



Technical Efficiency and Its Determinants in Tidal Swampland Rice Farming: The Roles of Land Size and Farming Experience

Inda Ilma Ifada^{1,2*} , Nuhfil Hanani³ , Rosihan Asmara³ , Abdul Wahib Muhaimin³ 

¹ Agricultural Science Study Department, Faculty of Bio-Industry Agriculture and Forestry, Brawijaya University, Malang 65145, Indonesia

² Department of Agribusiness, Faculty of Agriculture, Islamic University of Kalimantan Muhammad Arsyad Al Banjari, Barito Kuala 70582, Indonesia

³ Department of Agricultural Socio-Economics, Faculty of Bio-Industry Agriculture and Forestry, Brawijaya University, Malang 65145, Indonesia

Corresponding Author Email: indailmaifada@student.ub.ac.id

Copyright: ©2026 The authors. This article is published by IETA and is licensed under the CC BY 4.0 license (<http://creativecommons.org/licenses/by/4.0/>).

<https://doi.org/10.18280/ijdne.210820>

ABSTRACT

Received: 17 June 2026

Revised: 18 August 2026

Accepted: 25 August 2026

Available online: 31 August 2026

Keywords:

farming experience, local rice farming, Stochastic Frontier Analysis, technical efficiency, tidal swampland

Local rice farming in tidal swamplands plays a strategic role in food security but is hampered by ecological vulnerabilities. This study aims to evaluate the technical efficiency and its determinants of local rice farming in Banjar Regency in 2025. Using a multistage sampling method, data from 272 active farmers were collected through structured interviews and analyzed using Stochastic Frontier Analysis (SFA) with the Cobb-Douglas specification via Maximum Likelihood Estimation (MLE). The results show that land area, NPK fertilizer, and herbicides significantly affect production, while other inputs do not. The average technical efficiency of 0.82 indicates that actual production reaches 82% of the potential frontier limit. Farming experience has a significant negative impact on technical inefficiency, while also serving as a crucial form of human capital for improving farming management capabilities on vulnerable swampland. Theoretically, this study broadens the scope of research by taking an integrative approach to technical efficiency components, examining the relationship between land area and farming experience within the framework of human capital theory, while focusing on farmers' ecological adaptive capacity in the face of farming threats. Practically, this study recommends strategies for sustainable tidal flat land management by balancing agricultural inputs and local ecological knowledge.

1. INTRODUCTION

Rice is still the main crop that supports food security, especially in developing countries. Rice production is still a focus in agricultural development. Tidal swampland is a potential land to support food security. To ensure food security and environmental sustainability, ten countries—including India, Bangladesh, Myanmar, Thailand, Vietnam, China, Malaysia, Egypt, Iraq, and Indonesia—have converted peatlands into agricultural areas [1]. The largest area used as tidal rice fields in South Kalimantan is 156,480 hectares planted with rice, and the potential for tidal rice farming is around 32,252 hectares in Banjar Regency [2, 3]. One type of tidal land that has the potential to be developed and is suitable for rice cultivation is tidal land type B. Rice farming in vulnerable areas, such as tidal swamplands, cannot be evaluated solely in terms of production; it also requires ecological adaptability to maintain yields and ensure the sustainability of farming operations. The condition of the land is periodically flooded at high tide or full moon. The success of the use of the land for farming is highly dependent on micro-water management, the use of adaptive local varieties, and the

application of cultivation techniques according to local conditions. Farmers must be able to take into account the determination of planting time, irrigation, and the implementation of cultivation techniques. Local varieties are able to adapt to flooding, low pH, and salinity in vulnerable ecological conditions, all of which cannot be separated from ecological experience and local cultural knowledge that are passed down from generation to generation, helping farmers maintain their production and have adaptive capabilities [4, 5].

The theory used is the theory of frontier production efficiency [6], introduced using the stochastic frontier production function approach [7], which states that farmers can achieve maximum output based on the combination of existing inputs. Technical efficiency can identify the ability of farmers to manage inputs to get maximum output in tidal areas. The issue of the technical efficiency of tidal land is very important, considering that the intensification of chemical inputs does not guarantee an increase in yield due to the phenomenon of chemical input washing due to the movement of tides. In this condition, technical efficiency does not only look at the quantity of inputs, but also at the ability of farmers to harmonize the use of inputs with the ecological conditions

of tidal land, especially water movement and the right planting time. This ability is gained from the experience of farmers from hereditary heritage over several years that shape local ecological knowledge. In accordance with the human capital theory of studies [8, 9], which states that farming experience is a non-formal investment of farmers in improving their ability and productivity. This set of experiences helps farmers understand the conditions of tidal fluctuations, determine planting time, and apply appropriate cultivation techniques so as to make farmers more resilient to the conditions of tidal land. Farming experiences are framed within the human capital theory, positioning experience-based knowledge as a driver of ecological adaptability—enabling the application of local wisdom gained over years of farming to minimize risks and ensure technical efficiency.

Technical efficiency can be achieved in farming when farmers are able to obtain maximum rice production by allocating a combination of inputs and technology. Success in achieving technical efficiency in farming ideally depends on the ability to allocate inputs appropriately, supported by the adoption of available technology. If everything is met, the risk of production can be reduced, and high productivity is achieved. Land area plays an important role in rice farming in tidal areas. It is not only a physical input but also determines the management of sustainable farming by taking into account water fluctuation conditions, soil conditions, garden and maintenance time, and the number of other inputs used. In addition, farming experience contributes as human capital based on local wisdom. This experience can minimize the risk of tidal ecological uncertainty. Farmers who have experience will be able to understand the tidal pattern of water so that they can adjust cultivation techniques, especially planting time and harvest. Knowledge based on experience makes technical application more precise. Land area and experience have different roles. Land area is an input that supports increased production, while experience, as a managerial ability supported by ecological adaptive capacity, helps farmers reduce farming inefficiencies and minimize the risk of yield loss. An effective and sustainable way to mitigate production risks on tidal land is to implement farming cultivation based on local wisdom [10].

However, even though tidal land has potential, ecological factors are often challenges and threats to farming, so optimal and adaptive management is needed. Research [11] shows that the average national rice yield is significantly higher than that of local or traditional crop varieties. The productivity gap reflects the ecological vulnerability to ups and downs, requiring appropriate management strategies. Tidal flat soils are characterized by high acidity, low levels of NPK nutrients, high aluminum and iron content, and the effects of tidal fluctuations [12]. Tidal swampland has considerable and challenging risks in rice cultivation, such as soil acidity levels and fluctuations in water levels due to tides that can interfere with crop productivity [5].

