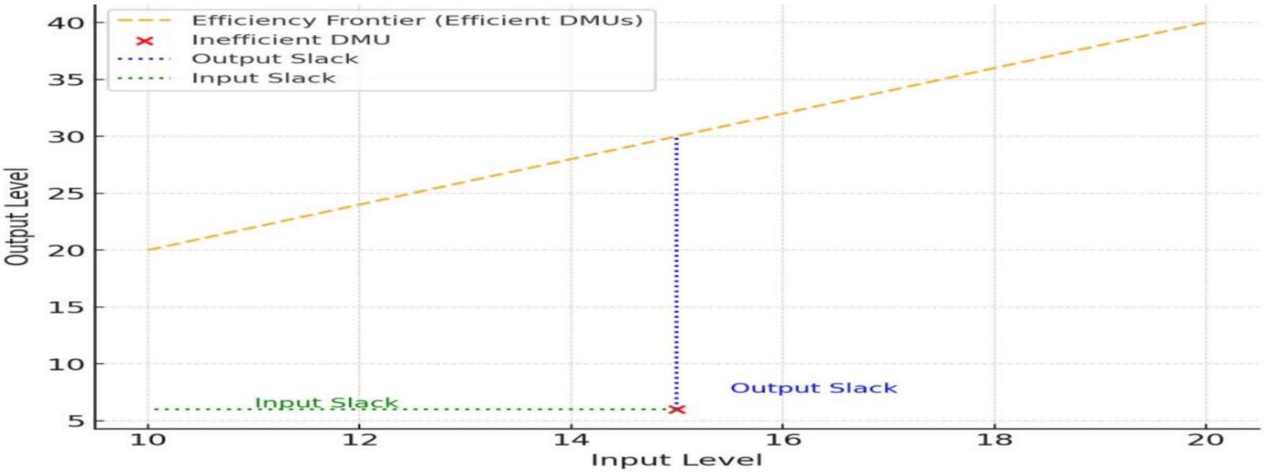
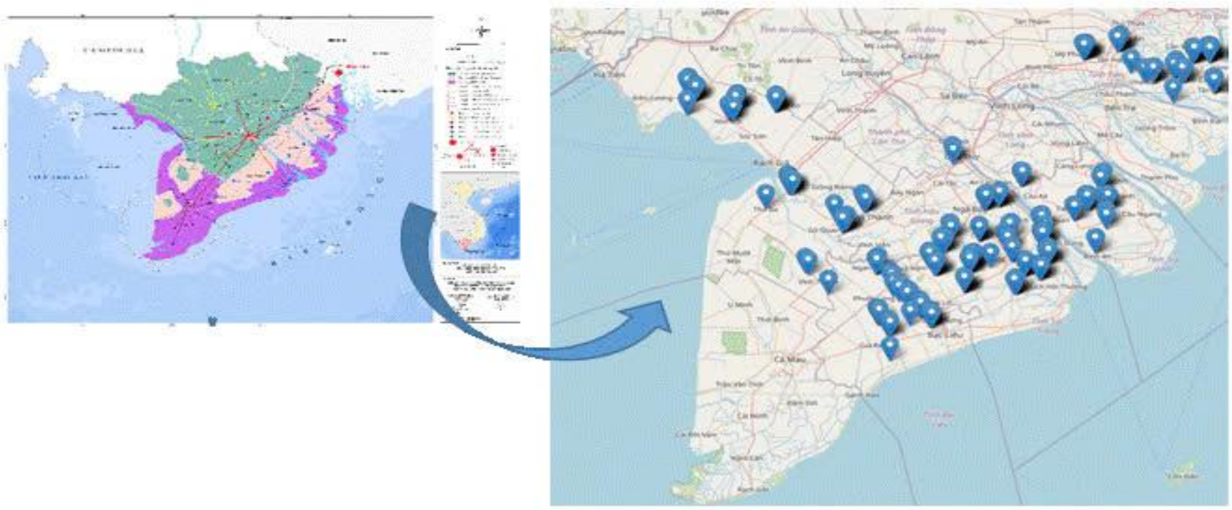


Figure 1: Input slack and output slack in the SBM-DEA model

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.

