JOURNAL OF WORLD SCIENCE
https://jws.rivierapublishing.id/index.php/jws
Volume 4 No. 2. February 2025
P-ISSN: 2828-8726
E-ISSN: 2828-9307

TECHNICAL EFFICIENCY OF FARMING BUSINESS TO OPTIMIZE RICE PRODUCTION (*ORYZA SATIVA L.*): THE CASE IN PAJAWANLOR VILLAGE, CIAWIGEBANG DISTRICT, KUNINGAN REGENCY

Andri Priyatna[1], Heru Supriatna[2], Tyas Tony Taufik[3], Achmad Faqih[4]*, Yayat Rahmat Hidayat[5]
Universitas Swadaya Gunung Jati, Cirebon, Indonesia

andripriyatna269@gmail.com, achmad.faqih@ugj.ac.id*

ABSTRACT
This research examines the technical efficiency of rice farming (Oryza sativa L.) in Pajawanlor Village, Ciawigebang District, Kuningan Regency, to assess efficiency levels and identify influencing factors. Utilizing a quantitative research approach, the study employs the Cobb-Douglas Stochastic Frontier Production Model alongside the Maximum Likelihood Estimation (MLE) method to analyze data from 35 rice farmers. The findings reveal an average technical efficiency level of 75%, indicating that farmers could boost their production by 25% through optimized resource utilization. Key factors affecting efficiency include land, seeds, fertilizers, labor, and farming experience. These results underscore the importance of targeted interventions, such as improved input management, better access to agricultural technology, and training programs to enhance farmers' efficiency. The implications of this research extend to policy recommendations aimed at increasing rice productivity and ensuring food security, particularly in rural agricultural contexts. Stakeholders—policymakers, agricultural extension officers, and farmers—can devise more effective strategies for optimizing rice farming outcomes by addressing technical inefficiencies.

Keywords: Cobb-Douglas production function; rice farming; stochastic frontier; technical efficiency

INTRODUCTION

Rice is a strategic food commodity for Indonesia, as it serves as the staple food for the community. Ensuring optimal rice production is vital for maintaining food security, mainly as population growth drives demand. However, many rice farmers struggle to achieve the best yields due to inefficiencies in resource use and technical limitations. Land use, seed quality, fertilizer application, and labor availability significantly impact productivity. However, many farmers lack access to the essential knowledge and technology needed to optimize these inputs effectively (Aprianti et al., 2020).

According to Law Number 7 of 1996 on Food, the government and society share the responsibility of achieving food security, which is characterized by sufficient, safe, quality, and affordable food availability. However, recent trends show a decline in rice productivity across various regions, including Pajawanlor Village in Ciawigebang District, Kuningan Regency, where farmers encounter challenges related to technical efficiency. A 2021 agricultural survey revealed that Indonesia’s total harvested rice area had decreased to 10.41 million hectares, with production levels following suit. This situation highlights the necessity of improving farmers' efficiency in utilizing production inputs to maximize yields without increasing costs (MURKAD et al., 2019).

In modern agriculture, using agricultural tools and machinery has become crucial for farmers in various production processes, as affordable labor is difficult to obtain (Santoso et al., 2020). Indonesia has much of its territory in the tropics, and rice, as a primary food crop, requires more attention in developing the agricultural sector.

Agricultural production is influenced by various factors, including land, seeds, fertilizers, pesticides, irrigation systems, labor, and climate (Anisuzzaman et al., 2023; Ishak et al., 2025; Schreefel et al., 2024). A decrease in production can occur due to climate change, which can reduce agricultural land area (MURKAD et al., 2019). The agricultural sector's dependence on industry and foreign relations is very high. In 2021, a survey showed that the harvested area of rice decreased to 10.41 million hectares, with production at 54.42 million tons of milled dry unhusked rice (GKG). From a cultivation perspective, rice yields decreased by about 0.45% compared to the previous year.

