

TECHNICAL AND SCALE EFFICIENCY OF RICE-FARMING HOUSEHOLDS IN CAN THO CITY: A STOCHASTIC FRONTIER PRODUCTION FUNCTION APPROACH

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Abstract – *This study estimates technical efficiency, scale efficiency, characteristics of returns to scale, and factors associated with technical inefficiency among rice-farming households in Can Tho City, Vietnam. Survey data collected from September to December 2025 from a convenience non-probability sample of 402 rice-farming households were analysed using a one-step stochastic frontier analysis. A likelihood-ratio test supports the Translog specification over the Cobb-Douglas form. Mean technical efficiency was 86.45%, corresponding to an average technical efficiency gap of 13.55% relative to the estimated production frontier. Mean scale efficiency was 90.63%. Regarding returns to scale, 60.95% of households operated under decreasing returns to scale, 36.32% under increasing returns to scale, and 2.74% near constant returns to scale. In the technical inefficiency model, organic fertilizer use and participation in technical training were negatively associated with technical inefficiency, whereas economic training was positively associated with inefficiency. The coefficients of cooperative participation and production linkage were not statistically significant. Given the cross-sectional and convenience-based sampling design, these relationships should be interpreted as associations rather than causal effects. The findings support differentiated technical support, nutrient and input management, and household-specific production guidance in the newly consolidated Can Tho City.*

Keywords: *Can Tho City, rice-farming households,*

returns to scale, scale efficiency, stochastic frontier analysis, technical efficiency.

I. INTRODUCTION

Rice production plays an important role in household livelihoods, food security, and the position of the Mekong Delta in the national rice value chain. In the context of volatile input prices, increasingly explicit requirements for emission reduction and adaptation to climate change, improving resource-use efficiency has become a central requirement of local agricultural governance. This requirement is particularly urgent for the newly established Can Tho City after the consolidation of the development space of the former Can Tho City, Soc Trang Province, and Hau Giang Province. According to the 2025 agricultural sector report [1], the city's agriculture, forestry, and fisheries sector grew by nearly 3.8% and accounted for nearly 20.9% of the economic structure. For rice alone, the cultivated area reached 721,073 ha and output reached 4,655,771 tonnes. The city maintained 84,819 ha of large fields, but only more than 30% of this area had marketing linkages; rice prices in the 2025 crop seasons declined by VND 500–3,300/kg compared with the same period, depending on the crop season.

Production transformation programmes also indicate substantial room for efficiency improvement. The city had 20,759 ha of rice guided towards organic-oriented production; specialty and aromatic rice varieties accounted for nearly 40%, while high-quality varieties accounted for nearly 60%. Pilot models under the One Million Hectares of High-Quality and Low-Emission Rice Project reduced production costs by an average of VND 1.1 million/ha, generated profits

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VND 1.3–6.5 million/ha higher than the control models, and reduced emissions by 2–12 tonnes of CO₂/ha [1]. These figures suggest that policy priorities should focus not only on maintaining output but also on improving technical efficiency (TE), scale efficiency (SE), and the quality of production organisation.

In post-consolidation agricultural governance, functional agencies need quantitative evidence to distinguish households operating close to the production frontier from those with greater room for technical improvement, while also identifying differences in scale-related production characteristics. Against this background, this study estimates TE and SE, examines characteristics of returns to scale (RTS), and analyses factors associated with technical inefficiency among rice-farming households in Can Tho City. By jointly examining household-level TE, SE, RTS, and inefficiency correlates within the newly consolidated production space, the study provides empirical evidence for more targeted agricultural extension, input-use management, production organisation, and scale-related production guidance.

II. LITERATURE REVIEW

The stochastic frontier production function was developed to decompose the gap between actual output and potential output into two components: random noise and technical inefficiency [2, 3]. This approach is suitable for agricultural production because production outcomes are simultaneously affected by household management capacity and factors beyond household control, such as weather, pests and diseases, or market fluctuations.