Previous research has been limited to discussing in depth the area of land and farming experience affecting rice production and technical efficiency in tidal land. Rice production in Central Kalimantan's tidal lands still has low technical efficiency and recommends land expansion and intensive fertilization strategies to increase rice production, but this study has not addressed the relationship between land area and shared experience as determinants of technical efficiency [13]. Research [14] found that land area has a positive effect on production but has not included farming

experience in the study as a variable. In Vietnam, the success of farming is driven by the use of scale farming; farmers with more than 2 hectares of land have higher technical efficiency, but the study has not explained the specifics of land size and experience [15]. Technical efficiency averaged 64.7% for irrigated land and 66.2% for non-irrigated land [16]. In flood-prone areas of Central Java, average technical efficiency reached 76.05%, with land, labor, seeds, and fertilizer having a positive impact on rice production [17]. Based on previous research, it was found that research gaps are still limited; namely, there are still limited specific explanations distinguishing the influence of land area as a determining factor for production and farming experience as a factor that suppresses the technical inefficiency of local rice farming in tidal land.

Research is conducted to fill the gap. Land area is positioned as an input in the production function to analyze its influence on local rice production. Farming experience is positioned as a variable in the inefficiency to analyze its effect on minimizing the distance between actual output and the frontier. The novelty of this study lies in its integrated approach, which considers land area as a factor influencing production and farming experience as an ecological adaptation capacity capable of reducing farming inefficiencies on ecologically vulnerable tidal swamplands. In tidal areas, the key to the success of farming does not only depend on modern chemical inputs and technology but also needs to consider the managerial ability of farmers to apply cultivation techniques according to agricultural ecological conditions. This ability is obtained from years of experience that forms an adaptive understanding based on local wisdom. The objective of this study is to analyze the technical efficiency and its determinants in local rice farming in tidal swamp lands by examining the role of land area as a determinant of production and farming experience as a driver of reduced inefficiency. Although the qualitative aspects of traditional farming are also highlighted, they serve only as a descriptive context to support the explanation of the mechanisms underlying the quantitative results at the efficiency frontier. The study confirms that technical efficiency does not only depend on the intensification of inputs but is also determined by the ability of farmers to manage land-based farming and translate their experiential knowledge into operational capacity under vulnerable swampland conditions. Theoretically, this study broadens the scope of scientific research on agricultural technical efficiency by examining the relationship between land area and human capital based on farming experience, and highlights this capacity. Practically, this study provides strategies for the sustainable management of tidal swamp lands by balancing agricultural inputs and experience-based managerial capacity.

2. METHODOLOGY

2.1 Research location

The research location is in Sungai Tabuk District, Banjar Regency, South Kalimantan Province, and will be carried out from March 2025 to December 2025. Banjar Regency has an area of 4,688.50 km² with a population of more than 595,717 people. This area consists of 20 sub-districts and 290 villages. Banjar Regency is located in a wetland zone consisting of upland areas generally located in the areas of Mataraman,

Simpang 4, Sambung Makmur, Pengaron, Sungai Pinang, Telaga Bauntung, Paramasan, Aranio, and Karang Intan Districts. Meanwhile, those in the Lowland zone are farmers in the areas of Sungai Tabuk, Cintapuri, West Martapura, East Martapura, Martapura, Astambul, Gambut, Beruntung Baru, Kertak Hanyar, and Aluh Aluh. The Sungai Tabuk subdistrict is a local rice-producing region in the tidal lowlands that

consistently applies local wisdom in managing agricultural cultivation on its swamplands. The area of Sungai Tabuk District is 147.30 km², consisting of 21 villages. The area often experiences flooding due to tides of seawater that submerge settlements and agricultural sites. The map of the research location shown in Figure 1 is in Pematang Panjang Village, Gudang Hirang, and Sungai Pinang Lama.