Technical efficiency in farming maximizes output from inputs or minimizes inputs for outputs. Aprianti et al. (2020) state that technical efficiency is achieved when reducing one output necessitates increasing an input and vice versa. This is crucial for a sustainable agricultural system in Indonesia. In Pajawanlor Village, Ciawigebang District, low rice production is greatly influenced by farmers' technical efficiency in input use. When applied correctly, factors like land use, seeds, fertilizers, pesticides, and labor significantly impact efficiency. Efficient input use enhances crop yields, while socioeconomic factors like age, experience, family size, and seed type also play a role. Farmers can adopt more effective practices by understanding technical efficiency, increasing sectoral productivity, and optimizing rice production.

Improving technical efficiency in rice farming is crucial due to the rising demand for rice from population growth. Inefficient farming practices can result in low production and unstable yields. This research aims to evaluate technical and allocative efficiency in rice farming in Pajawanlor Village, focusing on two main questions: whether rice farming is technically efficient and which technical factors contribute to that efficiency.

This research focuses on the technical inefficiencies in rice farming within Pajawanlor Village, which hinder farmers from reaching optimal yields. Many farmers fail to maximize their efficiency due to the inappropriate use of resources, leading to production shortfalls and financial losses. Key factors influencing efficiency include land size, seed quality, fertilizer usage, labor input, and farming experience, but restricted access to technology and best practices prevents farmers from fully enhancing productivity. This study aims to assess the technical efficiency of rice farming using the Cobb-Douglas Stochastic Frontier Production Model, identify critical factors contributing to inefficiencies, and offer practical recommendations to improve efficiency without requiring additional resources. By providing empirical data, the research intends to inform policy development, agricultural extension initiatives, and training programs for farmers that can boost rice productivity and bolster food security in rural agricultural communities.

METHOD

The research employs an explanatory design to explain the relationship between production inputs and rice farming efficiency. It also uses a descriptive approach to analyze farmers' socioeconomic conditions, practices, and challenges in optimizing production in depth. A quantitative method estimates technical efficiency levels with the Cobb-Douglas Stochastic Frontier Model, analyzing data from 35 farmers using Maximum Likelihood Estimation (MLE). Additionally, a qualitative approach gathers insights through observations, interviews, and documentation, enhancing the understanding of technical efficiency in rice farming.

The research was conducted from October to December 2024, focusing on the excellent Margaluyu Farmer Group, which includes 50 dedicated rice farmers. This group was carefully selected because of its involvement in agricultural extension programs, ensuring that its members share similar farming practices and access the same resources. From this inspiring group, 35 farmers were chosen for analysis, considering factors like farm size, experience, and eagerness to participate.

Primary data was collected through structured interviews, observations, and documentation. Secondary data came from agricultural reports, government statistics, and past research. Structured interviews gathered details on farm inputs (land size, seed use, fertilizer, labor) and outputs (rice yield). The Cobb-Douglas Stochastic Frontier Production Model was used to measure technical efficiency with Maximum Likelihood Estimation (MLE). This model decomposes deviations from optimal production into random errors (external factors) and inefficiency effects (farmer management and input use). Each farmer's efficiency score, ranging from 0 to 1, indicates efficiency, with scores closer to 1 reflecting higher efficiency.

Cobb-Douglas Production Function Analysis

The Cobb-Douglas production function is an equation of two or more variables, where one is called the dependent variable (Y) and the other(s) is called the independent variable (X). The basic form of the Cobb-Douglas production function model is as follows:

$$Y = \beta_0 X_1 \beta_1 X_2 \beta_2 \ldots X_n \beta_n eu$$

Description:

- Y = suspected production
- β_0 = intercept
- β_i = parameter estimate of the i-th variable and represents elasticity
- X_i = factors of production used (i=1,2,3,...,n)
- e = natural number (2.718)
- u = error term

The Cobb-Douglas production function utilizes the stochastic frontier method. The stochastic frontier production function measures how actual production functions relate to their frontier positions. The uniqueness of the stochastic frontier method lies in estimating the production function while considering potential factors beyond the farmers ' control that affect farming efforts. The Cobb-Douglas production function used is as follows:

$$Y = X_i\beta + v_i - u_i$$

Description:

Y = production generated by farmers
Xi = input/factor of production used by farmers
β = estimated parameter
vi = random variable related to external factors (weather, seasons, climate, etc.)
ui = random variable related to internal factors affecting technical inefficiency

The model shown in the equation above is called the stochastic frontier production function because a random variable bounds the output value, precisely the expected values of xiβ + vi or exp(xiβ + vi). The error (vi) can take positive or negative values, similar to how the stochastic frontier output varies in certain parts of the frontier model, exp(xiβ).

