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Impact of integrated crop management on rice farming efficiency in semi-arid West Timor, Indonesia

UMBU JOKA[1,♥], AGUSTINUS NUBATONIS[1], JEFRIANUS NINO[2], OKTOVIANUS TABENU[1], DIAN GRACE LUDJI[3]

[1]Study Program of Agribusiness, Faculty of Agriculture, Science and Health, Universitas Timor. Jl. Km. 09, North Central Timor 85613, East Nusa Tenggara, Indonesia. Tel./fax.: +62-380-881085, ♥email: umbu.joka@research.uwa.edu.au; umbujoka@unimor.ac.id

[2]Study Program of Agrotechnology, Faculty of Agriculture, Science and Health, Universitas Timor. Jl. Km. 09, North Central Timor 85613, East Nusa Tenggara, Indonesia

[3]Study Program of Information Technology, Faculty of Agriculture, Science and Health, Universitas Timor. Jl. Km 09, North Central Timor 85613, East Nusa Tenggara, Indonesia

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Abstract. *Joka U, Nubatonis A, Nino J, Tabenu O, Ludji DG. 2025. Impact of integrated crop management on rice farming efficiency in semi-arid West Timor, Indonesia. Intl J Trop Drylands 9: 148-158.* This study assesses the impact of Integrated Crop Management (ICM) on the technical efficiency of rice farmers in the semi-arid border regions of West Timor, Indonesia, specifically North Central Timor and Kupang District. These regions face significant agricultural challenges, including low soil fertility, erratic rainfall, and limited access to modern farming technologies. Despite national promotion of ICM, there is a lack of empirical evidence on how ICM adoption influences technical efficiency in semi-arid border environments, representing a critical research gap that this study aims to address. Using data from a structured survey of 150 rice farmers, the research applies a Stochastic Frontier Analysis (SFA) with a Cobb-Douglas production function to estimate technical efficiency. The study revealed that seed input and labor significantly influence rice output, while education and full-time farming engagement are associated with reduced inefficiency. The mean technical efficiency score is 0.705, indicating that farmers operate at approximately 70.5% of their potential output. The gamma value of 0.821 suggests that 82.1% of output variation is due to inefficiency rather than random shocks. Comparative analysis revealed that high ICM adopters achieved higher efficiency (0.717) and yields (6,502 kg/ha) than low adopters (0.697 and 5,664 kg/ha, respectively). These findings demonstrate that ICM adoption improves resource-use efficiency and productivity, but its benefits depend on enabling conditions such as education, farm specialization, and extension access. Strengthening context-specific ICM adaptation, farmer training, and supportive policies is essential for enhancing resilience and reducing productivity gaps in semi-arid rice ecosystems.

Keywords: ICM, productivity, rice, technology, Timor

INTRODUCTION

Indonesia ranks among the world's top rice producers, with over 10.20 million hectares of paddy fields, yielding approximately 53.63 million tons of dry, unhusked rice, equivalent to around 30.90 million tons of rice (BPS 2025). Such substantial production underscores rice's importance as a staple food and key agricultural commodity in Indonesia. However, productivity remains uneven across regions, particularly in climate-vulnerable and economically marginal areas such as the border regions of West Timor.

Border agriculture presents unique challenges and opportunities. These regions often suffer from underinvestment, weak institutional support, and limited access to modern technologies. However, they are critical for regional food systems and cross-border trade, especially in areas adjacent to Timor-Leste. The average rice yield in these border zones is approximately 4.2 tons/ha, significantly below the national average of 5.2 tons/ha (BPS East Nusa Tenggara Province 2025). Addressing this gap is essential for local development and national resilience in the face of climate change and geopolitical pressures. The border regions are crucial to West Timor's rice output, as lowland rice is a primary food source. In 2023, rice production in these areas was approximately 443.69 thousand tons, a modest increase of 0.85 thousand tons, or 0.19% from the previous year (BPS East Nusa Tenggara Province 2025). Despite this growth, farmers continue to face multiple constraints: semi-arid climates, low soil fertility, rugged terrain, and limited rainfall, all of which hinder consistent, high-yield rice cultivation. Economic hardship and technological adoption barriers further exacerbate these challenges.