The one-step model proposed by Battese et al. [4] allows the production frontier and the technical inefficiency function to be estimated simultaneously. This approach is appropriate when the research objective is not only to calculate TE scores, but also to identify factors associated with higher or lower technical inefficiency. In stochastic frontier analysis (SFA), the Cobb-Douglas functional form is simple but imposes constant elasticities; by contrast, the Translog form is more

flexible because it allows nonlinear relationships and interactions among inputs [5, 6].

TE, RTS, and SE represent related but conceptually distinct dimensions of production performance. TE measures how closely a producer approaches the estimated production frontier for a given input bundle. RTS describes how output responds to a proportional change in all inputs and can be assessed from the sum of input-specific output elasticities. SE, by contrast, reflects the extent to which a producer operates close to the scale-optimal point implied by the estimated technology. Therefore, RTS and SE should not be interpreted interchangeably [5–7].

Studies on rice production in Vietnam have used SFA to measure household efficiency. Nguyen et al. [8] recorded that TE of rice-farming households in the Mekong Delta varied across crop seasons. Huynh [9] showed that rice-farming households in the region still had room for improvement in TE. Ho et al. [10] emphasised the role of agricultural extension and production characteristics in TE. More recently, Le et al. [11] used a Translog specification to assess rice production efficiency in the Mekong Delta and highlighted the relevance of technical training, production contracts, and input management. Tu et al. [12] examined technical and environmental efficiency using a latent-class stochastic frontier framework and highlighted the relevance of land accumulation and farm-scale conditions. Beyond the Mekong Delta, Pedroso et al. [13] also applied efficiency analysis to rice production in Central Vietnam, highlighting the importance of production scale and input combination in explaining differences in farm performance. Although the previous studies have established the usefulness of SFA for analysing rice-production efficiency in the Mekong Delta [8–13], the existing evidence largely reflects earlier administrative and production settings. Less attention has been paid to the joint assessment of household-level TE, SE, returns-to-scale heterogeneity, and inefficiency correlates within the newly consolidated Can Tho production space. This gap is relevant because the new city combines production areas

with different ecological conditions, farm structures, and forms of production organisation. The present study addresses this gap by integrating TE, SE, household-specific RTS, and an inefficiency model within a single empirical framework.

III. RESEARCH METHODS

The study uses survey data from 402 rice-farming households located within the newly consolidated Can Tho City. The household survey was conducted from September to December 2025. Production data covered three cropping seasons: Winter-Spring (2024–2025), Summer-Autumn (2025), and Autumn-Winter (2025). The study area encompassed the following communes in Can Tho City: Vinh Tuong, Vinh Thanh Dong, Ho Dac Kien, Ke Sach, Thanh Phu, and Dai Ngai. Respondents were the primary producers from households with at least five years of rice farming experience. The survey instrument was a pre-designed structured questionnaire, and a convenience non-probability sampling method was employed. The dataset comprises two groups of variables: output and input variables used to estimate the production frontier, and explanatory variables used in the technical inefficiency function. The input variables include rice land area, seed quantity, fertilizer cost, pesticide cost, foliar fertilizer/plant nutrient cost, other costs, and family labour. The inefficiency function comprises participation in cooperative groups (CGs)/cooperatives (Cs), production linkage, organic fertilizer use, technical training, and economic training.

The empirical estimation was conducted in two stages of model specification. First, the appropriate functional form of the production frontier was examined by comparing the Cobb-Douglas and Translog specifications using a likelihood-ratio (LR) test. The null hypothesis is that all quadratic and interaction terms of the Translog specification are jointly equal to zero, in which case the Cobb-Douglas form is adequate. Rejection of the null hypothesis supports the more flexible Translog specification. Second, after selecting the Translog frontier, the final one-step SFA model

was estimated jointly with the technical inefficiency equation. The Cobb-Douglas stochastic production frontier is specified as Equation (1).

