Australian Journal of Crop Science AJCS

Aust J Crop Sci. 19(03):292-300 (2025) | https://doi.org/10.21475/ajcs.25.19.03.p294 ISSN:1835-2707

Enhancing efficiency in lowland rice farming: The role of gender, human capital, and agricultural practices

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Received: 10/12/2024

Revised: 11/01/2025

Accepted: 20/01/2025

Abstract: Rice has historically been very important for humans, especially in Asia, because human life has depended on the quantity and stability of rice production. Most of the rice was produced on a small scale, but small-scale agriculture was a source of inefficiency. Increased efficiency could help lowland rice farmers subsequently, increasing household income. This study was conducted as a survey, collecting data using a questionnaire. Data collected include farmer education, age, gender, farming experience, number of family members, farming scale, use of production inputs, prices of production inputs, participation of female farmers, use of semi-organic fertilizers, rice cultivation systems, and other data related to the objectives of the study. Using the DEA method (Data Envelopment Analysis), this study analyzed the efficiency of lowland rice farming in Indonesia. The results showed that there are inefficiencies in lowland rice farming in Indonesia. This implies that lowland rice farmers in Indonesia have the potential to increase their farming efficiency. Increased efficiency of lowland rice farming could be accomplished by the use of more superior seeds, access to extension services, and cultivation systems (semi-organic and inorganic). In addition, farmers with small-scale farming can join to become large-scale, and managers with less than elementary school education. They could access more counseling so that their experience and knowledge of rice farming increase. Male and female farmers were advised to further increase their available resources so that the efficiency of lowland rice farming could be improved. To increase farming efficiency and farmers' household incomes, the government could more often offer extensions to farmers in rural communities.

Keywords: Lowland rice production; superior seeds; farming scale; farming efficiency.
Abbreviation: AE_Allocative efficiency; CRS_Constant Return to Scale; DEA_Data Envelopment Analysis; DMG_Dry Milled Grain; DMU_Decision Making Units; EE_Economic efficiency; TE_Technical Efficiency; VRS_Variable Return to Scale.

Introduction

Agriculture is an important source of food and income in developing countries, especially for the poor (Carletto et al., 2015; Kadiyala et al., 2014; Ruel and Alderman, 2013). In Indonesia, agriculture contributes 13.35 percent (second highest after the industrial sector) of gross domestic product (BPS, 2020), and around 76.84 percent of economically active women work in agriculture (Susanto, 2019).
Women's access to resources is a strong determinant of their adoption of agricultural practices and technologies that increase yields, protect the environment, and improve agricultural biodiversity (Ndiritu et al., 2014; Fisher and Carr, 2015; Simtowe et al., 2016). Technology allows women to maximize the benefits of their limited time, labor, land, and capital (Quisumbing and Pandolfelli, 2010; Ragasa et al., 2014). Using balanced fertilizers by utilizing local resources is a technology that could increase rice production.
Rice is an important agricultural product that reduces hunger for half of humanity or more than 3 billion people worldwide (IRRI, 2019). One of the rice-producing countries is Indonesia. Rice production in Indonesia throughout 2023 decreased by 1.40 percent compared to 2022 (BPS, 2024a). This decrease in production was caused by a reduction in the area of rice harvest in 2023 by 2.29 percent (BPS, 2024a). In addition, the reduction in rice production was also caused by a combination of various factors. Several factors that affect rice production are increasing prices of fertilizers and superior seeds, availability of technology, and smaller investment

opportunities for farmers (Effendy, 2010; Futakuchi et al., 2021; Effendy et al., 2022). Farmers could not meet these needs so that production could decrease.

In Indonesia, especially in Central Sulawesi, many farmers produce rice commercially, but they are limited by low education and technology adoption (Effendy et al., 2021; Arouna et al., 2021; Amoussohoui et al., 2023) and inefficient use of resources. This leads to high production costs and loss of cost advantages compared to imported rice. However, Central Sulawesi can increase its comparative advantage in rice production and marketing with increased efficiency. This increase in efficiency can help close the current gap in rice productivity (currently 4.59 tons/ha of dry milled grain (DMG) (BPS, 2024b), but has the potential to reach 5.29 tons/ha DMG (BPS, 2024b). This allows rice farmers to meet the demand for rice in Central Sulawesi and outside Central Sulawesi.

Central Sulawesi has diverse agroecological conditions and climate variations, providing a rare opportunity for farmers to produce rice yearly. However, farmers must achieve higher productivity and agricultural efficiency to increase comparative advantage. Several reports indicate that poor seed quality (Arouna et al., 2017), poor water management (Dossou-Yovo et al., 2022; Senthilkumar, 2022), low irrigated rice fields (Saito et al., 2023), abiotic stresses (soil and climate-related) (van Oort, 2018; Saito et al., 2019; Ibrahim et al., 2022), biotic constraints (weeds, birds, rodents, insects, and diseases) (Diagne et la., 2013), and suboptimal fertilizer management practices (Johnson et al., 2023) limit the productivity of lowland rice farming. While these are undoubtedly true, these general statements do not provide specific policy prescriptions for areas where lowland rice farming is practiced.

In recent years, studies on agricultural efficiency have emphasized the importance of addressing resource use efficiency and technology adoption (Guye et al., 2025; Belloc and Valentini 2024; Abdul-Rahaman et al., 2021). These studies highlighted the critical role of site-specific analysis to identify key inefficiency sources in diverse agricultural settings. However, limited research exists on Central Sulawesi's unique conditions, necessitating a more focused examination to inform tailored interventions. Furthermore, this study aims to address the following research questions: What are the primary sources of inefficiency in lowland rice farming in Central Sulawesi? How can efficiency improvements contribute to bridging the productivity gap and enhancing farmers' livelihoods in the region? This study aimed to analyze the efficiency and primary sources of inefficiency in lowland rice farming in Indonesia and make recommendations to improve the efficiency of inefficient lowland rice farming.