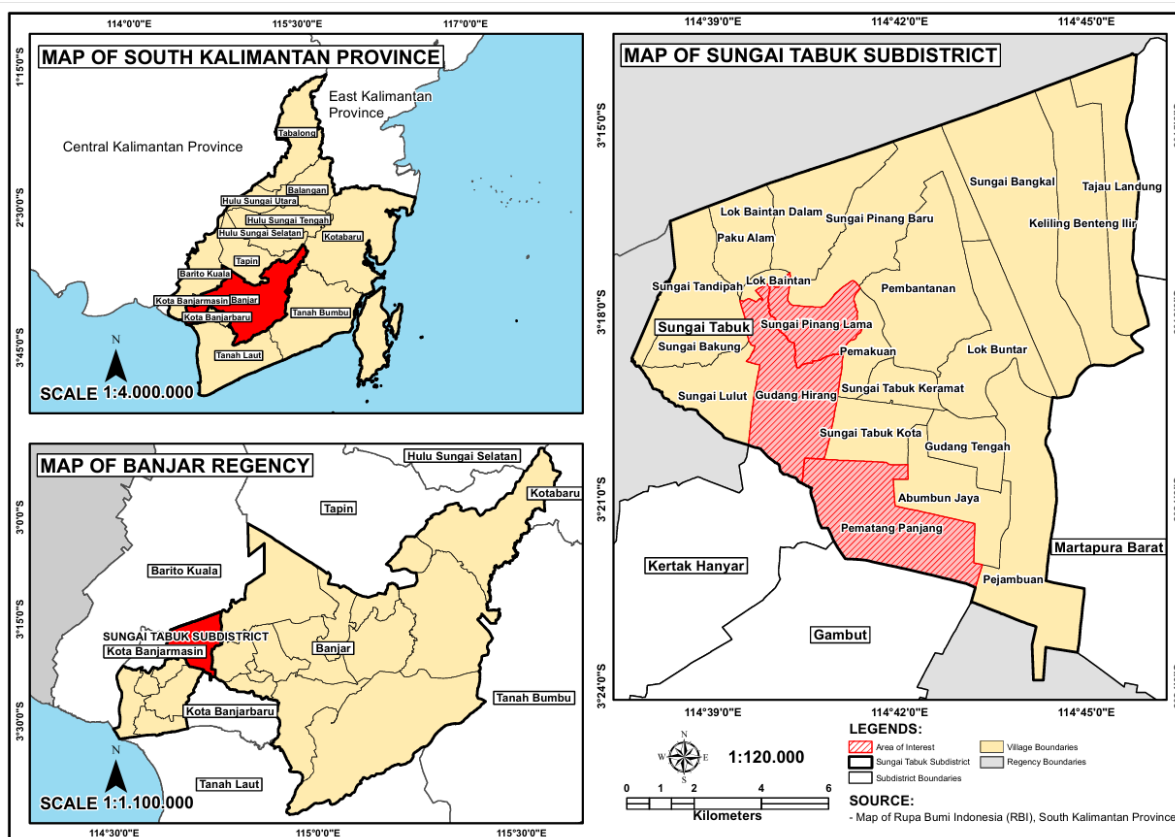


Figure 1. Map of the research location

2.2 Data and data collection

This study employed a multistage sampling design consisting of three stages. In the first stage, the Sungai Tabuk subdistrict was purposively selected as a local center for tidal rice cultivation. In the second stage, village quotas were determined from among the 21 villages in the subdistrict, with three representative areas—Pematang Panjang, Gudang Hirang, and Sungai Pinang Lama—being purposively selected. The third stage involved selecting respondents using simple random sampling in each of these villages to ensure that all active farmers had an equal chance of being selected. The total population of active farmers in these three villages was 850 people. Using the Slovin formula with a margin of error of 5%, a minimum sample size of 272 respondents was determined. Subsequently, this sample of 272 farmers was distributed proportionally based on the farmer population of each village. The result was 136 farmers from Pematang Panjang Village, 76 farmers from Sungai Pinang Lama Village, and 60 farmers from Gudang Hirang Village. This transparent sampling process is important to avoid errors while meeting the data requirements for Maximum Likelihood Estimation (MLE).

The research used primary and secondary data. The data collection method used structured and in-depth surveys and

interviews was assisted by questionnaires according to the variables in the research objectives. Primary data were taken directly from respondents related to the technical efficiency of local rice farming and the determining factors. Secondary data were also used to provide additional and complementary information for the research, derived from books, websites, related agencies, previous research, and other literature related to the research.

The questionnaire was designed in a structured manner to meet the data analysis requirements for technical efficiency using Stochastic Frontier Analysis (SFA) and to account for the characteristics of local rice farming on tidal swampland. The questionnaire covers farmers' socioeconomic characteristics (age, education level, farming experience, number of family members, gender), as well as information on the amount of inputs used and outputs obtained during a single growing season (land area, production, and the amount of urea, NPK fertilizer, and herbicides used, as well as labor). The final section includes questions regarding the characteristics of farming practices and cultivation techniques, as well as local knowledge related to rice farming on tidal swampland, which are described in a qualitative, descriptive manner to support the SFA analysis. These practices are used only as descriptive-qualitative supporting explanations in the Discussion section. This is done to explain the on-the-ground conditions that

influence the achievement of technical efficiency in farming.

The input and output variables in the estimation of the production frontier function are calculated using the real cumulative consumption and crop yields over one production cycle in 2025. The variables for seeds (kg), NPK fertilizer (kg), urea fertilizer (kg), herbicides (liters), labor (person-days), and land area (hectares) are measured according to the amounts used in farming operations. Local rice production is measured based on the amount of paddy produced by farmers in a single growing season (kg). Data on farmer characteristics—including age, farming experience, and formal education—are measured in years, while household size is calculated based on the number of dependents. Gender is treated as a dummy variable, with a value of 1 for males and 0 for females.

Field data collection began in March 2025 and continued through December 2025, spanning 10 months. This timeline was aligned with the local rice planting season in Banjar Regency. This period included the survey, face-to-face interviews with respondents, verification of information, and the collection of supporting data from government agencies.

Data quality and accuracy were ensured through data quality control procedures. The first stage involved a pilot test with 30 farmers outside the tidal flat area. This was done to evaluate the clarity of the questionnaire's questions and eliminate phrasing that was ambiguous or confusing to respondents. The second stage involved training enumerators to ensure a shared understanding of the research objectives and the intent behind each question in the questionnaire. Thus, in this study, face-to-face interviews with respondents were conducted by the research team with the assistance of enumerators. Enumerators are field staff who possess strong communication skills and understand research data collection techniques in the field. The next stage involved rechecking the data—specifically, synchronizing and standardizing the units of each variable—before analyzing it using SPSS and Frontier 4.1.

2.3 Data analysis

Quantitative approaches used in the research. Frontier 4.1 software was used to analyze technical efficiency using the SFA approach, while aspects of the implementation of cultivation practices were described in a descriptive manner. Before the model was estimated using SFA, all independent variables were tested for multicollinearity by analyzing the Variance Inflation Factor (VIF) values using SPSS software. In accordance with the criteria established by studies [18, 19], the model is considered free of multicollinearity if the VIF value for each independent variable is less than 10. The purpose of detecting multicollinearity is to ensure there are no strong linear relationships among the independent variables that could distort the standard errors and bias the production elasticity coefficients. Once the VIF data were obtained and the model was confirmed to meet the criteria, the model was immediately estimated using SFA. Tests for other classical assumptions, such as heteroscedasticity and autocorrelation, were not performed because SFA already addresses these issues. SFA divides the residuals into two components: random error (v_i) and technical inefficiency effects (u_i). Both components are estimated using the MLE method.

The Cobb-Douglas production function was used because

its coefficients directly reflect the elasticity of production and are appropriate for the study's sample size ($N = 272$). The fit of the SFA model specification was evaluated by determining the generalized likelihood ratio (LR) and gamma values. The LR test was conducted to assess the validity of the presence of a technical inefficiency effect, and the gamma parameter was analyzed to measure the proportion of error variance purely attributable to farmers' managerial inefficiency. All physical input variables were transformed into natural logarithms (ln). This was done so that the model would follow the Cobb-Douglas production function specification, allowing the obtained parameter values (β) to be interpreted as production elasticities. The technical inefficiency variable was not transformed into a logarithmic form but was retained in its original linear form. All farmers used these inputs during a single growing season. Therefore, no farmer had zero input usage.