Scope and sampling

This study focuses on analyzing the technical efficiency of rice monoculture farms in the Winter-Spring crop surveyed in the year 2020 in the MD's coastal provinces. Amongst seven coastal provinces, the study area comprises five provinces: Tien Giang, Tra Vinh, Soc Trang, Bac Lieu, and Kien Giang. The reason is that Ben Tre has rapidly transitioned to other agricultural activities while Ca Mau predominantly practices rice-shrimp farming, which falls outside the scope of this research. Besides, a multi-stage random sampling method was employed via the following steps. Firstly, the survey initially identified 57 districts affected by salinity across five coastal provinces in the MD. This was based on the 2016 salinity intrusion map by the Southern Institute for Water Resources Research and consultations with experts and provincial agricultural departments. Secondly, from the identified districts, there were 100 hamlets randomly selected. Thirdly, within each hamlet, eight rice-farming households were chosen, resulting in an initial sample of 800 households. Finally, from the initial dataset, the study narrowed its focus to 342 households that practiced the Winter-Spring crop in the year 2020 within the five target provinces. This refined sample forms the basis for evaluating the technical efficiency of rice monoculture farms.



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

Source: CIAT (2020)

Figure 2: Study site and sample selection of the study

RESULTS AND DISCUSSION

Description of sample characteristics

The survey on 342 rice monoculture farms shows that 90% of the household heads are male, with an average age of 53 years. Most farmers (80%) belong to the Kinh ethnic group, and the household size mean is 3-4 persons. About the production conditions of farms, 63% of the farms have access to a complete internal irrigation system, and 55% of them have internal saline gates to protect against salinity intrusion. Despite these measures, 80% of the farms face salinity intrusion risks, and 53% of surveyed farms are located in salinity-prone areas. Regarding farming practices, 67% of farms purchase agricultural inputs on credit. The rice area mean is approximately 2.3 hectares, with the largest being 38 hectares and the smallest 0.15 hectares. In the Winter-Spring crop, the average rice yield is 7.3 tons/ha. Input variables include irrigation, land preparation, seed, herbicide, fertilizer, pesticide, and labor costs. For Winter-Spring, the mean irrigation cost is 457 thousand VND/ha, while land preparation costs reach 1,436 thousand VND/ha. Seed usage is about 150 kg/ha, with herbicide and fertilizer costs at 572 and 269 thousand VND/ha, respectively. Pesticide cost is significantly higher at 3,869 thousand VND/ha, and the mean labor input is 15 days/ha.

Table 1: Descriptive Statistics of critical variables in the SBM-DEA model

Variable	Variable Description	N	Min	Max	Mean	Std. Dev.
Yield_dx	Yield (kg/ha)	342	2,466	13,200	7,270	1,692
Irri_ha_dx	Irrigation cost (thousand VND/ha)	342	0	6,500	457	638
Land_power_ha_dx	Land preparation cost (thousand VND/ha)	342	0	3,550	1,436	520
Seed_volume_ha_dx	Seed (kg/ha)	342	37	307	150	38.91
Herb_ha_dx	Herbal cost (thousand VND)	342	0	3,701	572	580
Fert_dx_ha	Fertilizer cost (kg/ha)	342	22	835	269	117
Pest_ha_dx	Pesticide cost (thousand VND/ha)	342	0	20,000	3,869	3,135
Labor_ha_dx	Labor (days/ha)	342	2	53	15	7
Labor_ha_ht	Labor (days/ha)	342	1	45	13	7

Technical efficiency scores

Figure 3 shows the VRSTE (Variable Returns to Scale Technical Efficiency) values of farms across provinces in the Winter-Spring crop. The VRSTE mean, or the TE, in the Winter-Spring crop is 0.662. Regarding the TE of provinces, the results show that in the Winter-Spring crop, Soc Trang, Kien Giang, and Tien Giang sequentially have the highest TE scores at 0.695, 0.693, and 0.693, respectively, with Soc Trang having the highest VRSTE mean at approximately 0.695, while Bac Lieu has the lowest at approximately 0.536.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