Results and Discussion

Statistics summary of study variables

Statistics summary of the study variables are shown in Table 1.

Table 1 indicates that the average size of lowland rice fields is classified as small-scale (≤ 2 ha), with an average rice production exceeding 4 tons per farm. Additionally, most of lowland rice farmers (77%) utilized superior seeds, in which women contributed an average of 26.2%. The average lowland rice farming manager graduated from elementary school and had experience in farming (more than 14 years). In addition to being experienced in lowland rice farming, managers also often participate in food crop agriculture extension. Less than 50% of farmers used semi-organic lowland rice farming systems, which shows that most farmers still use pesticides in lowland rice farming.

Table 1 shows that the average area of a lowland rice field is categorized as small scale (≤ 2 ha), and the average rice production is more than 4 tons/farm. Most of the lowland rice farmers (77%) used superior seeds, which play a significant role in increasing rice productivity. Using superior seeds has increased yields and production quality; thus, contributing to national food security (Muhardi and Effendy, 2021). Women's contribution to lowland rice farming reaches an average of 26.2%. Women's role in agriculture is very important, especially in the production process and decision-making (Effendy et al., 2022). Empowering women farmers can increase agricultural efficiency and productivity and act as agents of change in agriculture (Effendy et al., 2019).

Efficiency score of lowland rice farming

The average efficiency score of lowland rice farming (economic efficiency, technical efficiency, allocative efficiency, and scale efficiency) analyzed by the DEAP 2.1 program (Coelli, 1996) is shown in Table 2.

Table 2 shows that about 16.717% to 93.617% of the observed efficiency scores do not reach 0.9 under the CRS (Constant Return to Scale) and VRS (variable return to scale) approaches. Farmers used different technology in lowland rice farming, while it was more than 50% inefficient. Farmers had to adopt superior technology so that efficiency could be increased. The average efficiency score of lowland rice farming (TE, AE, EE) was higher under the VRS assumption than the CRS, aligning with the findings of Murthy et al. (2009); Shrestha et al. (2016); and Effendy et al. (2019). This difference arises because the VRS assumption allows for variations in scale efficiency by accounting for farms operating at increasing, constant, or decreasing returns to scale, whereas the CRS assumption assumes all farms operate at an optimal scale. Consequently, VRS provides a more flexible and nuanced measurement of efficiency, often resulting in higher scores.

The averages of TE, AE, and EE were found to be 0.837, 0.837 and 0.705, respectively, under the CRS assumption, and 0.882, 0.860, and 0.760, respectively, under the VRS assumption, while they have not yet reached the frontier efficiency level. This shows that there were still inefficiencies in lowland rice farming in Indonesia. Substantial reduction of input variables was still possible without reducing lowland rice production. Estimation of the levels of technical, allocative, and economic inefficiency generally indicates that significant reductions in input variable costs could be achieved in lowland rice farming to achieve a frontier efficiency level. In addition, cost reduction could be achieved through more efficient use of inputs (technical efficiency) and reallocation of inputs (allocation efficiency).

Factors that affected the efficiency of lowland rice farming

An analysis of the factors (such as type of seeds, gender contribution, farming experience, education, extension,

Table 1. Statistics summary of study variables.

Variables	Units	Mean	Std. Deviation
Output	kg/farm	4643	1874.059
Land	ha/farm	1.933	0.613
Labor	man-days/farm	207.978	59.522
Type of seeds	dummy	0.771	0.421
Gender contribution	dummy	0.738	0.441
Experience	Year	14.674	5.061
Education	dummy	0.701	0.458
Extension	number	6.119	2.902
Cultivation system	dummy	0.640	0.481

Table 2. Average efficiency score of lowland rice farming under DEA, CRS, and VRS models.

Efficiency score	TE		AE		EE	
	CRS	VRS	CRS	VRS	CRS	VRS
	%		%		%	
< 0.4	0.304	0.000	0.000	0.000	1.216	0.000
0.4 - 0.499	0.608	0.000	0.304	0.304	3.647	0.304
0.5 - 0.599	1.824	0.000	0.000	0.000	22.796	11.854
0.6 - 0.699	5.471	3.951	1.520	0.608	21.277	20.973
0.7 - 0.799	31.307	24.012	30.395	27.356	20.973	26.140
0.8 - 0.899	26.444	22.188	48.328	36.474	23.708	25.836
≥ 0.9	34.043	49.848	19.453	35.258	6.383	14.894
Mean Efficiency	0.837	0.882	0.837	0.860	0.705	0.760

** Significant α 1%; * Significant α 5%.

harvested area, and cultivation system) that affect the efficiency of lowland rice farming (TE, AE, EE, and SE) was conducted using Tobit regression. The results of the Tobit regression analysis are presented in Table 3.