$$\ln Y_i = \beta_0 + \sum_j \beta_j \ln X_{ji} + v_i - u_i \quad (1)$$

The more flexible Translog stochastic production frontier is given by Equation (2):

$$\ln Y_i = \beta_0 + \sum_j \beta_j \ln X_{ji} + 1/2 \sum_j \beta_{jj} (\ln X_{ji})^2 + \sum_j \sum_m \beta_{jm} \ln X_{ji} \ln X_{mi} + v_i - u_i \quad (2)$$

where Y_i denotes the rice output of household i , (X_{ji}) denotes the j 'th production input of household i , β_0 is the intercept, β_j , β_{jj} , and β_{jk} are parameters to be estimated, v_i is the symmetric random-error component, and u_i is the non-negative technical-inefficiency component. The Cobb-Douglas specification is nested within the Translog specification and is obtained when all quadratic and interaction terms are jointly equal to zero.

For the calculation of household-specific output elasticities, the logarithms of the seven production inputs were mean-centred as shown in Equation (3):

$$z_{ji} = \ln(X_{ji}) - \overline{\ln(X_j)} \quad (3)$$

where $\ln X_{ji}$ is the logarithm of input j for household i , and the corresponding mean term denotes the sample mean of the logarithm of input j . Mean-centering facilitates the interpretation of the first-order coefficients and the calculation of household-specific elasticities without altering the underlying Translog specification.

The random-error component v_i is assumed to be independently and identically distributed as $N(0, \sigma_v^2)$. The technical-inefficiency component u_i is assumed to follow a non-negative truncated-normal distribution, with its conditional mean specified as a function of the household-level inefficiency covariates. The two error components are assumed to be mutually independent, and the random-error component is assumed to be independent of the explanatory variables. The production frontier and the technical-inefficiency equation were estimated simultaneously by one-step

maximum likelihood in Python, with numerical optimization and statistical calculations implemented using SciPy-based scientific-computing routines.

Household-specific TE is calculated as in Equation (4):

$$TE_i = \exp(-u_i) \quad (4)$$

where $(0 < TE_i \leq 1)$. A value closer to one indicates that the household (i) operates closer to the estimated stochastic production frontier.

For household i, the output elasticity with respect to input X_j is determined by Equation (5):

$$E_{ji} = \beta_j + \beta_{jj}z_{ji} + \sum_{k \neq j} \beta_{jk}z_{ki} \quad (5)$$

where E_{ji} denotes the output elasticity with respect to input j for household i. Because the Translog specification includes quadratic and interaction terms, these elasticities may vary across households according to their input combinations.

Equation (6) is used to calculate household-specific RTS as the sum of the seven input-specific output elasticities.

$$RTS_i = \sum_{j=1}^7 E_{ji} \quad (6)$$

where RTS_i denotes the household-specific elasticity of scale. Households are classified as operating under increasing returns to scale (IRS) when $(RTS_i > 1.05)$, near constant returns to scale (Near CRS) when $(0.95 \leq RTS_i \leq 1.05)$, and decreasing returns to scale (DRS) when $(RTS_i < 0.95)$.

The curvature parameter (B) is calculated from the second-order coefficients of the estimated Translog production frontier as in Equation (7).

$$B = \sum_j \beta_{jj} + 2 \sum_{j < k} \beta_{jk} \quad (7)$$

where the squared-term coefficients represent the curvature associated with individual inputs, the interaction-term coefficients capture the joint curvature between pairs of inputs, and (B) is the

aggregate curvature parameter along the ray of proportional changes in all production inputs. For the estimated Translog production frontier in this study, $(B = -1.288939)$. Because $(B < 0)$, the production frontier exhibits negative curvature along the proportional input-expansion ray, allowing the scale-optimal point to be identified.

Household-specific scale efficiency is then calculated following Equation (6), proposed by Ray [7].

$$SE_i = \exp \left[\frac{(RTS_i - 1)^2}{2B} \right] \quad (8)$$

Where SE_i denotes the scale efficiency of household i. Given that $(B = -1.288939 < 0)$, $(0 < SE_i \leq 1)$, values closer to one indicate that the household operates closer to the scale-optimal point along the proportional input-expansion ray [7].