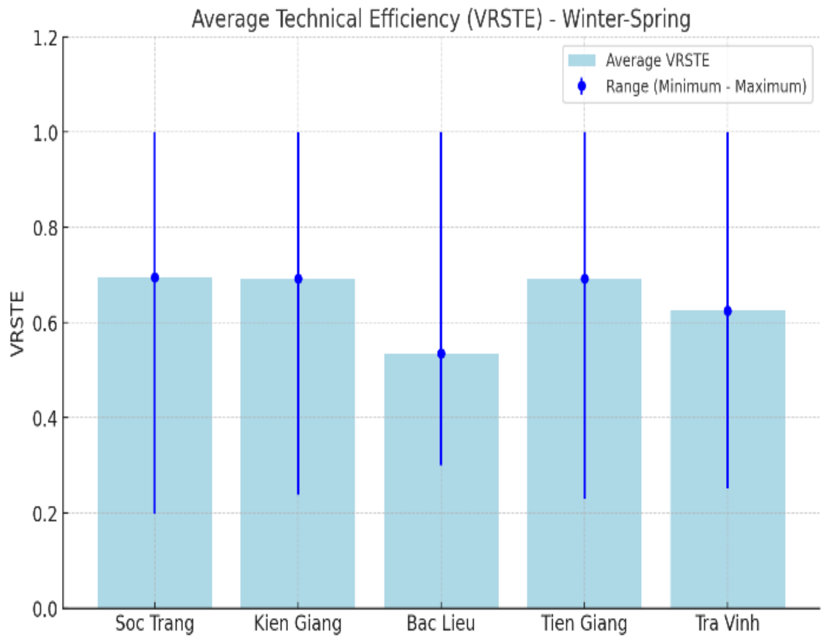


Figure 3: Technical efficiency measures of rice monoculture farms

The proportion of farms is grouped by their TE scores. 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 group, 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 and only a small proportion of farms obtain the highest score of 1.0. Table 2 provides a classification of rice monoculture farms based on their TE scores in the Winter-Spring crop. 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 type of farms. 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. The results show that in the Winter-Spring crop, 12.9% (44 farms) were classified as Type I, while 15.5% (53 farms) belonged to Type II. The majority of farms, 71.6% (245 farms), were classified under Type III, indicating that most farms were the least efficient ones.

Table 2: Classification on technical efficiency of rice monoculture farms

Type of farm	N	%
Type I	44	12.9
Type II	53	15.5
Type III	245	71.6
Total	***342***	***100.0***

Table 3 describes the proportion of types of farms corresponding to their technical efficiencies in the Winter-Spring crop. In the Winter-Spring crop, only 12.86% and 16.96% of Type I farms (N=44) and Type II farms (N=58) achieved optimal and quasi-optimal efficiencies, respectively. Meanwhile, 70.18% of Type III farms (N=240) indicate that the majority of rice monoculture farms in the coastal regions of the MD have not yet achieved optimal efficiency in the utilization of inputs in rice production. In the Winter-Spring season, 79.82% of Type III farms operate under Increasing Returns to Scale (IRS), suggesting significant potential for efficiency improvements through better resource utilization.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

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	44	1.000	1.000	1.000	44	0	0
Type II	58	0.701	1.000	0.701	5	7	46
Type III	240	0.462	0.531	0.870	2	56	182
Total	***342***				***51***	***63***	***228***

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.

Figure 4 represents the classification of farms by technical efficiency during the Winter-Spring season. The chart divides the farms into three types: Type I, representing 12.9% of the total farms, shown in light blue. Type II, comprising 15.5% of the farms, illustrated in orange. Type III, making up the majority with 71.6%, depicted in red. The chart highlights that Type III farms dominate in terms of quantity, while Type I and Type II are significantly smaller in proportion.