Table 3 shows that the efficiency of lowland rice farming is mostly related to the explanatory variables. The type of seeds has a significant and positive effect on TE and EE, indicating that superior seed varieties increase the technical and economic efficiency of lowland rice farming. The use of superior seed varieties has technical potential to increase lowland rice productivity and plays an important role in overcoming food insecurity for small farmers (Fuwa et al., 2007; da Silva Dias, 2010; Shrestha et al., 2016). Gender's contribution has a statistically positive and significant effect on TE, AE, and EE in lowland rice farming, suggesting that male contributions are more effective than those of their female counterparts. This outcome may reflect socio-cultural factors such as traditional gender roles, which often assign men greater access to resources, training, and decision-making authority in agricultural activities. Men might also engage more frequently in physically demanding tasks or those with higher technical complexity, which could enhance productivity. However, this finding underscores the need to explore strategies that empower women and address disparities in access to resources, training, and participation; thereby, optimizing the contributions of both genders in lowland rice farming. Though this result contradicts the findings of Gbigbi (2011) and Shrestha et al. (2016), it indicates that the greater involvement of males in lowland rice farming activities could increase production efficiency. This contradicting studies point to several factors that may contribute to such discrepancies in research outcomes. Variations in sample size can significantly affect the representativeness of the findings. Smaller sample sizes may lead to overgeneralization or underrepresentation of specific sub-groups, such as female farmers, who may play key roles in certain regions. Differences in methodologies, such as the choice of efficiency measurement models (e.g., Data Envelopment Analysis vs. Stochastic Frontier Analysis), variable selection, and data collection methods can lead to divergent results. Variations in demographic and socio-economic characteristics, such as education levels, access to resources, and cultural practices, can influence gender-specific outcomes.

The positive and significant effect of experience with lowland rice farming on TE and EE in lowland rice production shows that the length of time a farmer has been in his job plays a positive role in increasing the efficiency of lowland rice farming. The greater experience of farmers could increase their knowledge in using agriculture technology to increase farming efficiency. Education has a positive and significant effect on TE, EA, and EE in lowland rice farming, which indicates that the higher the education of farmers, the greater the increase in the efficiency of lowland rice farming. Access to extension statistically has a positive and significant effect on TE and EE in lowland rice farming, which implies that access to extension could increase farmers' insights into the management of lowland rice crops so that farming inefficiencies could be reduced. Farming experience, education, and access to extension helped farmers in decision-making, such as in the selection of seed varieties, use of technology, and product marketing (Akobundu et al., 2004; Shrestha et al., 2016). Field schools for lowland rice farmers have been established to develop farmer competencies in fertilization and integrated pest control (Rasyid et al., 2016). This activity was to encourage the use of appropriate and environmentally friendly inputs to help increase the health of producers and consumers (Atreya, 2007).

The scale of lowland rice farming has a statistically positive and significant effect on TE, EA, and EE, which implies that the wider the area of agriculturally cultivated land, the greater the increase in technical, allocative, and economic efficiency in lowland rice farming. This result is

Table 3. Factors that affected technical, allocative, and economic efficiency in lowland rice production.

Model	TE		AE		EE	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Intercept	0.576	0.018	0.708	0.014	0.377	0.019
Type of seeds	0.041**	0.013	0.002	0.010	0.035*	0.014
Gender cotribution	0.025*	0.011	0.018*	0.008	0.034**	0.011
Manager's farming experience	0.002*	0.001	0.000	0.001	0.002*	0.001
Manager's education	0.076**	0.012	0.074**	0.009	0.122**	0.013
Access to extension	0.004**	0.002	0.001	0.001	0.005**	0.002
Farming scale	0.054**	0.008	0.026**	0.006	0.068**	0.008
Cultivation system	0.045**	0.011	0.010	0.008	0.045**	0.012
Sigma	0.076**	0.003	0.057**	0.002	0.082**	0.003
Log likelihood	366.260		472.330		355.72	

** Significant α 1%; * Significant α 5%.

consistent with the findings of Kočišová (2015) which show that the largest total agricultural area utilized has the strongest positive impact on efficiency. These findings indicate that relatively small-scale lowland rice farming could increase its efficiency by combining farms to operate on a larger scale.

The cultivation system positively and significantly affects TE, AE, and EE, implying that the semi-organic lowland rice cultivation system can increase farming productivity. These results are consistent with previous findings (Krasachat, 2012; Effendy et al., 2019), which state that using organic materials can increase technical, allocative, and economic efficiency; thereby, increasing farming productivity. Organic farming can improve rice quality, environmental protection, farmer welfare, and soil fertility maintenance (Makower, 2009; Al-Taie et al., 2015).

Potential for cost reduction of lowland rice farming

The potential for cost reduction in lowland rice farming is described in Table 4.

Table 4 highlights statistically significant differences between several factors and their impact on efficiency (EE) and cost reduction in lowland rice farming. The significant factors include Seed Type (Local vs. Superior Seeds): Superior seeds are associated with higher EE and lower levels of potential cost reduction compared to local seeds. This suggests that adopting superior seeds enhances farming efficiency by optimizing input use and reducing unnecessary expenditures. The findings align with studies emphasizing the genetic advantages of superior seeds, such as their resistance to pests and adaptability to environmental stresses (Sakhno et al., 2024).

Manager's gender (Female vs. male contribution): Male-managed farms exhibit higher EE and lower potential cost reductions than female-managed farms. This difference may tend from disparities in access to resources, decision-making autonomy, or labor intensity between male and female managers (Julien et al., 2023). Female managers often encounter barriers that may limit their efficiency and cost management capabilities. Women usually have restricted access to or ownership of land, which limits their ability to invest in long-term improvements and leverage their assets for credit. Female managers may have less access to financial services, including loans and subsidies, hindering their ability to purchase quality inputs such as fertilizers, seeds, or machinery. Programs that provide women-specific grants, microfinance opportunities, and land rights reforms could help bridge these gaps. Women in many regions have fewer opportunities to participate in agricultural training programs or extension services, resulting in less awareness of modern farming techniques. Limited exposure to or familiarity with agricultural technologies can reduce female managers' efficiency. Gender-inclusive training programs and technology demonstrations tailored to women's needs and schedules could improve their skills and efficiency. In many cultures, women are expected to balance farming responsibilities with household and childcare duties, leaving less time for farm management. While male managers may currently exhibit higher efficiency in lowland rice farming, the disparity likely reflects structural and systemic challenges female managers face rather than inherent differences in capability. Targeted interventions to address these barriers can enable female managers to realize their full potential, contributing to a more equitable and efficient agricultural sector.