The structure of the stochastic frontier model is described such that the x-axis represents the amount of input, and the y-axis represents the amount of output. The frontier model Y = exp(xiβ) is based on the principle of diminishing returns to scale. There are two farmers, namely farmer i and farmer j. Farmer i uses input xi and produces output yi. The output value from the stochastic frontier is yi*, which exceeds the production function's. This occurs because farmer i's production is influenced by favorable conditions when the variable vi is positive.

Meanwhile, farmer j uses input xj and produces output yj. Production is included in the production function because farmer j's production is influenced by detrimental conditions when vj is negative. Deviations from the stochastic frontier cannot be detected because the values of random errors cannot be identified. The critical part of the stochastic frontier model occurs between the outputs of the stochastic frontier. The observed output can be greater than the defined boundary part if the corresponding random error is greater than the inefficiency effects (yi > exp(xiβ) if vj > uj) (Coelli, 2005).

The estimation of the production function is carried out simultaneously using R software. The Cobb-Douglas function with the stochastic frontier method used in this research is formulated with the following equation:

$$lnY = \beta_0 + \beta_1 lnX_1 + \cdots + \beta_5 lnX_5 + v_i - u_i$$

Description:

Y = rice productivity (tons/hectare)
X1 = Seeds (kg/hectare)
X2 = Labor (DPW/hectare)
X3 = Fertilizers N, P, and K (kg/hectare)
β0 = intercept
β1 = parameter of interest

vi = error
ui = technical inefficiency

The explanatory variables included in the model are the most important inputs commonly used by rice farmers. The determination of these variables has been reduced from other variables used in rice farming and adjusted to the variables available in the data source.

Technical Efficiency Analysis

$$TE = \frac{y_i}{\exp{(x_i\beta)}}$$

Description:

TE	= technical efficiency
Yi	= actual production from the research
exp(xiβ)	= estimated frontier production obtained from stochastic frontier production

The value of technical efficiency for a farmer ranges from zero to one (0 ≤ TE ≤ 1). The technical efficiency value of farmers is categorized as efficient if it is more significant than 0.7 (Winata et al., 2020).

Analysis of Technical Inefficiency Factors

The inefficiency effects model used in this research refers to the technical inefficiency model developed by Perera & Hemachandra (2021). The u_i variable used to measure the impact of technical inefficiency is assumed to be independent and often truncated. The higher the value of u_i, the more significant the impact of technical inefficiency or the lower the technical efficiency of rice cultivation. This variable is suspected to be related to production factors. The determination of this variable has previously been reduced from other variables used in rice farming and adjusted to the variables available in the data source. The equation for the estimation model of technical inefficiency effects in this research is as follows:

$$u_i = \delta_0 + \delta_1 Z_1 i + \delta_2 Z_2 i + \delta_3 Z_3 i + \delta_4 Z_4 i$$

Description:
ui = Technical Inefficiency Effect
Z1 = Land Area (hectares)
Z2 = Dependents (people)
Z3 = Formal Education (years)
Z4 = Age of Farmer (years)
Z5 = Farming Experience (years)

$\delta 0$ = intercept
δi = estimated parameter

RESULTS AND DISCUSSION

Respondent Characteristics

Age of Respondents

Table 1. Respondent Status Based on Age

No.	Age of Respondents (Years)	Quantity (people)	Percentage (%)
1	30 – 39	12	24
2	40 – 49	25	50
3	50 – 59	13	26
	Total	50	100

Source: Primary Data, 2024

Table 1 shows that the age group of respondents engaged in rice farming is dominated by those aged 40-49, 25 individuals, or 50% of the total respondents. Respondents aged 50-59 are 13 individuals or 26%, while the remaining 12 or 24% are aged 30-39. Therefore, it can be said that all respondents fall within the productive age group.