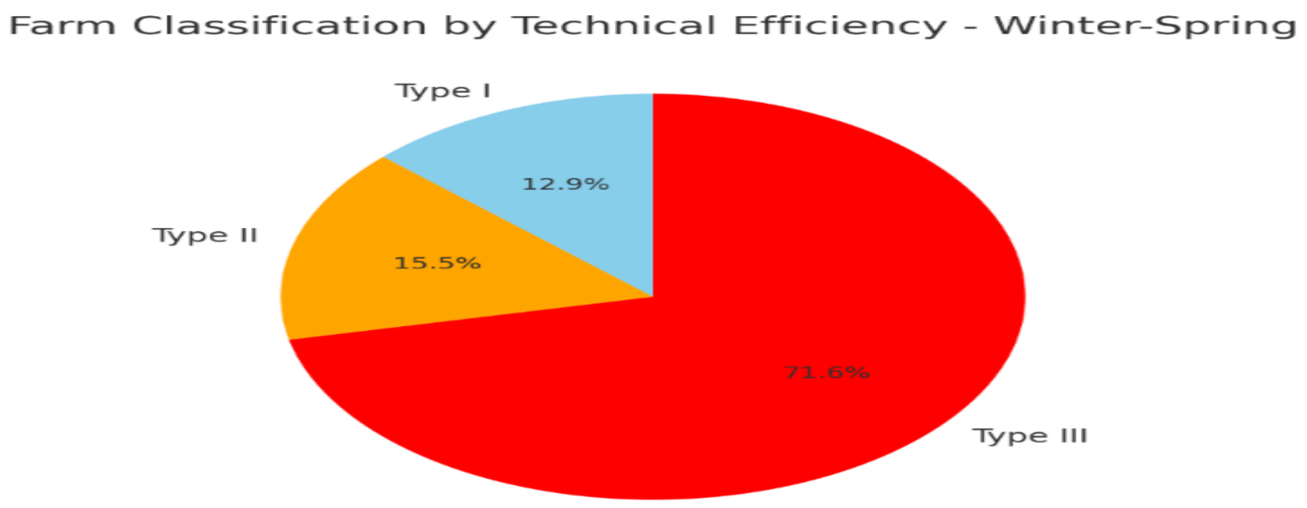


Figure 4: Describes the classification of farms by technical efficiency for the Winter-Spring season

Input Use Improvement

Radial and slack analyses in the DEA model provide a more detailed assessment of the efficiency in using input factors. Definitively, the 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 efficiency farms (Type III) in the Winter-Spring crop. In the Winter-Spring crop, radial movements are at approximately 47.72%-51.49% of the inputs, indicating significant potential to uniformly reduce input uses. Regarding slack movements, the analysis results show that despite different levels of surplus usage, all inputs are being used excessively beyond necessary levels from highest to lowest: pesticides, irrigation costs, labor, herbicides, fertilizers, land preparation costs, and seeds. Thus, it can be seen that in the Winter-Spring crop, seed, land preparation, and fertilizers are the lowest overused inputs, while pesticide and irrigation costs are the highest levels of abundance. These analyses suggest the possibility of reducing input uses while maintaining the same level of productivity and efficiency.

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		848	2,558	3,455	1,223	8,937	6,783	5,254
Redundancy								
Movement (thousand VND)	Radial	437	1,223	1,661	595	4,265	3,356	2,594
	Slack	128	197	205	259	702	898	726
	Total	565	1,420	1,867	854	4,966	4,254	3,320
Movement (%)	Radial	51.49	47.84	48.11	48.67	47.72	49.48	49.38
	Slack	15.10	7.70	5.95	21.20	7.85	13.24	13.81
	Total	66.59	55.54	54.06	69.87	55.57	62.72	63.19

Figure 5 displays the redundancy rates of different agricultural inputs during the Winter-Spring season. The inputs analyzed are Irrigation, Land Preparation, Seeds, Pesticides, and Fertilizers. Each bar is split into two components: Radial (shown in blue): Represents inefficiencies that can be reduced by proportional scaling down of inputs. Slack (shown in orange): Reflects excess input usage beyond the proportional reduction. Key Details: Irrigation has the highest total redundancy rate of about 70%, with most of it coming from radial inefficiency. Land Preparation and Seeds exhibit similar redundancy rates, around 60%, with a slightly higher proportion of radial inefficiency than slack. Pesticides show the highest slack inefficiency among all inputs, contributing significantly to a total redundancy rate of about 70%. Fertilizers have the lowest total redundancy rate at approximately 55%, with radial inefficiency being the dominant source. Summary, the chart highlights substantial inefficiencies across all input categories, with Pesticides having the most prominent slack inefficiency. Efforts to optimize resource use could focus on reducing both radial and slack inefficiencies, particularly for pesticides and irrigation.