Farming experience (≤ 11 Years vs. > 11 Years): Experienced managers (farming for over 11 years) demonstrate greater EE and lower cost reduction potential. This finding corroborates research suggesting that experience enhances resource allocation, risk management, and adaptive strategies in farming (Xu, 2024).

Education level (Not graduated from elementary school vs. other levels): Managers with higher education levels achieve superior EE and reduced cost reduction opportunities. Education improves technical knowledge and adoption of innovative practices, which are critical for efficient farming operations (Lozano and Adenso-Díaz, 2021).

Access to extension services (< 5 Times vs. ≥ 5 Times): Frequent access to extension services (≥ 5 times) significantly enhances EE and minimizes cost reduction potential. This reflects the importance of technical guidance and information dissemination in addressing inefficiencies (Argaw et al., 2023).

Land area (≤ 2 ha vs. > 2 ha):

Larger farms (≥ 2 ha) demonstrate higher EE and reduced cost potential compared to smaller farms. Economies of scale allow for more efficient input use and better resource allocation (Lozano and Adenso-Díaz, 2021).

Table 4. Potential for cost reduction in lowland rice farming.

Variables	n	Mean Economic efficiency	Actual cost (IDR)	Minimum cost (IDR)	cost reduction (IDR)	Cost reduction (%)
Cost minimization by type of seeds						
Local seeds	76	0.584	1,260,395	12,538,203	8,722,191	41.03
Superior seeds	253	0.741	24,592,794	18,534,279	6,058,515	24.64
t-value (local seeds vs superior seeds)		-10.072**	-3.705**	-6.879**	6.884**	
Cost minimization by gender contribution						
Female	87	0.646	22,514,698	14,772,407	7,742,292	34.39
Male	242	0.726	24,293,339	18,003,622	6,289,717	25.89
t-value (Female contribution vs male contribution)		-4.833**	-2.040*	-3.701**	3.750**	
Cost minimization by farming experience						
Farming experience <11 years	99	0.632	22,320,997	14,287,940	8,033,057	35.99
Farming experience =>11 years	230	0.736	24,469,514	18,380,739	6,088,775	24.88
t-value (<11 years vs => 11 years)		-6.772**	-2.572*	-4.952**	5.328**	
Cost minimization by manager education						
Not graduated in primary school	99	0.562	21,660,556	12,299,551	9,361,005	43.22
Others	230	0.766	24,753,791	19,236,611	5,517,180	22.29
t-value (Not graduated in primary school vs others)		-17.099**	-3.744**	-9.053**	12.183**	
Cost minimization by access to extension						
Access to extension < 5 times	113	0.660	22,487,356	15,045,732	7,441,624	33.09
Access to extension =>5 times	216	0.777	25,472,882	20,126,481	5,346,401	20.99
t-value (Access to extension < 5 times vs Access to extension =>5 times)		-4.416**	-2.521*	-3.963**	3.233**	
Cost minimization by farming scale						
Land area =< 2 ha	226	0.651	20,913,667	13,531,296	7,382,371	35.30
Land area > 2 ha	103	0.853	31,915,625	27,212,670	4,702,955	14.74
t-value (Land area =< 2 ha vs Land area > 2 ha)		-15.537**	-17.406**	-29.052**	7.304**	
Cost minimization by cultivation system						
Semi-organic	119	0.607	21,696,499	13,425,691	8,270,808	38.12
Non-organic	210	0.760	25,012,227	19,231,490	5,780,737	23.11
t-value (semi-organic vs non-organic)		-11.571**	-4.220**	-7.700**	7.394**	
Average cost reduction						29.83

** Significant α 1%; * Significant α 5%.

Cultivation system (Non-organic vs. semi-organic): Semi-organic farming systems show lower EE and higher cost reduction potential than non-organic systems. Although semi-organic systems are associated with environmental benefits, their cost structure requires further optimization to match the efficiency levels of non-organic systems (Gamage et al., 2023).

The minimum cost is the total cost incurred in lowland rice farming if it operates at the level of technical efficiency and full allocation. The minimum cost is calculated by multiplying the actual cost with the EE score of each lowland rice farm. The potential cost reduction is the actual cost reduction with the minimum cost. The results of the study show that lowland rice farmers could reduce their actual costs by 30%, if they operate on the frontier. This study found inefficiencies in lowland rice farming.

Materials and Methods

Study area and sampling techniques

This study was done in Central Sulawesi (area of 61,841.29 km^2) which has a tropical climate (BPS, 2024b). Parigi Moutong and Sigi Regency were selected for the study location because they have the largest lowland rice harvesting areas in Central Sulawesi, namely 29.30% (54,388 ha) and 7.46% (17,568 ha), respectively. The productivity of these regencies was also the highest in Central Sulawesi (BPS, 2024b). Three villages from each regency was randomly selected for survey. The villages selected were Ranteleda, Tanah Harapan, Tongoa (representing Sigi Regency), and Balinggi, Astina, and Nambaru (representing Parigi Moutong Regency).

The samples used were 329 lowland rice farms which were selected by proportional sampling: Ranteleda Village of 56 farms, Tanah Harapan Village of 44 farms, Tongoa Village of 52 farms, Balinggi Village of 65 farms, Astina Village of 52 farms, and Nambaru Village of 60 farms. Data were collected from June to August 2024 using a questionnaire.