Level of Education of Respondents

Table 2. Level of Education of Respondents

No.	Level of Education	Quantity (people)	Percentage (%)
1	Primary School	14	28
2	Junior High School	13	26
3	High School	16	46
	Total	50	100

Source: Primary Data, 2024

Table 2 shows that 14 respondents, or 28%, have a primary school education. Thirteen people, or 26%, have a junior high school education, while 16 people, or 32%, have a high school education. The low level of education among respondents results in a slower technology adoption process.

Family Dependents of Respondents

Respondents' family dependents in this research consist of wives, children, and other family members supported by the respondents as family heads.

Table 3. Family Dependents of Respondents

No.	Family Dependents	Number (people)	Percentage (%)
1	<3	16	32

2	3	34	68
Total		50	100

Source: Primary Data, 2024

Table 3 shows that most farmers, amounting to 34 people or 68%, have more than three family dependents, while 16 respondents or 32% have fewer than three family dependents. The number of family dependents increases the economic burden that these respondents must bear.

Farm Land Ownership Area of Respondents

Table 4. Farm Land Ownership Area of Respondents

No.	Land Area (Ha)	Number of Respondents (people)	Percentage (%)
1	<0,5	41	82
2	≥0,5	9	18
Total		50	100

Source: Primary Data, 2024

Table 4 shows that 41 respondents, or 82%, have farmland ownership of less than 0.5 hectares, which falls into the category of small land ownership. Meanwhile, nine respondents, or 18%, own 0.5 hectares or more land. Utami (2021) states that land ownership of less than 0.5 hectares is small.

Experience in Farming of Respondents

Table 5. Experience in Farming of Respondents

No.	Farming Experience (Years)	Number (People)	Percentage (%)
1	5 – 10	22	44
2	11 – 16	22	44
3	17 – 22	6	12
Total		50	100

Source: Primary Data, 2024

Table 5 shows that 22 people, or 44%, have farming experience between 5 and 10 years. Respondents with farming experience between 11 and 16 years also total 22 people, or 44%. Meanwhile, six people, or 12%, have farming experience between 17 and 22 years.

Factors Affecting Production in Rice Farming

The stochastic production frontier function used is the Cobb-Douglas model transformed into a natural logarithmic linear form. The production function estimation incorporates several variables, namely output in the form of rice production measured in kilograms (kg). Inputs include land (ha), seeds (kg), fertilizer (kg), pesticides (liters), and labor (HOK).

Table 6. Results of Production Function Estimation using the MLE Method

Variable	Parameter	Coefficient	Standard Error	t-ratio
Constant	β_0	0,2739	0,9826	0,2788
Land	$\beta 1$	0,4113	0,6028	0,6824
Seeds	β_2	0,3137	0,8234	0,3810
Fertilizer	β_3	0,5662	0,5867	0,9650
Pesticides	β_4	0,6235	0,8981	0,6943
Labor	β_5	-0,1035	0,8773	-0,1180
Sigma square	□2	0,1215	0,2829	0,4296
Gamma	□	0,9940	0,2873	0,3459
Log likelihood function	= -0,2011			
LR Test	= 0,1365			

Note: ***, **, * indicate significance at α 1% (2.704), 5% (2.021), and 10% (1.684), respectively

Source: Primary Data Analysis, 2024

The estimated parameter value γ in the model is statistically different from zero, although not significantly. The LR test statistic for the parameter γ is 0.1365, higher than the critical value in the Kodde and Palm Table. This indicates a technical inefficiency effect in the stochastic model. This fact shows that rice farmers in Pajawanlor Village, Ciawigebang District, are not yet fully efficient in their farming operations.

The estimated parameter value γ of 0.9940 indicates that the error term is solely due to inefficiency (ui) and not from noise (vi). This model is quite good as the value of γ is close to 1. Conversely, if γ approaches zero, it is interpreted that the entire error term is due to noise (vi), such as weather, pests, diseases, etc., rather than inefficiency. If this is the case, then the inefficiency coefficient parameter becomes meaningless.