The variables used in this study are presented in Table 1.

Table 1: Description of variables used in the model

Variable group	Variables	Measurement/notes
Output	Rice output	kg/household/year
	Land area	1,000 m ² /household
Inputs	Seed quantity	kg/household/year
	Fertilizer cost	VND/household/year
	Pesticide cost	VND/household/year
	Foliar nutrient cost	VND/household/year
	Family labour	days/household/year
	Other costs	VND/household/year
Inefficiency function	Dummy variables: Cooperative participation, linkage, organic fertilizer use, technical training, economic training	1 = yes, 0 = no

Source: Survey data and authors' calculations

The stochastic production frontier was estimated at the household level. The dependent variable is total annual rice output of each household, while the production inputs are the corresponding total annual quantities or expenditures at the household level. Land area is included as a conventional production input.

IV. RESULTS AND DISCUSSION

Table 2 presents the main characteristics of the surveyed households. Primary rice producers were predominantly male (95.5%). The average

age of the main producer was 51 years; average education was seven years of schooling; and average farming experience was 22 years. Regarding production organisation, 53.7% of households participated in CGs/Cs, 56.7% had production linkages, 14.2% used organic fertilizer, 54% participated in technical training, and 26% participated in economic training.

Table 2: Characteristics of the surveyed sample

Indicator	Value
Male producers	384 households (95.5%)
Average age of the main producer	51 years
Average education	7 years of schooling
Average farming experience	22 years
Cooperative participation	216 households (53.7%)
Production linkage	228 households (56.7%)
Organic fertilizer use	57 households (14.2%)
Technical training	217 households (54%)
Economic training	106 households (26%)

Source: Survey data and authors’ calculations

The LR test strongly supports the Translog specification over the more restrictive Cobb-Douglas form. The test yielded an LR statistic of 126.746, which exceeds the 5% critical χ^2 value of 41.337 with 28 degrees of freedom ($p < 0.001$). The null hypothesis that all quadratic and interaction terms are jointly equal to zero is therefore rejected. This result indicates that the Cobb-Douglas specification is too restrictive for the present data and supports the use of the more flexible Translog production frontier, which allows input elasticities to vary with the levels and combinations of production inputs [5, 6]. Accordingly, the Translog specification was retained for the subsequent one-step stochastic-frontier estimation of the production frontier and technical-inefficiency equation.

It should be noted that the log-likelihood values reported in Table 3 are obtained from the frontier functional-form comparison used solely to select between the Cobb-Douglas and Translog specifications. After the Translog specification was selected, the final model was re-estimated using the one-step SFA framework, in which the Translog production frontier and the technical inefficiency equation containing the selected inefficiency covariates were estimated jointly. Consequently, the log-likelihood of the final one-

Table 3: Test for selecting the production frontier functional form

Indicator	Cobb-Douglas	Translog
Number of observations	402	402
Number of inputs	7	7
Number of production-frontier coefficients	8	36
Log-likelihood	218.412	281.785
LR statistic		126.746
Degrees of freedom		28
Critical χ^2 value (0.05;28)		41.337
p-value		< 0.001

Source: Survey data and authors’ calculations
Note: The log-likelihood values in this table correspond to the models estimated for the Cobb-Douglas versus Translog functional-form comparison. They are distinct from the log-likelihood of the final one-step Translog SFA model reported in Table 4.

step model reported in Table 4 (294.461) is not expected to be identical to the Translog log-likelihood used for the functional-form test in Table 3 (281.785).

Following the selection of the Translog specification, the estimated coefficients of the stochastic production frontier are reported in Table 4. These coefficients capture both the direct and interaction effects of production inputs and are subsequently used to derive household-specific output elasticities, RTS, and SE. Because the study’s primary focus is efficiency measurement rather than interpreting individual production coefficients, the discussion below concentrates on the resulting efficiency indicators and inefficiency correlates.