Integrated Crop Management (ICM) has emerged as a promising strategy to enhance productivity and sustainability in smallholder systems (Lankamo et al. 2025). ICM combines best practices, such as improved seed varieties, intermittent irrigation, balanced fertilization, pest control, and conservation agriculture, tailored to local agroecological conditions (Billah et al. 2025; Ewulo et al. 2025). Evidence from the Mekong Delta, Ghana, and Bangladesh shows that ICM can improve technical efficiency by 10-24% and boost productivity by up to 76% compared to non-adopters (Villano et al. 2015; Abdulai et al. 2018).

However, the success of ICM is highly context-dependent. In marginal ecologies, drylands, uplands, and border regions, adoption is often hindered by financial constraints, limited extension services, and low education levels (Wossen et al. 2017; Acevedo et al. 2020; Girma 2022). In Indonesia, while national programs have promoted ICM in irrigated lowlands, its implementation in border regions remains partial and inconsistent (Novitaningrum et al. 2020; Sumaryanto et al. 2023). Despite the limitations, ICM components remain applicable for adoption in dryland areas, where rainfed is the primary water source, offering clear solutions that include targeted training and full support or protection for inputs.

The Indonesian Ministry of Agriculture (Departemen Pertanian 2003) classifies ICM components into location-specific and efficiency-based groups. Five components are considered essential: selecting locally adapted varieties, proper land preparation and levelling, efficient water management, balanced fertilizer application, and regular farm monitoring. Further research is needed to assess how economic and policy strategies enhance technical efficiency and to understand the impact of these factors on efficiency.

Globally, modern agricultural technologies, such as precision agriculture, digital tools, and ICM, have shown strong potential to boost farm productivity. However, a significant research gap persists regarding how environmental, geographic, and socio-economic factors jointly hinder technology adoption in climate-vulnerable border areas (Balyan et al. 2024; Fragomeli et al. 2024; Geng et al. 2024). In Indonesia, this gap is especially evident, with limited empirical evidence on how policies and economic strategies can address these obstacles. Although ICM approaches in semi-arid regions, such as West Timor, show clear agronomic benefits, including drought-tolerant crops, livestock integration, and water-smart practices, their success depends heavily on adaptable design, strong local participation, and responsiveness to physical and socio-economic conditions (Tjoe et al. 2019; Benu et al. 2024). Failures in similar contexts are often due to rigid, top-down planning that overlooks key issues, such as water scarcity, labor availability, and insecure land tenure (Borrell et al. 1997).

This research aims to fill these gaps by examining the technical efficiency of ICM adoption in West Timor's border regions, where these challenges are most severe. The border region of West Timor is a distinct and under-studied agroecological zone characterized by harsh climate, poor soil, and proximity to Timor-Leste, which influences cross-border socio-economic interactions (Tjoe 2017). Unlike Indonesia's fully irrigated rice belts, this area faces seasonal water shortages, fragmented landholdings, and elevated poverty levels- about 18.1% in 2024 (BPS East Nusa Tenggara Province 2025). Districts such as North Central Timor and Kupang exhibit persistent poverty, primarily due to low agricultural innovation and productivity. Previous studies by Dewi and Yustikaningrum (2018) and Taena et al. (2023) have highlighted the lack of tailored agricultural policies and the underutilization of technology in these marginal areas. This research aims to investigate how ICM can be adapted to address these constraints, providing insights into the adoption of technology in frontier farming systems. Building on these contextual challenges and knowledge gaps, this study seeks to clarify whether the extent of ICM adoption translates into measurable efficiency gains under the unique biophysical and socio-economic conditions of West Timor's semi-arid border regions. We hypothesize that higher ICM adoption is associated with higher technical efficiency among rice farmers in the semi-arid region of West Timor.

MATERIALS AND METHODS

Research sites

The study was conducted in the border regions between the Republic of Indonesia and Timor-Leste, specifically in North Central Timor and Kupang District, as shown in Figure 1. These regions are characterized by semi-arid conditions, low soil fertility, and limited rainfall, creating substantial obstacles for rice farming. The selected sites are significant due to their key role in regional rice production and high poverty levels, underscoring the need for targeted agricultural interventions.