Table 6 shows that all the variables studied do not significantly affect production outcomes. The positive coefficient value for the land variable indicates that production can be increased by adding farming land. The coefficient value of 0.4113 signifies that an increase of 1% in land will increase production by 0.41% (Omoare & Oyediran, 2020).

The positive value of the seed coefficient indicates that production can be increased with an additional amount of seeds used. A seed coefficient value 0.3137 indicates that adding 1% of seeds tends to increase production by 0.31%. Thus, farmers can improve their production by using certified seeds. This aligns with the research by Sapkota et al. (2021).

The positive value of the fertilizer coefficient indicates that additional fertilizer usage can increase production. A value of 0.5662 shows that adding 1% of fertilizers increases production by 0.57%.

The positive value of the pesticide variable coefficient indicates that additional pesticide use can increase production. A pesticide coefficient value of 0.6235 indicates that adding 1% of pesticide usage increases production by 0.62%. Thus, farmers can improve their production by increasing pesticide use. However, farmers need to consider the rise in production costs resulting from the increased use of pesticides.

The negative value of the labor variable coefficient indicates that production can be increased with reduced labor. A labor coefficient value of -0.1035 suggests that reducing labor usage by 1% tends to increase production by 0.10%.

This research reveals that the factors influencing production in rice farming in Pajawanlor Village, Ciawigebang District, Kuningan Regency, are land, seeds, fertilizers, pesticides, and labor. Farmers can increase their production by expanding their land, using certified seeds, increasing fertilizer usage, enhancing pesticide usage, and reducing labor.

Level of Technical Efficiency Achieved in Paddy Farming

The technical efficiency of paddy farming measures how much production can be achieved from the potential that farmers can attain. The estimation of the technical efficiency of paddy farming is conducted using the Frontier 4.1c program by Winata et al. (2020). The Frontier 4.1c program not only analyzes production functions but also simultaneously calculates technical efficiency.

Table 7. Distribution of Technical Efficiency in Paddy Farming

Technical Efficiency Range (%)	Frequency
41 – 50	1
51 – 60	1
61 – 70	9
71 – 80	14
81 – 90	23
91 – 100	2
Average technical efficiency level	= 78,06
Standard deviation	= 9,64
Minimum	= 49,09
Maximum	= 92,87

Source: Processed primary data, 2024

Table 7 shows that there are 39 farmers who achieved technical efficiency above 71%, while 11 farmers achieved technical efficiency below 71%. The lowest technical efficiency value attained by farmers is 49.09, and the highest is 92.87, with an average of 78.06. This technical efficiency value indicates that, on average, paddy farmers can achieve 78.06% of the potential production generated with the inputs utilized using existing technology. This suggests that, in the short term, there is still an opportunity for farmers to increase their production by 21.94%, which can be achieved by applying the best management practices using available technology.

The average technical efficiency of 78.06 indicates a gap of inefficiency of 21.94. The implication is that a 21.94% increase in production can be achieved without necessarily adding inputs, or the use of inputs can be minimized to achieve an equivalent amount of output. The technical efficiency value obtained shows that, on average, farmers can save about 21.94% to reach the highest level of technical efficiency attained by other farmers.

According to Rachmasari Ariani (2021), the differences in the technical efficiency levels achieved by farmers indicate varying levels of mastery and application of agricultural technology. The differing levels of technological mastery are caused by attributes inherent to farmers, such as education level and age, and external factors, such as a lack of extension services. Domiah & Januar (2019) and Ghee-Thean et al. (2012) state that efforts to improve efficiency will be more cost-effective compared to the introduction of new technology as a means to increase agricultural productivity if farmers are not already using efficient technology.

Factors Affecting Technical Inefficiency in Rice Farming

Identifying the factors that influence technical inefficiency in paddy rice farming can assist policymakers in formulating appropriate programs that correspond to farmers' conditions. It is assumed that the factors determining technical inefficiency stem from knowledge and skills regarding technology, the application of which in the field depends on internal factors related to farmers' managerial capabilities.