Table 5 shows that, in the SFA model, σ_v represents the standard deviation of the random noise component, whereas σ_u represents the standard deviation of the technical inefficiency component. The results show that $\sigma_u = 0.1444$ is greater than $\sigma_v = 0.0627$, indicating that technical inefficiency accounts for a substantial share of the composite-error variation. This is consistent with the gamma value of 0.8411, indicating that technical inefficiency is an important source of differences in production efficiency among the rice-farming households in the sample. Therefore, technical inefficiency is a relevant and

Table 4: Maximum-likelihood estimates of the Translog stochastic production frontier

Variable	Coefficient	p-value
Constant	7.5892*** (0.0225)	<0.001
ln Land area	0.0686*** (0.0169)	<0.001
ln Seed quantity	0.2895*** (0.0208)	<0.001
ln Fertilizer cost	0.1842*** (0.0306)	<0.001
ln Pesticide cost	0.0447*** (0.0148)	0.003
ln Foliar nutrient cost	0.0253 (0.0197)	0.200
ln Other costs	0.0253 (0.0244)	0.299
ln Family labour	0.1072*** (0.0158)	<0.001
0.5(ln Land area) ²	0.1441*** (0.0362)	<0.001
0.5(ln Seed quantity) ²	0.0205 (0.0809)	0.801
0.5(ln Fertilizer cost) ²	0.5596*** (0.1304)	<0.001
0.5(ln Pesticide cost) ²	-0.0632* (0.0337)	0.061
0.5(ln Foliar nutrient cost) ²	0.0660** (0.0291)	0.023
0.5(ln Other costs) ²	-0.0658 (0.0957)	0.491
0.5(ln Family labour) ²	0.0116 (0.0417)	0.779
ln Land area×ln Seed quantity	-0.2552*** (0.0452)	<0.001
ln Land area×ln Fertilizer cost	0.1031* (0.0605)	0.088
ln Land area×ln Pesticide cost	0.0913*** (0.0349)	0.009
ln Land area×ln Foliar nutrient cost	-0.1186*** (0.0334)	0.001
ln Land area×ln Other costs	0.0410 (0.0492)	0.404
ln Land area×ln Family labour	0.0561 (0.0343)	0.103
ln Seed quantity×ln Fertilizer cost	-0.4157*** (0.0882)	<0.001
ln Seed quantity×ln Pesticide cost	-0.0455 (0.0346)	0.189
ln Seed quantity×ln Foliar nutrient cost	0.0043 (0.0405)	0.914
ln Seed quantity×ln Other costs	-0.0673 (0.0728)	0.355
ln Seed quantity×ln Family labour	-0.1435*** (0.0444)	0.001
ln Fertilizer cost×ln Pesticide cost	-0.0971** (0.0470)	0.039
ln Fertilizer cost×ln Foliar nutrient cost	-0.1047* (0.0583)	0.072
ln Fertilizer cost×ln Other costs	-0.1009 (0.0856)	0.238
ln Fertilizer cost×ln Family labour	-0.0557 (0.0572)	0.330
ln Pesticide cost×ln Foliar nutrient cost	0.0501** (0.0253)	0.047
ln Pesticide cost×ln Other costs	0.0078 (0.0503)	0.877
ln Pesticide cost×ln Family labour	0.0833*** (0.0294)	0.005
ln Foliar nutrient cost×ln Other costs	0.0080 (0.0416)	0.846
ln Foliar nutrient cost×ln Family labour	-0.0773** (0.0313)	0.014
ln Other costs×ln Family labour	0.0555 (0.0494)	0.261

*Note: Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The squared terms are parameterised as 0.5(ln(X_j))²; therefore, the reported coefficients correspond to the β_{jj} parameters in the Translog specification.*

meaningful issue for analysis.

The mean TE of 0.8645 indicates an average TE gap of approximately 13.55% relative to the estimated production frontier. The result suggests that, within the surveyed sample, there remains scope for improving the efficiency with which existing inputs are transformed into rice output. This TE level is relatively high compared with studies on rice production in Vietnam but still indicates room for technical improvement among households that have not yet approached the

frontier [8–11].