Analysis of the stochastic frontier production function to estimate the parameters of the Cobb-Douglas production function using MLE:

$$Y = \beta_0 X_1^{\beta_1} X_2^{\beta_2} X_3^{\beta_3} X_4^{\beta_4} e^{\varepsilon_i}$$

Converted to linear form of natural logarithms:

$$\ln Y = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \beta_6 \ln X_6 + \varepsilon_i$$

where,

Y = Local Rice Production (kilograms)

X_1 = Seeds (kilograms)

X_2 = NPK Fertilizer (kilograms)

X_3 = Urea Fertilizer (kilograms)

X_4 = Land area (hectares)

X_5 = Labour (man-day equivalent)

X_6 = Herbicide (liters)

β_0 = Intercept

$\beta_1, \dots, \beta_6$ = Regression Coefficient

ε_i = error term

Technical efficiency analysis uses the formula:

$$TE_i = \frac{Y_i}{\hat{Y}_i} = \frac{\exp(x_i \beta + v_i - u_i)}{\exp(x_i \beta + v_i)} = \exp(-u_i)$$

where,

Y_i = Actual output

$\hat{Y}_i$ = Potential output

Furthermore, the effects of technical inefficiency are analyzed with the equation:

$$u_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 D_1 + \varepsilon_i$$

where,

u_i = The effect of technical efficiency

δ_0 = Constant

$\delta_1, \dots, \delta_5$ = Coefficients of the estimated parameters

Z_1 = Age of the farmer (years)

Z_2 = Farming Experience (years)

Z_3 = Farmer Education Level (years)

Z_4 = Number of family members (people)

D_1 = Gender (1 = Male; 0 = Female)

3. RESULTS

3.1 Respondent characteristics

The characteristics of the 272 respondents are shown in Table 1. The majority of farmers are men, accounting for 70%. The majority of farmers' education levels are from junior high school to senior high school. Based on the age of farmers, the majority of respondents (49%) were between the ages of 41 and 61, which means that the agricultural workforce is dominated by the final productive age to the elderly and unproductive. The majority of farmers also have farming experience of 19–35 years, at 54%.

Table 1. Respondent criteria

Criteria	Number of People	Percentage (%)
Sex		
Male	189	70
Female	83	30
Educational Background (year)		
≤6	119	44
7–12	121	44
>12	32	12
Age (year)		
20–40	107	39
41–61	132	49
62–82	33	12
Farming Experience (year)		
2–18	98	36
19–35	148	54
36–52	26	10

3.2 Technical efficiency of farming

Local rice cultivation of tidal swamp land is carried out in stages starting from the selection of local varieties, seedlings, land preparation, planting, maintenance, and harvesting. The local varieties cultivated are Siam Unus, Siam Rukut, Siam Pandak, and Mayang. The seeds used are seeds from previous crops. Seeds for the seedbed are carried out by seed selection. Rice varieties are chosen because they are adapted to tidal swamp land conditions. Planting is carried out in March or early April. Seedbeds are carried out three times. Planting seedbeds are known as taradakan, which are maintained until the age of 30–35 days. The second seedbed is called a ramp and is carried out in December or January with the aim of breaking or dividing the plant into several parts so that it can grow many strong saplings. Seedlings are grown for 35–40 days. The location of the seedbed in the rice field is considered high. Before the third seedbed is carried out, farmers usually clear the land for the preparation of a track on the edge of the rice field. The third seedbed is called a track, which is maintained for 60–75 days so that the saplings grow in number and strength.

Land preparation is carried out in February using traditional tools such as tajak, but there are also farmers who have large plots of land using tractors. Slashed grass is usually left by farmers to rot to become natural fertilizer. After that, planting is carried out. Planting activities are carried out with a system of materials or mutual cooperation between farmers. Maintenance is carried out by fertilizing with chemical fertilizers, namely urea. Pests and diseases that attack include rats, stem borers, rice field snails, and walang sangit. The time waiting for the harvest period until September or October is

used by farmers to do other side jobs, such as planting chili peppers with a surjan system, or work outside the farm, such as construction work, handyman work, or odd jobs. Harvest is done in September or October. Harvesting is also carried out with a system of materials or mutual cooperation. The sale of crops is carried out a few months after harvest by looking at fluctuations in grain prices.

The entire implementation of these cultivation activities determines the number of production factors used by farmers. The diversity of variations in the number of outputs and input usage is shown in Table 2. The diversity of variation is a point indicator in measuring the level of technical efficiency in farming.

To avoid bias in the relationships between variables, multicollinearity was checked prior to estimation using SFA. The results of the multicollinearity test are shown by identifying the VIF values in Table 3. A VIF value of less than 10 for all independent variables indicates that there is no multicollinearity.

Table 2. Descriptive statistics of production inputs and output

Variable	Min	Max	Average	Standard Deviation
Cultivated Area (hectares)	0.14	3.00	0.94	0.62
Production (kilograms)	330	11550	3125.56	3075.39
Number of Seeds (kilograms)	1.7	40	11.44	8.46
Amount of NPK Fertilizer (kilograms)	2	1260	87.34	108.05
Amount of Urea Fertilizer (kilograms)	10	840	81.23	74.16
Amount of Herbicide (liters)	0.17	24	2.00	2.20
Labour (in man-days)	11	177	44.06	22.04

Table 3. Detection of multicollinearity among all independent variables

Input Variable	VIF
Seeds (X ₁)	3.20
NPK Fertilizer (X ₂)	1.68
Urea Fertilizer (X ₃)	3.42
Land Area (X ₄)	5.06
Labour (X ₅)	1.31
Herbicide (X ₆)	1.79
Age (Z ₁)	2.32
Farming Experience (Z ₂)	2.61
Farming Education Level (Z ₃)	1.10
Number of Family Members (Z ₄)	1.09
Gender (D ₁)	1.05

Note: Variance Inflation Factor (VIF).

The technical efficiency of rice farming was analyzed using the stochastic frontier production function model to identify the factors that affect rice production and the value of each farmer's technical efficiency. Table 4 presents the results of the production function parameter estimates obtained using the MLE method.

The LR value is 74.30 and is significant at the 1% level, which means that the use of the SFA model is valid and appropriate. The gamma value of 99.19% indicates that

fluctuations in rice yields are caused by the farmers' own technical inefficiencies. Therefore, the application of SFA in the form of the Cobb-Douglas model using MLE is highly appropriate. The variable land area showed a significant influence at $\alpha = 1\%$. NPK fertilizer showed a significant influence at $\alpha = 10\%$. Herbicides have a significant effect on rice production at $\alpha = 5\%$.