Knowledge about the level of technical inefficiency is crucial to understanding the factors causing it. This knowledge can help to reduce the level of technical inefficiency, which can enhance technical efficiency. This also means an increase in production and productivity.

The sources of technical inefficiency are generally related to farmers' managerial skills. In this research, several characteristics, including age, education, farming experience, and family size, are considered to determine farmers' managerial capabilities. The factors determining technical inefficiency in paddy rice farming were estimated using SPSS version 16 software.

Table 8. Results of Inefficiency Function Estimation Using the OLS Method

Variable	Parameter	Coefficient	Standard Error	t-ratio	Sig
Constant	δ_0	-0,894	1,628	-0,549	0,586
Age	δ_1	-1,088	0,462	-2,356	0,023
Education	δ_2	0,719	0,176	4,080	0,000
Experience	δ_3	0,796	0,207	3,848	0,000
Family Size	δ_4	0,181	0,148	-1,227	0,226
R^2 = 0,456					
Adj. R^2 = 0,408					
F-hitung = 9,440					

Source: Primary Data Analysis, 2024

The research results show that the sources of technical inefficiency collectively significantly affect the level of technical inefficiency in rice farming. Age, education, and experience have a significant impact on the level of technical inefficiency, while the family burden variable does not have a significant effect.

The regression coefficient for the age variable is negative but significant at the 5% level. This indicates that younger farmers are technically less efficient compared to older farmers. This may be due to younger farmers tending to have less farming experience, which affects the decline in work productivity (Domiah & Januar, 2019; Sapkota et al., 2021; Winata et al., 2020).

The average age of farmers is 44 years, with the youngest being 31 years old and the oldest 58 years old. According to Perera & Hemachandra (2021), the productive age is defined as between 15 and 55 years, while the non-productive category is below 15 and above 55 years. If we use this age classification, the average technical efficiency of farmers aged up to 55 years is 0.75, while the average technical efficiency achieved by farmers over 55 years old is 0.79.

The regression coefficient for the education variable is positive and significant at the 5% and 1% levels. This indicates that farmers with higher education have a higher level of technical inefficiency (Adnan et al., 2020; Ghee-Thean et al., 2012; T. M. H. Nguyen et al., 2003).

The regression coefficient of the variable "experience in agriculture" is positive and significant at the 5% and 1% levels. This result indicates that the longer the experience in running agricultural enterprises, the higher the level of technical inefficiency achieved, or the lower the level of technical efficiency. This occurs because the more experience farmers have, the more resistant they tend to be in accepting new technological innovations, as they feel comfortable with the rice farming system they have practiced. This research result aligns with the findings of Bich Tho & Umetsu (2022), Maulidiyah et al. (2024), and T. T. Nguyen et al. (2022).

Schreefel et al. (2024) state that agricultural experience is an important asset for the success of agricultural activities. The differing levels of experience among farmers will also lead to varying mindsets in applying innovations in their agricultural practices. The application of effective technology and management will influence farmers' behavior in conducting their agricultural endeavors.

The regression coefficient of the family size variable has a positive impact, although it is not significant. This indicates that the larger the number of family members, the higher the level of technical inefficiency, or the more family members there are, the lower the level of technical efficiency that can be achieved. This result is in alignment with the findings of Ishak et al. (2025) and Mishra et al. (2018).

The more dependents a family has, the greater the burden borne by the head of the family. Conversely, the fewer family members there are, the smaller the burden will be (Alanazi et al., 2021). A large number of family members leads farmers to seek additional income outside of their agricultural activities, thereby reducing the time they can dedicate to rice farming, which results in decreased efficiency.

This research shows that age, education, and experience significantly influence technical inefficiency in agricultural enterprises. An increase in age, improvement in education, and increase in experience tend to elevate technical inefficiency among farmers.

CONCLUSION

This research examines the technical efficiency of rice farming in Pajawanlor Village, Ciawigebang District, Kuningan Regency, using the Cobb-Douglas Stochastic Frontier Production Model. The findings indicate that rice farmers' average technical efficiency level is 75%, suggesting that production could be increased by up to 25% with better resource utilization. Key factors influencing efficiency include land area, seed quality, fertilizer use, labor input, and farming experience. While farmers demonstrate a relatively high level of efficiency, inefficiencies suggest the need for targeted interventions to optimize input use and farming techniques. Expanding access to quality agricultural inputs, modern farming technologies, and structured training programs could play a vital role in bridging the efficiency gap.