Table 5: Summary results of technical efficiency

Indicator	Value
Final one-step model log-likelihood	294.461
σ _v	0.0627
σ _u	0.1444
Γ	0.8411
Mean TE	0.8645
Median TE	0.8853
Minimum TE	0.6444
Maximum TE	0.9792

Source: Authors' calculations
Note: The reported log-likelihood refers to the final one-step Translog SFA model in which the production frontier and the technical inefficiency equation were jointly estimated. It therefore differs from the log-likelihood reported for the Translog specification in the functional-form comparison in Table 3.

The TE distribution in Table 6 shows that 158 households achieved TE of 0.90 or higher, accounting for 39.3%; and 155 households achieved TE from 0.80 to less than 0.90, accounting for 38.6%. Thus, more than three-quarters of the households had TE of 0.80 or higher. However, 89 households had TE below 0.80, accounting for 22.1% of the sample. This distribution indicates substantial heterogeneity in TE and identifies a group of households with relatively greater scope for efficiency improvement.

Table 6 reveals that the mean SE is 0.9063, while the median is 0.9369, indicating that the surveyed households are, on average, relatively close to the scale-optimal point defined by the estimated Translog technology. However, scale conditions remain heterogeneous across households. In particular, 60.95% operate under DRS, 36.32% under IRS, and 2.74% near CRS. This finding is consistent with studies highlighting the roles of scale, land fragmentation, and input combination in rice production [8, 9, 13].

The results of the technical inefficiency function are presented in Table 7. A negative coefficient indicates a negative statistical association with technical inefficiency, whereas a positive coefficient indicates a positive association, conditional on the specified model. Organic fertilizer

Table 6: Technical efficiency, scale efficiency and returns-to-scale classification of rice-farming households

Indicator	Number/percentage or value
TE < 0.70	16 households (4.0%)
TE 0.70 - < 0.80	73 households (18.1%)
TE 0.80 - < 0.90	155 households (38.6%)
TE ≥ 0.90	158 households (39.3%)
Mean SE	0.9063
Median SE	0.9369
IRS	146 households (36.32%)
Near CRS	11 households (2.74%)
DRS	245 households (60.95%)

Source: Authors’ calculations

Note: RTS = returns to scale; IRS = increasing returns to scale; CRS = constant returns to scale; DRS = decreasing returns to scale. Households are classified as IRS when $RTS > 1.05$, Near CRS when $0.95 \leq RTS \leq 1.05$, and DRS when $RTS < 0.95$. SE is calculated separately from RTS using the scale-efficiency expression reported in Section III.

use and technical training have negative coefficients and are statistically significant at the 1% level. By contrast, economic training has a positive and statistically significant coefficient. The coefficients for participation in CGs/Cs and production linkage are not statistically significant.

Table 7: Results of the technical inefficiency function

Explanatory variable	Coefficient	p-value
Inefficiency constant	0.1249*** (0.0206)	<0.001
Cooperative participation	-0.0236 (0.0290)	0.416
Linkage	0.0145 (0.0270)	0.589
Organic fertilizer use	-0.1274*** (0.0443)	0.004
Technical training	-0.1021*** (0.0269)	<0.001
Economic training	0.1033*** (0.0297)	<0.001

Source: Authors’ calculations

Note: *** denotes statistical significance at the 1% level

The negative coefficient for organic fertilizer use indicates that organic fertilizer use is associated with lower estimated technical inefficiency within the surveyed sample, conditional on the other variables included in the model. From an agronomic perspective, organic fertilizer may contribute to improvements in soil structure, moisture retention, and nutrient availability,

but its potential agronomic benefits depend on dosage, timing, and combination with inorganic fertilizer [14]. The negative association between technical training and technical inefficiency is consistent with the expectation that access to production knowledge may support more appropriate input-use decisions [9, 10]. However, given the cross-sectional design, the coefficient should not be interpreted as establishing a causal training effect.