Data Envelopment Analysis (DEA)

The DEA method has often been used to measure the technical efficiency of input use in agricultural land (Candemir and Koyubenbe, 2006; Lilienfield and Asmild, 2007; Davidova and Latruffe, 2007; Haji, 2007; Bojnec and Latruffe, 2008; Murthy et al., 2009; Watkins et al., 2014; Toma et al., 2015). Data Envelopment Analysis (DEA) is a non-parametric approach (linear programming) that is used to assess the efficiency of the decision-making unit (DMU) by involving many inputs and several outputs to estimate technical, allocative, pure technical, economic and scale efficiencies (Charnes et al., 1978).

DEA assumptions regarding the type of technology can be in the form of constant return to scale (CRS) or variable return to scale (VRS).

In this study, we evaluated the efficiency of small-scale lowland rice farming in CRS, as in Charnes et al. (1978), and VRS, as in Banker et al. (1984). The CRS assumption proposed by Charnes et al. (1978) scored the overall technical efficiency by solving Equation 1 (the objective function of the linear programming model). Suppose n decision making units (DMU), lowland rice farming produces one type of output using different inputs (m). Yi = the resulting output; Xi = input vector (m × 1); Y is the output vector (1 × n); and X is the DMU input matrix (m × n). Then the problem can be stated as follows:

$$min_{\theta,\lambda}\theta^{CRS},$$

Subject to:
$$y_i \leq Y\lambda,$$
$$\theta_{X_i} \geq X\lambda,$$
$$\lambda \geq 0, \qquad (1)$$

θ = scalar which is the technical efficiency score of i DMU under CRS

λ = n x 1 vector of constants

if θ = 1, then the DMU is technically efficient assuming CRS; and if θ < 1, DMU is not technically efficient.

The CRS assumption is only appropriate if all DMU operate at optimal scale (each additional input will produce the same output). Imperfect competition, financial constraints, etc. can cause the DMU to not operate optimally (Coelli et al., 2005). The use of the CRS specification, when not all DMU operate at the optimal scale will result in the TE size being confounded by the scale efficiency (SE). The use of the VRS specification will allow the calculation of TE without SE effect. Banker et al. (1984) suggested an extension of the DEA CRS model to account for variable returns to scale (VRS) situations. The CRS linear programming problem can be modified to VRS by adding the convexity constraint: N1'λ =1 on the equation (1):

$$min_{\theta,\lambda}\theta^{VRS},$$

Subject to:
$$y_i \leq Y\lambda,$$
$$\theta_{X_i} \geq X\lambda,$$
$$N1\lambda' = 1,$$
$$\lambda \geq 0, \qquad (2)$$

Where; N1 = N x 1 vector of ones.

The VRS approach, as in Banker et al. (1984), is commonly found on farms. Based on this, we analyzed the efficiency of small-scale lowland rice farming in Indonesia using the DEA, CRS, and VRS approaches. To obtain the overall economic efficiency (EE), we can solve the cost-minimizing DEA model (Equation 3) assuming CRS, which is the objective function of the linear programming model (Fare et al., 1985; 1994).

$$min_{\lambda,X_i^{*}}W_i'X_i^{*}$$

Subject to:
$$y_i \leq Y\lambda,$$
$$X_i^{*} \geq X\lambda,$$
$$\lambda \geq 0, \qquad (3)$$

X_i^{*} = cost-minimizing input vector (economically efficient for the i^th^ DMU),

W_i' = input price vector,

yi = output.

The economic efficiency for i^{th} farm is calculated as the ratio of the minimum cost to the observed cost (Equation 4), if EE = 1 indicates economically efficient, and EE < 1 indicates economically inefficient. Economic efficiency for DMU can also be defined as the product of technical and allocation efficiency (Farrel, 1957).

$$EE_i = \frac{W_i X_i^{*}}{W_i X_i} \qquad (4)$$

Allocative efficiency (AE) is the ability of the farm to select inputs by minimizing costs (Equation 5).

$$AE_i = \frac{EE_i}{\theta_i^{CRS}} = \frac{W_i' X_i^{*}}{W_i'(\theta_i^{CRS} X_i)}$$

$$AE_i = \frac{EE_i}{Q_i} \text{ or}$$

$$AE_i = \frac{W_i X_i^{*}}{W_i(Q_i X_i)} \qquad (5)$$

AE = 1 indicates that the farm is efficient in allocation, and AE < 1 indicates the maximum cost proportion that can be saved by technically efficient farming by minimizing cost (Chavas and Aliber, 1993).

Technical efficiency (TE) refers to the ability of a farm to produce an optimal output from a given range of inputs, or to produce a given output from a minimum number of inputs for a given technology. Allocative efficiency (AE) or price efficiency is a measure of the extent to which the farm equates the product of marginal value with marginal cost.

Tobit analysis

Two-limit Tobit regression model was used to analyze the factors that affect the efficiency of lowland rice farming. The factors analyzed were type of seed, manager's gender, manager's experience in farming, manager's education, access to extension by managers, and access to credit in farming. The dependent variable in the Tobit regression equation (6) has an efficiency score that is constrained between zero and one; thus, we estimated the Tobit regression model with the maximum likelihood approach (Tobin, 1958).

$$EE_i^{*} = \alpha_0 + \sum_{j=1}^{J} \alpha_j P_{ij} + \mu_i \qquad \mu_i \sim \text{ind}\ (0, \sigma^2) \qquad (6)$$

where EE* represents the dependent variable (economic efficiency variable) obtained from the efficiency score estimated from DEA, α_0 and α_j are the parameters to be estimated, P_{ij} is the independent variable associated with lowland rice farming; and μ_i is error term.