Table 4. Maximum Likelihood Estimation (MLE) parameter estimates for the Cobb-Douglas rice production function

Input Variable	Maximum Likelihood Estimation		
	Coefficient	Standard Error	t-Ratio
Constant ($\text{Ln}\beta_0$)	8.1752	0.1506	54.2963
Seeds ($\text{Ln}\beta_1$)	-0.0243	0.0201	-1.2071
NPK Fertilizer ($\text{Ln}\beta_2$)	0.0156	0.0090	1.7346 (***)
Urea Fertilizer ($\text{Ln}\beta_3$)	0.0051	0.0214	0.2363
Land Area ($\text{Ln}\beta_4$)	0.9586	0.0266	36.0912 (*)
Labour ($\text{Ln}\beta_5$)	0.0247	0.0227	1.0878
Herbicide ($\text{Ln}\beta_6$)	-0.0357	0.0157	-2.2741 (**)
Sigma-squared (σ^2)	0.6773	0.2610	2.5954
Gamma (γ)	0.9919	0.0036	274.8893
LR	74.3025		

Note: (*) significant at the 1% alpha level ($|t| > 2.576$); (**) significant at the 5% alpha level ($|t| > 1.96$); (***) significant at the 10% alpha level ($|t| > 1.645$).

The average local rice farming in tidal swampland is technically efficient, meaning that farmers can reach 82% of their potential output at the existing technology level and input levels. A TE value between 0.23 and 0.98 indicates that there is still a difference in the ability to manage farming. The results of the technical efficiency analysis are shown in Table 5. The gap between actual and potential production is shown in Figure 2.

The majority of local rice farmers achieved a high

efficiency level of 68.75%, with a technical efficiency (TE) value greater than or equal to 0.80 ($\text{TE} \geq 0.80$). The group of farmers with high technical efficiency, on average, had a farm size of 1.01 hectares and 24 years of farming experience. Farmers with technical efficiency ($\text{TE} < 0.50$) have, on average, 0.79 hectares of land and 11 years of farming experience.

Figure 2 shows the gap between farmers' actual and potential production based on SFA analysis. In the scatter plot, each smallholder farmer in the sample is plotted vertically, with a small empty circle representing actual production and a solid dark circle indicating the corresponding potential production limit. Figure 2 illustrates the diversity in production variation, reflecting differences in farmers' ability to optimize the combination of available inputs into output. The smaller the gap—or vertical distance—between the actual production circle and the potential production circle, the higher the level of technical efficiency—and vice versa. These variations in production gaps among farmers can serve as a basis for analyzing the factors contributing to agricultural inefficiency. These variations in the production gap among farmers can serve as a basis for analyzing factors contributing to farming inefficiencies.

Table 5. Technical efficiency (TE) results

Interval	Number of People	Percentage (%)	Average Land Area (hectares)	Average Farming Experience (years)
$\text{TE} < 0.50$	13	4.78	0.79	11
$0.50 \leq \text{TE} \leq 0.59$	12	4.41	0.71	12
$0.60 \leq \text{TE} \leq 0.69$	17	6.25	0.92	15
$0.70 \leq \text{TE} \leq 0.79$	43	15.81	0.81	18
$\text{TE} \geq 0.80$	187	68.75	1.01	24
Total	272	100.00		

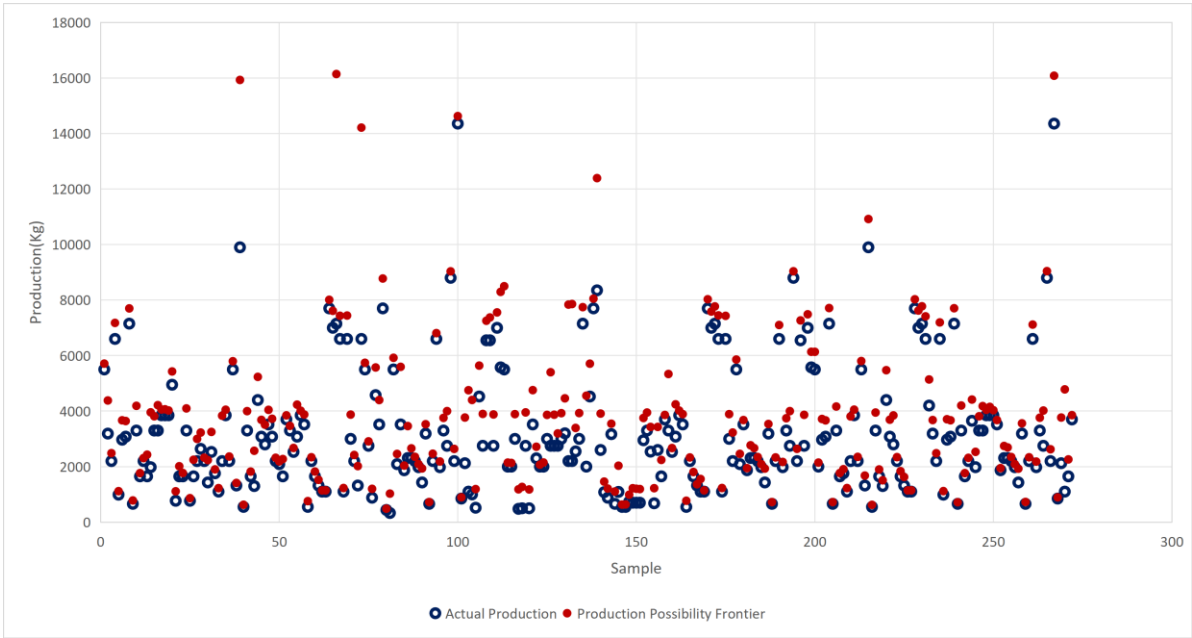


Figure 2. A scatter plot comparing observed actual production with predicted marginal potential production ($\hat{Y}_i$) for each local rice farmer ($N = 272$)

Note: The horizontal axis represents individual farmer samples scaled to 300 for visual clarity, and the vertical axis represents production output in kilograms (kg). Small empty circles represent actual production achieved, while solid red circles indicate the corresponding frontier yields estimated using Stochastic Frontier Analysis (SFA) in Frontier 4.1.

The results of estimating the effects of technical inefficiencies are described in Table 6.

Based on the results of the estimation in the inefficiency table, it can be seen that the variables that significantly increase farming efficiency are farming experience, the farmer's age, and the number of family members, while the variables of formal education level and gender do not have a significant effect on inefficiency.

Table 6. Results of estimation of the effects of technical inefficiency of local rice farming in tidal swamp land

Input Variables	Coefficient	Standard Error	t-Ratio
Constant	0.6728570	0.3319382	2.0270547
Age (Z ₁)	-0.0170372	0.0099300	-1.7157387 (**)
Farming Experience (Z ₂)	-0.1089946	0.0445178	-2.4483346 (*)
Farming Education Level (Z ₃)	0.0037299	0.0171595	0.2173679
Number of Family Members (Z ₄)	-0.1522480	0.0719970	-2.1146439 (**)
Gender (D ₁)	-0.012660	0.1289834	-0.0981520

Remarks: (*) has a significant effect at $\alpha = 1\%$; (**) has a significant effect at $\alpha = 5\%$.