The research findings have significant implications for agricultural policies and farming practices. Government interventions, such as subsidies for high-quality seeds and fertilizers, financial support for small-scale farmers, and improved agricultural extension services, could help enhance efficiency. Training programs focused on optimal input usage, precision farming, and mechanization should also be expanded to improve farmers' technical skills. Encouraging technology adoption, including irrigation systems and digital farm management tools, could further optimize production. Lastly, strengthening farmer cooperatives and peer-to-peer knowledge sharing can facilitate the spread of best practices, allowing less efficient farmers to learn from those who have successfully improved their productivity. Farmers can increase rice yields, reduce production costs, and contribute to national food security by addressing these inefficiencies through policy support, education, and technology-driven solutions. Future research should explore broader socio-economic factors, such as market access and climate resilience strategies, to provide a more comprehensive understanding of agricultural efficiency in rural settings.

REFERENCES

Adnan, N., Nordin, S. M., & Anwar, A. (2020). Transition pathways for Malaysian paddy farmers to sustainable agricultural practices: An integrated exhibiting tactics to adopt Green fertilizer. *Land Use Policy*, *90*. https://doi.org/10.1016/j.landusepol.2019.104255

Alanazi, A. D., Alouffi, A. S., Alshahrani, M. Y., Alyousif, M. S., Abdullah, H. H. A. M., Allam, A. M., Elsawy, B. S. M., Abdel-Shafy, S., Alsulami, M. N., Khan, A., & Iqbal, F. (2021). A report on tick burden and molecular detection of tick-borne pathogens in cattle blood samples collected from four regions in Saudi Arabia. *Ticks and Tick-Borne Diseases*, *12*(3). https://doi.org/10.1016/j.ttbdis.2021.101652

Anisuzzaman, Hossain, M. S., Hatta, T., Labony, S. S., Kwofie, K. D., Kawada, H., Tsuji, N., & Alim, M. A. (2023). Food- and vector-borne parasitic zoonoses: Global burden and impacts. *Advances in Parasitology*, *120*, 87–136. https://doi.org/10.1016/bs.apar.2023.02.001

Aprianti, A., Noor, T. I., & Isyanto, A. Y. (2020). Analisis Efisiensi Teknis Usahatani Padi Sawah Di Desa Ciganjeng Kecamatan Padaherang Kabupaten Pangandaran. *Jurnal Ilmiah Mahasiswa Agroinfo Galuh*, *7*(3). https://doi.org/10.25157/jimag.v7i3.4012

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 and Environment*, *326*. https://doi.org/10.1016/j.agee.2021.107775

Domiah, A., & Januar, J. (2019). Studi Komparatif Usahatani Padi Semi Organik Dan Konvensional Di Desa Watukebo Kecamatan Blimbingsari Kabupaten Banyuwangi. *JSEP (Journal of Social and Agricultural Economics)*, *11*(3). https://doi.org/10.19184/jsep.v11i3.9146

Ghee-Thean, L., Ismail, M. M., & Harron, M. (2012). Measuring technical efficiency of Malaysian paddy farming: An application of stochastic production frontier approach. *Journal of Applied Sciences*, *12*(15). https://doi.org/10.3923/jas.2012.1602.1607

Ishak, A. H., Amira Mohamad, S. N., Ab Manan, S. K., Yahaya, M. H., Wan Daud, W. N., & Sharif, D. (2025). The critical success factors of waqf land development for sustainable agriculture. *Social Sciences and Humanities Open*, *11*. https://doi.org/10.1016/j.ssaho.2024.101244

Maulidiyah, R., Salam, M., Jamil, M. H., Tenriawaru, A. N., Rahmadanih, & Saadah. (2024). Examining the effects of input allocation on potato production, production efficiency, and technical inefficiency in potato farming: Evidence from the Stochastic Frontier Model in search of sustainable farming practices. *Sustainable Futures*, *7*. https://doi.org/10.1016/j.sftr.2024.100218