Variable specifications

Lowland rice production in this study is modeled as a function of land, chemical fertilizers, seeds, and labor which is stated in the following equation.

$$Y = f(X_1, X_2, X_3, X_4) \qquad (7)$$

where:

Y = Lowland rice production in the form of rice,

X_1 = Land,

X_2 = Chemical fertilizers,

X_3 = Seeds,

X_4 = Labor

The determinants of the efficiency of lowland rice farming are stated in the following equation:

$$EE_i^{*} = f(P_1, P_2, P_3, P_4, P_5, P_6, P_7) \qquad (8)$$

where:

EE_i^{*} = efficiency of i^{th} lowland rice farming from DMU of DEA model:

P_1 = type of seeds (Dummy)

0 = For local seeds

1 = For superior seeds

P_2 = Gender contribution (Dummy)
0 = For female
1 = For male
P_3 = Manager's experience in farming (year)
P_4 = Manager's education (Dummy)
0 = For those who not finish elementary school
1 = For others
P_5 = Access to extension by manager (number)
P_6 = Lowland rice farming scale (Dummy)
0 = For small scale (≤ 2 ha)
1 = For large scale (> 2ha)
P_7 = cultivation system (Dummy)
0 = for non-organic
1 = for semi-organic

Conclusion

This study used an input-oriented data envelopment analysis (DEA) model to analyze the efficiency of lowland rice production in Indonesia. The results show that most lowland rice farming operates inefficiently. The average technical, allocative, and economic efficiency are estimated at 0.837 and 0.837, respectively, which indicates there is potential to increase the technical and allocative efficiency of lowland rice farming. The average potential for cost reduction in lowland rice farming is 30% by adopting the best agricultural technology. The results of the Tobit model regression show that type of seeds, gender contribution, manager's experience, manager's education, access to extension by managers, land area, and cultivation system influenced technical efficiency and economic efficiency of lowland rice farming. The gender contribution, manager's education, and land area affected the allocative efficiency of lowland rice farming. These variables were important to increase efficiency of lowland rice farming, which could improve yield and income for the farmers. Therefore, these variables could be considered by policy makers interested in increasing the yield and income of lowland rice farming.

Acknowledgements

The authors would like to thank the reviewers for their valuable comments and suggestions and the Ministry of Education, Culture, Research, and Technology for providing research funding support under contract number 095/E5/PG.02.00.PL/2024 on June 11, 2024.

References

Abdul-Rahaman A, Issahaku G, Zereyesus YA (2012) Improved rice variety adoption and farm production efficiency: Accounting for unobservable selection bias and technology gaps among smallholder farmers in Ghana. Technology in Society, 64: 101471
Akobundu E, Alwang J, Essel A, Norton GW, Tegene A (2004) Does extension work? Impacts of a programe to assist limited-resource farmers in Virginia. Review of Agricultural Economics. 26: 361–372.
Al-Taie WAA, Rahal MKM, Al-Sudani ASA, Al-Farsi KAO (2015) Exploring the consumption of organic foods in the United Arab Emirates. Sage Open. 5(2): 1-12.
Amoussohoui R, Arouna A, Bavorova M, Verner V, Yergo W, Banout J (2023) Analysis of the factors influencing the adoption of digital extension services: evidence from the RiceAdvice application in Nigeria. J. Agric. Educ. Ext. 1–30. DOI: 10.1080/1389224X.2023.2222109.
Argaw B, Yehuala K, Aschalew A (2023) Review on the Role of Agricultural Extension Service on Increasing Farm Productivity in Ethiopia. International Journal of Finance Research, 4(2): 77-89.
Arouna A, Devkota KP, Yergo WG, Saito K, Frimpong BN, Adegbola PY, Depieu ME, Kenyi DM, Ibro G, Fall AA, Usman S (2021). Assessing rice production sustainability performance indicators and their gaps in twelve sub-Saharan African countries. Field Crop Res. 271: 108263.
Arouna A, Lokossou JC, Wopereis MCS, Bruce-Oliver S, Roy-Macauley H (2017) Contribution of improved rice varieties to poverty reduction and food security in sub-Saharan Africa. Glob. Food Secur. 14:54–60. https://doi.org/10.1016/j. gfs.2017.03.001.
Atreya K (2007) Farmers' willingness to pay for community integrated pest management training in Nepal. Agriculture and Human Values. 24: 399–409.
Banker RD, Charnes A, Cooper WW (1984) Models for the estimation of technical and scale inefficiencies in DEA. Management Science. 30: 1078–1092.
Belloc F, Valentini E (2024) Dissecting environmental efficiency: The role of technology adoption and usage. Journal of Economic Behavior & Organization, 228: 106776
Bojnec S, Latruffe L (2008) Measures of farm business efficiency. Industrial Management & Data Systems. 108: 258–270.
BPS (2020) Struktur Produk Domestik Bruto Menurut Lapangan Usaha Kuartal III 2019. Badan Pusat Statistik (BPS). https://databoks.katadata.co.id/datapublish/2020/01/29/kontribusi-pertanian-kedua-tertinggi-dalam-pdb-indonesia
BPS (2024a) Luas Panen dan Produksi Padi di Indonesia 2023 (Angka Tetap). Berita Resmi Statistik, No. 20/03/Th. XXVII, 1 Maret 2024. Badan Pusat Statistik (BPS).
BPS (2024b) Sulawesi Tengah dalam angka. Badan Pusat Statistik (BPS) Sulawesi Tengah.
Candemir M, Koyubenbe N (2006) Effeciency analysis of dairy farms in the province of izmir (Turkey): Data envelopment analysis (DEA). Journal of Applied Animal research. 29: 61–64.
Carletto G, Ruel M, Winters P, Zezza A (2015) Farm-Level Pathways to Improved Nutritional Status: Introduction to the Special Issue. The Journal of Development Studies. 51(8): 945–957.
Chaenes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision- making units. European Journal of Operational Research. 2: 429–444.
Chavas JP, Aliber M (1993) An analysis of economic efficiency in agriculture: a nonparametric approach. Journal of Agricultural and Resource Economics. 18: 1–16.
Coelli T (1996) A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer Program). Department of Econometrics, University of New England, Armidale, Australia.