4. DISCUSSION

The data in Table 1 show that local rice farming on tidal lands is largely managed by experienced farmers (54%) with 19–35 years of experience. This indicates that farming experience is an important human capital factor in coping with the ecological uncertainties of tidal fluctuations. On the other hand, the data in Table 2 reveal the physical limitations of farming operations: the average farm size is only 0.94 hectares, with a harvest yield of 3,125.56 kg per season. This output remains below the national rice productivity rate due to farming constraints such as soil acidity and tidal water fluctuations.

Based on the results of the SFA analysis, it was found that the variables of land area, NPK fertilizer, and herbicides have a significant influence on production. Land area is the primary determining factor because it has the highest positive elasticity value. This means that a 1% increase in land area will increase local rice production by up to 0.9586% (assuming all other conditions remain constant). Adequate land area provides farmers with the flexibility to manage adaptive micro-irrigation systems. However, land expansion alone does not guarantee higher technical efficiency, as production performance also depends on farmers' ability to allocate inputs effectively. Adequate land area provides farmers with the opportunity to implement adaptive traditional land management practices, such as the surjan system through the integration of planned mounds and irrigation channels. A number of previous studies have also demonstrated that controlling a larger land area has the potential to increase efficiency, as farmers have greater leeway to allocate resources and organize their land for optimal use [14, 15, 17].

The NPK fertilizer variable has a significant positive effect on local rice production. A 1% increase in NPK fertilization can boost production by up to 0.0156%. This finding underscores the importance of a balanced supply of nutrients for rice growth, particularly in tidal areas. Plants require NPK to strengthen their roots and ensure proper grain filling in local

rice varieties. These findings are consistent with previous research showing that proper NPK application can increase rice productivity [20, 21]. Therefore, improvements in fertilizer management in the field should not only focus on increasing the dosage but also on optimizing the accuracy of the dosage and the timing of application to suit ecological conditions.

The use of herbicides has a significant negative impact on local rice production. A 1% increase in herbicide use reduces production by up to 0.0357%. However, we must be cautious in interpreting these results due to the potential for endogeneity bias arising from reverse causality. In reality, farmers whose fields are heavily infested with weeds tend to use more herbicides to save their crops. Thus, this negative coefficient may reflect high weed pressure rather than a direct damaging effect of the chemicals on the plants. Nevertheless, these data illustrate that weed control on vulnerable land remains a challenge because optimizing inputs does not yield a commensurate increase in output. The fact that the urea fertilizer variable had no effect indicates that marginal adjustments to the current application rate do not alter the production boundary line. Although the literature on tidal swampland often states that nitrogen uptake efficiency is low due to the structural acidity of the soil and the potential for nutrient leaching during high tide, the lack of direct soil and agronomic data in this study prevents definitive confirmation of these leaching mechanisms. Empirically, these non-significant results primarily indicate allocation inefficiencies at the farm level, confirming that simply expanding urea use within current traditional farming practices does not guarantee increased production. Other inputs, such as seeds, urea fertilizer, and labor, did not have a significant effect on production. The lack of a significant effect for the seed variable is likely due to farmers' practice of continuously using seeds from the previous harvest, resulting in a decline in genetic quality and yield potential. Meanwhile, the lack of a significant effect for the urea fertilizer variable indicates that marginal adjustments to the current application rate do not alter the production boundary. Although the literature on tidal swampland often states that nitrogen uptake efficiency is low due to the soil's structural acidity and the potential for nutrient leaching during high tide, this study did not directly measure soil conditions; therefore, these reasons cannot be empirically confirmed. These results confirm that the key to increasing production lies in improving management practices, not merely in increasing inputs.

Based on the SFA model, the average technical efficiency of farmers is 0.82. This means that farmers have achieved 82% of their maximum production potential with currently available technology. The remaining 18% gap reflects disparities in farmers' management capabilities in maximizing resources. The minimum TE value is 0.23, and the maximum is 0.98. A gamma value of 99.19% confirms that fluctuations in production are caused by farmers' technical inefficiencies, not by chance or natural disturbances (random noise). Therefore, the best strategy for improving efficiency on tidal swampland is to enhance farm management capabilities and strengthen adaptive agricultural technologies. The research findings are in accordance with the grand theory of technical efficiency [6] developed using the SFA approach [7].

The average technical efficiency value of 0.82 is consistent with previous studies. The 18% production gap indicates that farmers have not yet fully realized their production potential due to differences in management capacity, limited land area,

and experience-based human capital that shapes their ability to adapt to the tidal environment. The average technical efficiency was 0.76, with one distinguishing factor influencing farmers' managerial capabilities [1]. Farmers' managerial skills play a crucial role in determining variations in the technical efficiency of rice farming, particularly in effectively combining available inputs [22]. Rice cultivation on tidal swamp lands in Central Kalimantan has an average technical efficiency of 0.755, where the expansion of rice-planting areas and the use of NPK fertilizer significantly increased rice yields [13]. A comparison with previous studies from several regions shows that although farmers face challenges related to high ecological vulnerability, their local ecological knowledge can help address these issues, enabling them to manage water and inputs to minimize the risk of crop yield losses.

The distribution of technical efficiency reveals a gap in capabilities among farmers. Farmers with high technical efficiency ($TE \geq 0.80$) manage an average of 1.01 hectares of land and have 24 years of farming experience. In contrast, farmers with low technical efficiency ($TE < 0.50$) manage only 0.79 hectares of land and have 11 years of farming experience. This disparity demonstrates that farming experience is a key factor in improving technical efficiency. In line with human capital theory, years of farming experience build understanding and refine practical skills, while also sharpening farmers' ability to make precise decisions regarding the management of production factors.

On tidal swamplands, years of farming experience have equipped farmers with the ability to determine planting schedules, manage water systems, and select cultivation techniques suited to ecological conditions. Consistent with previous research, rice productivity on tidal lands is influenced by the suitability of the technology to ecological conditions and the ability to manage the farm [23]. Conversely, limited farming experience reduces farmers' ability to cope with the threat of ecological uncertainty, resulting in less effective input management. This mechanism helps explain how farming experience contributes to reducing technical inefficiencies in farming. However, since this study does not measure ecological adaptation quantitatively, this interpretation is presented only as a logical supporting explanation for the high technical efficiency scores of experienced farmers, rather than as a quantitative variable directly calculated in the SFA model. The results of the study are also in line with the research [13], which states that the longer the farmer's experience, the higher the achievement of technical efficiency. To achieve maximum production potential on tidal swampland, a targeted integration of experience-based farming skills and appropriate micro-water management is required [24]. In contrast to previous research findings, which suggest that experience does not always improve efficiency if it is not accompanied by the ability to adopt new technologies.