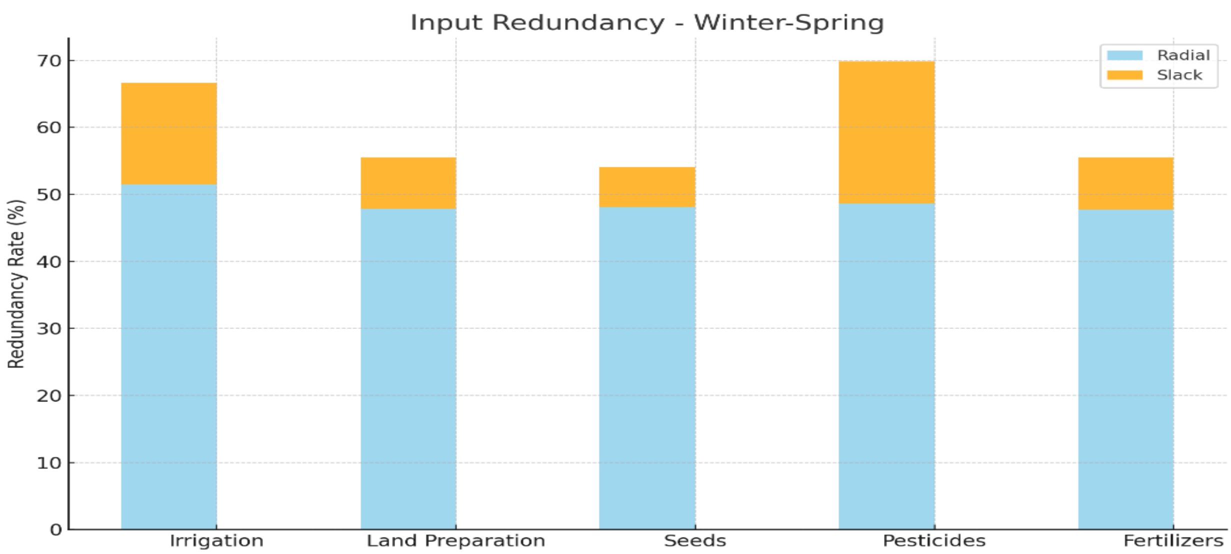


Figure 5: The chart illustrates input redundancy (Radial and Slack) in the Winter-Spring season

Input use efficiency of Winter-Spring seasons

Regarding the rank of overused inputs in rice production, the results show that in the Winter-Spring crop, pesticides had the highest redundancy, followed by irrigation and labor. In contrast, seed use has the lowest redundancy. For the Summer-Autumn crop, irrigation is the most redundant input and pesticide use is at the second position while seed use has the lowest redundancy. Thus, irrigation costs, pesticides and land preparation costs, seed are the most and least overused inputs in both crops, respectively. Table 5 presents the comparison of the redundant rates of input uses between the Winter-Spring and Summer-Autumn

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

seasons. Firstly, irrigation shows a higher redundancy in Summer-Autumn (30.06%) compared to Winter-Spring (15.10%), nearly doubling inefficiency. Secondly, land preparation and seed inputs have significantly lower redundancy in Summer-Autumn (3.10% vs. 1.77%) compared to Winter-Spring (7.70% vs. 5.95%), with difference ratios of 2.48 and 3.36, respectively, reflecting better efficiency in Summer-Autumn. Thirdly, fertilizer redundancy also decreases in Summer-Autumn (7.85% vs. 16.93%) while pesticide input shows a minor improvement (18.28% vs. 21.20%). Finally, herbicides and labor inputs remain relatively stable with minor variations between the two seasons. Overall, farms in the Summer-Autumn have greater efficiency in most inputs, particularly seed, land preparation, and fertilizers though irrigation inefficiency remains a challenge. These insights highlight opportunities to further optimize input uses across both crops.

Table 5: Redundant rates of input use of Winter-Spring seasons

Season	Irri.	Land. Prep	Seed	Pest.	Fert.	Herb.	Labor
Winter-Spring (1)	15.10	7.70	5.95	21.20	16.93	13.24	13.81
Difference (time) (3) = (1)/(2)	0.50	2.48	3.36	1.16	2.16	0.91	0.90