Coelli TJ, Rao DSP, O'Donnell CJ, Battese GE (2005) An introduction to efficiency and productivity analysis. (2nd ed.) New York, Springer.

da Silva Dias JC (2010) Impact of improved vegetable cultivars in overcoming food insecurity. Euphytica. 176: 125–136.

Davidova S, Latruffe L (2007) Relationships between technical efficiency and financial management for czech republic farms. Journal of Agrıcultural Economıcs. 58: 269–288.

Diagne A, Alia DY, Amovin-Assagba E, Wopereis MCS, Saito K, Nakelse T (2013) Farmers perceptions of the biophysical constraints to rice production in sub [1] Saharan Africa, and potential impact of research. In: Wopereis, M.C.S., Johnson, D. E., Ahmadi, N., Tollens, E., Jalloh, A. (Eds.), Realizing Africa's Rice Promise. CABI, Wallingford, Oxfordshire, UK, pp. 46–68.

Dossou-Yovo ER, Devkota KP, Akpoti K, Danvi A, Duku C, Zwart SJ (2022) Thirty years of water management research for rice in sub-Saharan Africa: Achievement and perspectives. Field Crop. Res. 283: 108548 https://doi.org/10.1016/j.fcr.2022.108548.

Effendy (2010) Efisiensi faktor produksi dan pendapatan usahatani padi sawah di Desa Masani Kecamatan Poso Pesisir Kabupaten Poso. J. Agroland. 17 (3) :233 – 240.

Effendy, Antara M, Muhardi, Pellokila MR, Mulyo JH (2021) Identification of Factors Affecting Decisions to Adopt Pesticides at Lowland Rice Farms in Indonesia. International Journal of Design & Nature and Ecodynamics. 16(6):717-723.

Effendy, Antara M, Muhardi, Pellokila MR, Mulyo JH (2022) Effect of Socio-Economic on Farmers' Decisions in Using Lowland Rice Production Inputs in Indonesia. International Journal of Sustainable Development and Planning. 17(1): 235-242.

Effendy, Pratama MF, Rauf RA, Antara M, Basir-Cyio M, Mahfudz, et al. (2019). Factors influencing the efficiency of cocoa farms: A study to increase income in rural Indonesia. PLoS ONE. 14(4): e0214569. https://doi.org/10.1371/journal.pone.0214569

Fare R, Grosskopf S, Lovell CAK (1985) The Measurement of Efficiency of Production. Kluwer-Nijhoff Publishing, Boston.

Fare R, Grosskopf S, Lovell CAK (1994) Production Frontiers. Cambridge University Press, Cambridge.

Farrell MJ (1957) The measurement of productive efficiency. Journal of the Royal Statistical Society. 120: 253–290.

Fisher M, Carr ER (2015) The influence of gendered roles and responsibilities on the adoption of technologies that mitigate drought risk: the case of drought-tolerant maize seed in eastern Uganda. Global Environmental Change. 35:82–92. https://doi.org/10.1016/j.gloenvcha.2015.08.009

Futakuchi K, Senthilkumar K, Arouna A, Vandamme E, Diagne M, Zhao D, Manneh B, Saito K (2021) History and progress in genetic improvement for enhancing rice yield in sub-Saharan Africa. Field Crop. Res. 267: 108159.

Fuwa N, Edmonds C, Banik P (2007) Are small-scale rice farmers in eastern India really inefficient? Examining the effects of micro-topography on technical efficiency estimates. Agricultural Economics. 36: 335–346.

Gamage A, Gangahagedara R, Gamage J, Jayasinghe N, Kodikara N, Suraweera P, Merah O (2023) Role of organic farming for achieving sustainability in agriculture. Farming System, 1: 100005

Gbigbi MT (2011) Economic efficiency of smallholder sweet potato producers in Delta state, Nigeria: a case study of Ughelli south local government area. Research Journal of Agriculture and Biological Sciences. 7: 163–168.

Guye A, Tefera T, Sileshi M, Abdi-Khalil E (2025) Impact of multiple maize technology package adoption on the production efficiency and food security of smallholder farmers in Ethiopia: Evidence from the Sidama region. Heliyon, 11(1): e41280

Haji J (2007) Production efficiency of smallholders' vegetable-dominated mixed farming system in eastern Ethiopia: A non-parametric approach. Journal of Afrıcan Economies. 16: 1–27.

Ibrahim A, Saito K, Kokou A, Johson JM, Diagne M, Djagba JF, Felix F, Slvia B, Martial HO (2022) Seizing opportunity towards sustainable rice cultivation in sub-Saharan Africa. Environ. Sustain. Indic. 15: 100189.

IRRI (2019) Feeding the world while caring for the planet. International Rice Research Institute (IRRI). https://www.irri.org/world-food-day-2019-rice-zero-hunger

Johnson JM, Ibrahim A, Dossou-Yovo ER, Senthilkumar K, Tsujimoto Y, Asai H, Saito K (2023) Inorganic fertilizer use and its association with rice yield gaps in sub-Saharan Africa. Glob. Food Secur. 38: 100708.

Julien JC, Bravo-Ureta BE, Rada NE (2023) Gender and agricultural Productivity: Econometric evidence from Malawi, Tanzania, and Uganda. World Development. 171: 106365.