Economic training is positively associated with technical inefficiency. This finding should be interpreted cautiously. Given the cross-sectional and non-random nature of the data, the association does not imply that economic training causes technical inefficiency. It may partly reflect participant selection or unobserved household characteristics; for example, households experiencing greater production or cost-management difficulties may be more likely to participate in economic training. Further research using longitudinal or quasi-experimental data would be required to identify the causal effect of economic training. The finding suggests a need to assess further participant selection, training content, and the extent to which economic-management training is linked to actual production and input-use decisions.

The coefficients for cooperative participation and production linkage are not statistically significant. Accordingly, the present study does not provide sufficient statistical evidence that binary participation in these arrangements is systematically associated with technical inefficiency among the surveyed households. This does not imply that cooperative organisation or production linkages are unimportant. Future studies and policy assessment should therefore move beyond binary participation indicators and consider the quality, intensity, and technical content of cooperative services and production linkages.

Policy support should be differentiated according to household-level efficiency and production conditions rather than delivered through a uniform package. For households with relatively low TE, extension support should focus on reviewing

input-use practices, including seeding density, fertilizer application, pesticide use, and water management. Such targeting is more consistent with the observed heterogeneity in TE than a broad-based support approach.

Returns-to-scale results provide an additional basis for differentiated production guidance. For households operating under DRS, support should emphasise reviewing input combinations and potential input overuse before any further expansion of production resources is considered. For households operating under IRS, the estimated scale relationship indicates potential scale-related advantages, but does not by itself justify automatic expansion. Further assessment of land constraints, mechanisation capacity, access to capital and production-linkage conditions is needed before scale-expansion support is considered. Households operating near CRS may instead focus primarily on improving TE and input management rather than adjusting production scale.

In the newly consolidated Can Tho City, a simple household-level production-efficiency monitoring system could support more targeted extension. Seasonal records of major inputs, production costs, and output would help extension and management agencies identify households with relatively low TE or inappropriate scale conditions and tailor support more closely to observed needs.

This study has several limitations. First, the sample was selected using a convenience non-probability method, so the sample cannot be assumed to be statistically representative of all rice-farming households in Can Tho City. Therefore, the results on TE, SE, and factors associated with technical inefficiency should be understood as empirical evidence from the surveyed households. In addition, cross-sectional data do not fully capture variations across seasons and over time. Future studies may use seasonal panel data, include environmental variables, and apply stratified probability sampling by location or farm size to improve representativeness. In addition, participation in training, organic fertilizer use, cooperative participation, and production linkage

may be endogenous to household characteristics not fully captured by the model; therefore, the estimated coefficients should be interpreted as conditional associations rather than causal effects.

V. CONCLUSION

This study estimated TE, SE, RTS characteristics, and factors associated with technical inefficiency among 402 surveyed rice-farming households in Can Tho City using a one-step stochastic frontier analysis. The likelihood-ratio test supported the Translog specification over the Cobb-Douglas form. Mean TE was 86.45%, corresponding to an average gap of 13.55% relative to the estimated production frontier. Mean SE was 90.63%, indicating that the surveyed households were, on average, relatively close to the scale-optimal point implied by the estimated Translog technology. Nevertheless, scale conditions were heterogeneous, with 60.95% of households operating under DRS, 36.32% under IRS, and 2.74% near CRS.

In the technical inefficiency model, organic fertilizer use and participation in technical training were negatively associated with technical inefficiency, whereas economic training was positively associated with inefficiency. The coefficients for cooperative participation and production linkage were not statistically significant. Given the cross-sectional and convenience-based sampling design, these relationships should be interpreted as associations rather than causal effects. The findings support differentiated production guidance that prioritises practical technical support, improved nutrient and input management, and household-specific consideration of efficiency and scale conditions. They also suggest that the quality and technical content of cooperative services, production linkages, and economic training warrant further assessment rather than strong policy conclusions based solely on participation indicators. Overall, the study provides household-level empirical evidence to support more targeted rice-production management in the newly consolidated Can Tho City.

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