Mathematically, the sum of all production coefficients yields a value of 0.943. Although a figure below one typically indicates a trend of diminishing returns as inputs are increased (decreasing returns to scale), this descriptive indicator must be interpreted with caution. This is because some inputs, such as seeds, urea fertilizer, and labor, do not have a significant effect; therefore, this figure cannot be used as a benchmark for determining the scale of operations. Empirically, the scale of local rice production on this tidal swampland is largely determined by the dominant and significant elasticity of land area (0.9586). Thus, the figure of 0.943 is not definitive

evidence of a decline in the scale of operations, but rather an indication that production growth is still constrained by limited land area.

The determinants of technical inefficiency—the farmer's age and the number of family members—significantly reduce technical inefficiency. In contrast, educational level and gender have no effect on efficiency. The influence of age suggests that accumulated experience and maturity in decision-making may enhance farmers' ability to manage production risks. Family size greatly aids in the availability of self-reliant labor, especially during the planting and harvesting seasons. Conversely, a high level of formal education does not guarantee better efficiency, as local rice cultivation on tidal lands requires practical knowledge and local experience related to the ecological conditions of the land.

Overall, the study's findings suggest that increasing local rice production requires an integrated approach that combines efficient input management with farmers' adaptive capacities—such as water management and timing of planting—which help farmers cope with the challenges posed by the uncertainty of tidal ecological conditions. However, in this study, these capabilities were not measured as quantitative variables. Therefore, future research needs to develop measurable indicators for this ecological adaptation—such as water management, the use of adaptive local varieties, and the activity of farmers' groups—so that their contribution to technical efficiency can be calculated more precisely. From a policy perspective, increasing rice production and ensuring the sustainability of rice farming on tidal lands cannot rely solely on strategies involving the intensification of chemical inputs. Government policy must focus on strengthening farmers' managerial capabilities, enhancing knowledge transfer among farmers, and developing technologies suited to local ecological conditions. Integrating scientific innovations with locally developed knowledge can support a more sustainable and resilient rice farming system in tidal environments.

5. CONCLUSIONS

Based on the SFA results, it was found that land area, NPK fertilizer, and herbicides have a significant effect on the production of local rice in tidal swampland. Other inputs had no effect. These results indicate that a substantial increase in the use of chemical inputs does not guarantee an increase in production if the ecological suitability of the land is not taken into account. Mathematically, this phenomenon is reflected in the total production elasticity value of 0.943. However, given that some inputs are not statistically significant, this value should be interpreted with caution as a descriptive trend rather than as definitive structural evidence of diminishing returns to scale. The results of this study confirm that local rice production remains highly dependent on land area as the primary structural determinant, indicating that insignificant increases in physical inputs in current farming practices do not guarantee improved efficiency or higher yields. The average technical efficiency value of 0.82 indicates that farmers' actual production is close to 82% of the potential production, but an 18% gap still exists at the observed levels of technology and inputs. This study confirms that the technical efficiency of local rice farming on tidal swampland is largely determined by land area and human capital based on farming experience. Land area influences the scale of production, and farming experience serves as a component of human capital that can

reduce agricultural inefficiencies. An average technical efficiency of 0.82 indicates that the majority of farmers are able to optimize their available resources to a level approaching their potential limit. Qualitatively, efficiency levels are closely linked to the accumulation of empirical knowledge regarding the dynamics of tidal swamplands.

Farming experience has a negative coefficient and affects farming inefficiency. The results of the analysis show that farming experience is able to reduce inefficiency in farming. More experienced farmers tend to be better able to determine planting time, manage water, choose appropriate varieties, and adjust cultivation techniques to tidal swamp land conditions. The results of the study prove that the experience of farming as a non-formal investment is in accordance with human capital theory.

The age of farmers has a negative and significant effect, meaning that an increase in efficiency will occur over time. The number of family members also increases efficiency, which plays a role in supporting the availability of labour in families who help with farming. The level of formal education and gender have no effect on inefficiency. The findings of the study emphasized that increasing efficiency does not depend on improving production facilities alone, but also requires an improvement in the managerial ability of farmers, supported by adaptive skills from farming experience, to minimize the ecological vulnerability of tidal swampland.

As a theoretical contribution, this study connects frontier production efficiency theory and human capital theory to explain the variation in agricultural output achievement with ecological vulnerability. Practically, the implication of this finding is that the strategy to increase production does not depend on the intensification of inputs but needs to be directed at land and water optimization that is adaptive to ecological conditions and supported by the transfer of strengthening experiences based on local wisdom between farmers. The application of technology also needs to pay attention to the suitability of land conditions combined with local wisdom in order to achieve sustainable farming. The limitations of this study are that it uses farming experience as a proxy for human capital and has not explicitly included ecological adaptation indicators as measurable variables in the SFA. Therefore, further research is recommended to incorporate ecological adaptation indicators as index or dummy variables in the model of farming inefficiency on tidal swamplands. Further research can be carried out by examining the application of local wisdom using panel data several times during the planting season.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support provided by the Islamic University of Kalimantan Muhammad Arsyad Al Banjari Banjarmasin for this research.

ETHICAL STATEMENT

This study involved human participants in accordance with ethical principles. The data collection process was approved by the relevant authorities, and all respondents participated voluntarily after being informed of the study's objectives. Respondent confidentiality was ensured, and the data were used for academic purposes. This study was approved by the

Ethics Committee of Brawijaya University (No. 204/EC/KEPK/05/2025).

DISCLOSURE STATEMENT

The grammar in this scientific article was edited with the assistance of ChatGPT (OpenAI). However, this article has been critically reviewed to ensure its accuracy.

DATA AVAILABILITY STATEMENT

The data presented in Figure 2 were generated from farmer-level observed production and predicted frontier output estimated using the Stochastic Frontier Analysis (SFA) model in Frontier 4.1. Due to confidentiality agreements with the farmer respondents, the complete farmer-level estimation results are not publicly available but can be obtained from the corresponding author upon reasonable request.