Kadiyala S, Harris J, Headey D, Yosef S, Gillespie S (2014) Agriculture and nutrition in India: mapping evi- dence to pathways. Annals of the New York Academy of Sciences. 1331(1):43–56.

Kočišová K (2015) Application of the DEA on the measurement of efficiency in the EU countries. Agric Econ Czech. 61(2): 51–62.

Krasachat W (2012) Organic production practices and technical inefficiency of durian farms in Thailand. Procedia Economics and Finance. 3: 445–450.

Lilienfeld A, Asmild M (2007) Estimation of excess water use in irrigated agriculture: A data envelopment analysis approach. Agrıcultural Water Management. 94: 73–82.

Lozano S, Adenso-Díaz B (2021) A DEA approach for merging dairy farms. Agric. Econ. – Czech. 67: 209–219.

Makower J (2009) Strategies for the Green Economy: Opportunities and Challenges in the New World of Business. McGraw-Hill, New York.

Muhardi, Effendy (2021) Technical efficiency and the factors that affect it in rice production in Indonesia. Asian Journal of Agriculture and Rural Development. 11(3): 230 - 235.

Murthy DS, Sudha M, Hegde MR, Dakshinamoorthy V (2009) Technical efficiency and its determinants in tomato production in Karnataka, India: data envelopment analysis (DEA) approach. Agricultural Economics Research Review. 22: 215–224.

Ndiritu SW, Kassie M, Shiferaw B (2014) Are there systematic gender differences in the adoption of sustainable agricultural intensification practices? Evidence from Kenya. Food Policy. 49. Part 1:117–127. https://doi.org/10.1016/j.foodpol.2014.06.010

Quisumbing AR, Pandolfelli (2010) Promising approaches to address the needs of poor female farmers: Resources, constraints, and interventions. World Development. 38(4): 581–592. https://doi.org/10.1016/j.worlddev.2009.10.006.
Ragasa CD, Sengupta M, Osorio N, Haddad Q, Mathieson K (2014) Gender-specific approaches, rural institu- tions and technical innovations. Rome: Food and Agricultural Organization of the United Nations, International Food Policy Research Institute, and Global Forum on Agricultural Research. http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/129039
Rasyid MN, Setiawan B, Mustadjab MM, Hanani H (2016) Factors that Influence Rice Production and Technical Efficiency in the Context of an Integrated Crop Management Field School Program. American Journal of Applied Sciences. 13(11): 1201.1204. DOI: 10.3844/ajassp.2016.1201.1204
Ruel MT, Alderman H (2013) Maternal and Child Nutrition Study Group. Nutrition-sensitive interventions and programmes: how can they help to accelerate progress in improving maternal and child nutrition? The lancet. 382(9891):536–51.
Saito K, Senthilkumar K, Dossou-Yovo ER, Ali I, Johnson JM, Mujawamariya G, Rodenburg J (2023) Status quo and challenges of rice production in sub-Saharan Africa. Plant Prod. Sci. 26(3): 320–333.
Saito K, Vandamme E, Johnson JM, Tanaka A, Senthilkumar K, Dieng I, Akakpo C, Gbaguidi, F, Segda Z, Bassoro I, Lamare D, Gbakatchetche H, Belay B, Jaiteh F, Kwame R, Dogbe W, Sekou K, Rabeson R, Kamissoko N, Maïga I, Dawi B, Oladele S, Kalisa A, Baggie I, Jasper G, Ablede K, Ayeva T, Nanfumba D, Wopereis MCS (2019) Yield-limiting macronutrients for rice in sub-Saharan Africa. Geoderma. 338: 546–554.
Sakhno T, Marenych M, Semenov A, Sakhno Y, Jaisi D (2024) Roles of seed priming in increasing the adaptability and productive potential of agricultural crops. Advances in Agronomy, Available online 22 December 2024.
Senthilkumar K (2022) Closing rice yield gaps in Africa requires integration of good agricultural practices. Field Crops Res. 285: 108591.
Shrestha RB, Huang WC, Gautam S, Johnson TG (2016) Efficiency of small- scale vegetable farms: policy implications for the rural poverty reduction in Nepal. Agric.Econ–Czech. 62(4): 181–195.
Simtowe F, Asfaw S, Abate T (2016) Determinants of agricultural technology adoption under partial population awareness: the case of pigeonpea in Malawi. Agric Econ. 4:1–21. https://doi.org/10.1186/s40100-016-0051-z
Susanto DN (2019) Perempuan, Pertanian, dan Kekuatan Ekonomi Indonesia. https://timurmedia.com/perempuan-pertanian-dan-kekuatan-ekonomi-indonesia/
Tobin J (1958) Estimation of relationships for limited dependent variables. Econometrica. 26: 24–36.
Toma E, Dobre C, Dona I, Cofas E (2015) DEA applicability in assessment of agriculture efficiency on areas with similar geographically patterns. Agriculture and Agricultural Science Procedia. 6: 704–711.
van Oort PAJ (2018) Mapping abiotic stresses for rice in Africa: drought, cold, iron toxicity, salinity and sodicity. Field Crops Res. 219:55–75 https://doi.org/10.1016/j.fcr.2018.01.0164.
Watkins KB, Hristovska T, Mazzanti R, Wilson CE, Schmidt L (2014) Measurement of technical, allocative, economic, and scale efficiency of rice production in Arkansas using data envelopment analysis. Journal of Agricultural and Applied Economics. 46, 89–106.
Xu B, Baležentis T, Štreimikienė D, Shen Z (2024) Enhancing agricultural environmental performance: Exploring the interplay of agricultural productive services, resource allocation, and marketization factors. Journal of Cleaner Production, 439: 140843.