Determinants of technical efficiency

The estimation of ordinal logistic regressions in the Winter-Spring 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. In the Winter-Spring season, statistically, male-headed farms and farms with larger cultivation areas have higher technical efficiency. Besides, farms in Bac Lieu province exhibit lower TE compared to Kien Giang province, which has better production resources. Location effects remain notable, with Bac Lieu and Tra Vinh provinces showing lower efficiency compared to Kien Giang province, indicating persistent location disparities. Table 6 presents the results of the estimation of ordinal logistic regressions in the Winter-Spring crop.Table 6: Results of ordinal logistic regression model

Variable	Description of variable	Coefficient
age	Head’s age (years)	-0.009 (0.567)
gender	Dummy variable: (1: male, 0: female)	0.495* (0.237)
d_edu	Dummy education variable (1: higher primary, 0: others)	0.906 (0.818)
number_family_member	Household size (persons)	-0.061 (0.093)
plot_area	Rice cultivation area (m²)	.0075* (0.039)
number_plot	Number of rice plot	0.157 (0.176)
trade_credit	Dummy variable: Purchase of agricultural inputs on credit (1: yes; 0: no)	-0.007 (0.216)
time_living	Residence duration at locality (years)	0.009 (0.012)

irri_system	Dummy variable: Irrigation system (1: complete; 0: incompleted)	-0.209 (0.249)
gate_protection	Dummy variable: Internal saline gate (1: yes; 0: no)	-0.070 (0.223)
d_type_ variety	Dummy variable: Rice type (1: specialty; 0: high-yield)	-0.172 (0.260)
variety_change	Dummy variable: Change of rice variety between 2 crops annually (1: yes; 0: no)	0.126 (0.216)
d_TienGiang	Dummy province variable (1: Tien Giang, 0: others)	0.217 (0.392)
d_TraVinh	Dummy province variable (1: Tra Vinh, 0: others)	-0.470 (0.499)
d_SocTrang	Dummy province variable (1: Soc Trang, 0: others)	0.061 (0.386)
d_BacLieu	Dummy province variable (1: Bac Lieu, 0: others)	-0.801* (0.415)
Chi square		65587.843***

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

Numbers in () are standard errors.

CONCLUSIONS AND RECOMMENDATIONS

This study highlights significant inefficiencies in resource uses among rice monoculture farms in the coastal provinces of Vietnam's Mekong Delta. The analysis of the TE using the SBM-DEA model reveals that most farms operate below optimal efficiency. In the Winter-Spring season, the TE score mean is 0.662, with only 12.9% of farms achieving Type I efficiency (CRSTE = 1, VRSTE = 1, SE = 1). The majority of farms belong to Type III (71.6% in Winter-Spring), characterized by low efficiency. Input redundancy analysis shows significant overuse of key resources. For instance, pesticides, irrigation, and labor exhibited the highest inefficiencies in the Winter-Spring crop, with redundancy levels of 21.20%, 15.10%, and 7.70%, respectively. Conversely, seed use exhibits the lowest redundancy at 5.95%, indicating better efficiency in this input. Determinants of the TE include gender, farm size, and irrigation systems. The results show that male-headed farms and those with larger cultivation areas have higher TE. In contrast, farms equipped with complete irrigation systems paradoxically exhibit lower TE, possibly due to poor management or high maintenance costs. Additionally, location disparity significantly impacts the TE, with farms in Bac Lieu and Tra Vinh consistently showing lower efficiency compared to those in Kien Giang.

To improve the TE of rice monoculture farmers, the following recommendations are proposed. Firstly, cost reduction through resource optimization will allow farms to achieve higher TE. As proposed, farmers could achieve up to a 21.20% reduction in pesticide use and a reduction in fertilizer use of 7.85% to 16.93% in the Winter-Spring crop without affecting TE. Second, enhancement in irrigation management should be considered. Investments in efficient irrigation systems and better training for farmers in their operation and maintenance are essential. Especially, addressing irrigation inefficiencies, which accounted for redundancy rates as high as 15.10% in the Winter-Spring crop, could substantially enhance productivity. Thirdly, interventions should promote the use of salt-tolerant rice varieties to 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. By addressing these inefficiencies, rice production of rice monoculture farms in the coastal region of the MD can achieve greater sustainability and resilience against climate change challenges.

ACKNOWLEDGEMENTS

The authors would like to thank the International Center for Tropical Agriculture and the Virginia Tech University of USA for sharing surveyed data followed by the contract number C-049-18 under which the article is written.

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ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VI June 2025

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