REFERENCES

- [1] Sulaeman, Y., Maftu'ah, E., Mukhlis, M., et al. (2022). Tidal rice yield assessment in Central Kalimantan, Indonesia, under different cultural practices. *Resources*, 11(12): 116. <https://doi.org/10.3390/resources11120116>
- [2] BPS Provinsi Kalimantan Selatan. (2016). Agricultural Land Area Survey by Land Use in South Kalimantan Province. <https://kalsel.bps.go.id/publication/2016/09/30/ecd671a3bb2e229e9662f46b/survei-pertanian-luas-lahan-menurut-penggunaannya-di-provinsi-kalimantan-selatan-2016.html>.
- [3] Riduan, A. (2018). This is the agricultural potential of Banjar Regency, with 8,538 hectares of lowland swamp land. Kalimantan Canal. <https://www.kanalkalimantan.com/ini-potensi-pertanian-di-kabupaten-banjar-lahan-rawa-lebak-8-538-ha/>.
- [4] Khairullah, I., Hairani, A., Nurzakiah, S., et al. (2024). A century of traditional rice farming in tidal swamplands of South Kalimantan, Indonesia: Its impact on breeding and conservation programs. *Chilean Journal of Agricultural Research*, 84(4): 575-587. <http://doi.org/10.4067/s0718-58392024000400575>
- [5] Puji Hastuti, K., Arisanty, D., Rajiani, I. (2022). Preserving the sustainability of natural resources and agro-ecosystems in tidal swampland through local wisdom in Indonesia. *Journal of Sustainability Science and Management*, 17(5): 77-97. <https://doi.org/10.46754/jssm.2022.05.006>
- [6] Farrell, M.J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A*, 120(3): 253-290. <https://doi.org/10.2307/2343100>
- [7] Aigner, D., Lovell, C.A.K., Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1): 21-37. [https://doi.org/10.1016/0304-4076\(77\)90052-5](https://doi.org/10.1016/0304-4076(77)90052-5)
- [8] Becker, G.S. (1993). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, 3rd Edition. University of Chicago Press.

- <https://doi.org/10.7208/chicago/9780226041223.001.0001>
- [9] Schultz, T.W. (1961). Investment in human capital: The role of education and of research. *The American Economic Review*, 51(1): 1-17. <https://la.utexas.edu/users/hcleaver/330T/350kPEESchultzInvestmentHumanCapital.pdf>.
 - [10] Arum Shafriani, K., Nisa, A.F., Salawati, U., Budiwati, N., Rosni, M. (2026). Production risk management for local rice varieties in tidal lands: A local wisdom approach in Barito Kuala Regency. *International Journal of Life Sciences and Agriculture Research*, 5(1): 68-74. <https://doi.org/10.55677/ijlsar/V05I01Y2026-10>
 - [11] Sulaeman, Y., Aryati, V., Suprihatin, A., et al. (2024). Yield gap variation in rice cultivation in Indonesia. *Open Agriculture*, 9(1): 20220241. <https://doi.org/10.1515/opag-2022-0241>
 - [12] Fahmid, I.M., Wahyudi, Agustian, A., Aldillah, R., Gunawan, E. (2022). The potential swamp land development to support food estates programmes in Central Kalimantan, Indonesia. *Environment and Urbanization ASIA*, 13(1): 44-55. <https://doi.org/10.1177/09754253221078178>
 - [13] Sabran, M., Darsani, Y.R., Qomariah, R., et al. (2025). Technical efficiency of rice production in tidal swampland: A stochastic model approach. *International Journal of Design & Nature and Ecodynamics*, 20(4): 715-722. <https://doi.org/10.18280/ijdne.200403>
 - [14] Ilham, N., Sumaryanto, Azis, M., et al. (2023). Technical efficiency of local rice farming in tidal swamp areas of Central Kalimantan, Indonesia: Determinants and implications. *International Journal of Design & Nature and Ecodynamics*, 18(5): 1235-1245. <https://doi.org/10.18280/ijdne.180526>
 - [15] Bich Tho, L.C., Umetsu, C. (2022). Sustainable farming techniques and farm size for rice smallholders in the Vietnamese Mekong Delta: A slack-based technical efficiency approach. *Agriculture, Ecosystems & Environment*, 326: 107775. <https://doi.org/10.1016/j.agee.2021.107775>
 - [16] Rondhi, M., Suherman, S.J.H., Hensie, C.B., et al. (2024). Urbanization impacts on rice farming technical efficiency: A comparison of irrigated and non-irrigated areas in Indonesia. *Water*, 16(5): 651. <https://doi.org/10.3390/w16050651>
 - [17] Ramadani, S.W., Antriyandarti, E., Qonita, R.R.A. (2024). Efficiency of rice farming in flood-prone areas of East Java, Indonesia. *Open Agriculture*, 9(1): 20220284. <https://doi.org/10.1515/opag-2022-0284>
 - [18] Marquardt, D.W. (1970). Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation. *Technometrics*, 12(3): 591-612. <https://doi.org/10.1080/00401706.1970.10488699>
 - [19] Salmerón-Gómez, R., García-García, C.B., Rodríguez-Sánchez, A. (2026). Enlarging of the sample to address multicollinearity. *Computational Economics*, 67: 1877-1899. <https://doi.org/10.1007/s10614-025-10920-5>
 - [20] Marlina, N., Haitami, A., Gusmiatun, G., et al. (2025). Optimization of rice production in tidal swamps by combining bio-organic fertilizers and cropping systems. *Journal of Ecological Engineering*, 26(9): 239-252. <https://doi.org/10.12911/22998993/203257>
 - [21] Trong Ho, P., Burton, M., Ma, C., Hailu, A. (2021). Quantifying heterogeneity, heteroscedasticity and publication bias effects on technical efficiency estimates of rice farming: A meta-regression analysis. *Journal of Agricultural Economics*, 73(2): 580-597. <https://doi.org/10.1111/1477-9552.12468>
 - [22] Tondi, K.M., Anshary, A., Effendy. (2025). Enhancing efficiency in lowland rice farming: The role of gender, human capital, and agricultural practices. *Australian Journal of Crop Science*, 19(3): 292-300. <https://doi.org/10.21475/ajcs.25.19.03.p294>
 - [23] Sari, N.N., Masganti, M., Abduh, A.M., et al. (2025). Advancing hybrid rice cultivation in Indonesia's tidal swamp areas: Challenges and innovations. *Chilean Journal of Agricultural Research*, 85(2): 287-298. <https://doi.org/10.4067/s0718-58392025000200287>
 - [24] Chandel, R.B.S., Khan, A., Li, X.J., Xia, X.L. (2022). Farm-level technical efficiency and its determinants of rice production in Indo-Gangetic Plains: A stochastic frontier model approach. *Sustainability*, 14(4): 2267. <https://doi.org/10.3390/su14042267>