Mishra, A. K., Bairagi, S., Velasco, M. L., & Mohanty, S. (2018). Impact of access to capital and abiotic stress on production efficiency: Evidence from rice farming in Cambodia. *Land Use Policy*, *79*, 215–222. https://doi.org/10.1016/j.landusepol.2018.08.016

MURKAD, M., MURSIDAH, M., & WIDURI, N. (2019). Efisiensi Usahatani Padi Sawah (Oryza sativa L.) Di Desa Tanah Abang Kecamatan Long Mesangat Kabupaten Kutai Timur (Efficiency of Paddy Farming (Oryza sativa L.) in Tanah Abang Village Long Mesangat Subregency East Kutai Regency). *Jurnal Agribisnis Dan Komunikasi Pertanian (Journal of Agribusiness and Agricultural Communication)*, *2*(1). https://doi.org/10.35941/akp.2.1.2019.2193.53-60

Nguyen, T. M. H., Kawaguchi, T., & Suzuki, N. (2003). A study on technical efficiency of rice production in the Mekong Delta-Vietnam by stochastic frontier analysis. *Journal of the Faculty of Agriculture, Kyushu University*, *48*(1–2). https://doi.org/10.5109/4553

Nguyen, T. T., Do, M. H., & Rahut, D. (2022). Shock, risk attitude and rice farming: Evidence from panel data for Thailand. *Environmental Challenges*, *6*. https://doi.org/10.1016/j.envc.2021.100430

Omoare, A. M., & Oyediran, W. O. (2020). Factors affecting rice farming practices among farmers in Ogun and Niger states, Nigeria. *Journal of Agricultural Extension*, *24*(2). https://doi.org/10.4314/jae.v24i2.10

Perera, K. L. P. A., & Hemachandra, D. (2021). Technical efficiency and its determinants: Paddy farming in Mahakanumulla cascade system. *Journal of Dry Zone Agriculture*, *7*(1). https://doi.org/10.4038/jdza.v7i1.34

Rachmasari Ariani, W. O. (2021). An analysis of technical efficiency and factors affecting rice farming business production in Bombana regency, Southeast Sulawesi. *Journal of Physics: Conference Series*, *1899*(1). https://doi.org/10.1088/1742-6596/1899/1/012009

Santoso, D., Rahajeng, G. Y., & Wijaya, R. (2020). Identifikasi Kebutuhan Alsintan Tanaman Pangan (Padi Dan Jagung) Di Kota Tarakan. *Jurnal Ilmiah Inovasi*, *20*(3). https://doi.org/10.25047/jii.v20i3.2277

Sapkota, B. K., Subedi, A. P., Tripathi, K. M., & Dhakal, S. C. (2021). Economics of Organic vs Inorganic Rice Production: A Case of Chitwan District of Nepal. *Journal of Nepal Agricultural Research Council*, *7*. https://doi.org/10.3126/jnarc.v7i1.36933

Schreefel, L., Creamer, R. E., van Zanten, H. H. E., de Olde, E. M., Koppelmäki, K., Debernardini, M., de Boer, I. J. M., & Schulte, R. P. O. (2024). How to monitor the 'success' of agricultural sustainability: A perspective. *Global Food Security*, *43*, 100810. https://doi.org/10.1016/J.GFS.2024.100810

Utami, E. P. (2021). Analisis Usahatani Budidaya Tanaman Selada Kepala Secara Konvensional: Studi Kasus di Gapoktan Lembang Agri. *Agribisnis*, *5*(2).

Winata, V. V., Rondhi, M., Mori, Y., & Kondo, T. (2020). Technical Efficiency Of Paddy's Farming In Various Types Of Paddy's Seeds In Indonesia. *JSEP (Journal of Social and Agricultural Economics)*, *13*(3). https://doi.org/10.19184/jsep.v13i3.20281

© 2025 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY SA) license (https://creativecommons.org/licenses/by-sa/4.0/).