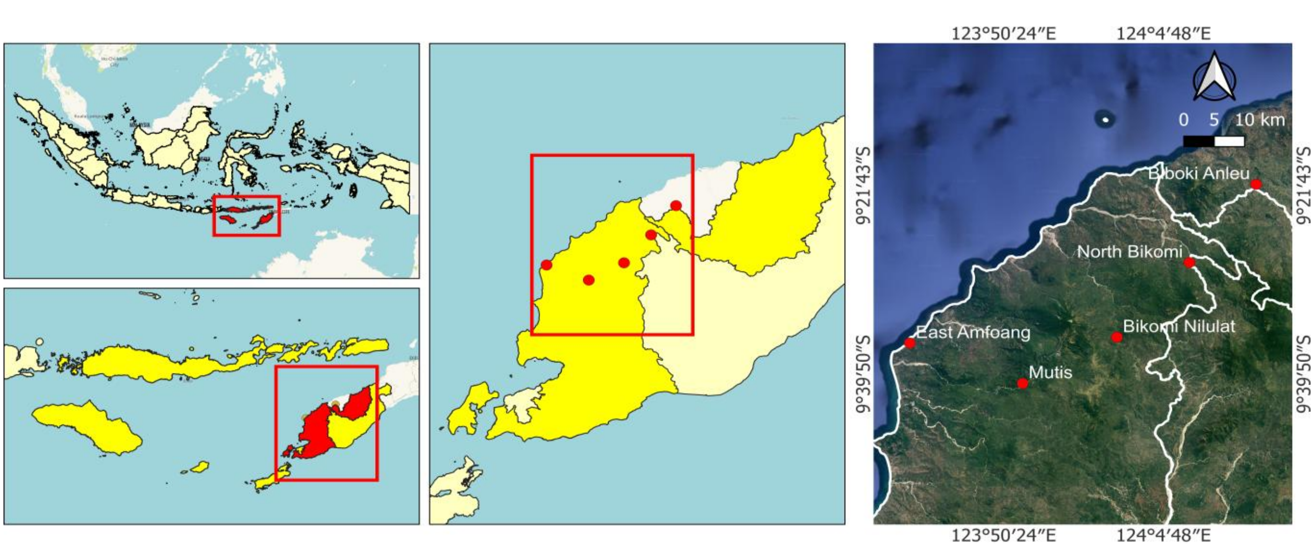

Figure 1. Map of the study area in Kupang and North Central Timor District, East Nusa Tenggara, Indonesia

Data collection

The study used purposive sampling to select 150 rice farmers from five sub-districts in North Central Timor and Kupang District: East Amfoang, Mutis, Bikomi Nilulat, North Bikomi, and Biboki Anleu. These regions were chosen due to their importance in lowland rice farming and their location in semi-arid, climate-vulnerable border areas. The farmers included in the study had adopted at least one component of the Integrated Crop Management (ICM) package. This approach ensured the sample represented a variety of ICM adoption levels and farming conditions relevant to the research aims. The survey gathered information on farmers' socio-economic backgrounds, farming methods, the extent of ICM use, and their opinions on how ICM affected productivity and livelihoods (FAO 2019). Field observations were also conducted to evaluate ICM implementation and assess the condition of rice fields, providing qualitative insights into the challenges and opportunities farmers face. Secondary data on rice production, yields, and input use were collected from local agricultural offices and national statistical agencies (BPS 2025). Additionally, relevant literature and reports regarding technical efficiency, ICM adoption, and agricultural practices in similar settings were reviewed to provide a thorough background for the research (Wang et al. 2017).

Data analysis

The production function parameters will be estimated using Maximum Likelihood Estimation (MLE), which separates random statistical noise (such as weather variations) from farm-specific inefficiency effects. This method produces Technical Efficiency (TE) scores for individual farms, indicating their ability to maximize output with available resources. At the same time, the half-normal assumption is tested empirically for goodness of fit and retained if it performs comparably to alternatives for interpretability and comparability. The analysis will then examine how ICM adoption affects these efficiency scores and assess the impact of socio-economic variables (such as education, farm size, and access to credit) on efficiency outcomes (Battese and Coelli 1995; Bravo-Ureta et al. 2007).

The framework (Figure 2) illustrates that the interplay of socio-economic factors and agricultural practices has a significant impact on farming outcomes, with education, credit access, and farm size directly influencing both the adoption of Integrated Crop Management (ICM) practices and overall farm efficiency. ICM adoption, quantified by the implementation of its various components, serves as a crucial mediating variable, directly affecting the productivity of inputs. Ultimately, these dynamics culminate in technical efficiency and rice yield, estimated through a stochastic frontier Cobb-Douglas production function, representing the primary outcomes. Improvements in efficiency and yield, in turn, contribute to enhanced farmer welfare and bolster local food security.

Functional form of the stochastic production function

The Technical Efficiency (TE) of rice farms using the ICM technology package is evaluated using a Stochastic Frontier Production Function, where Stochastic Frontier Analysis (SFA) helps quantify how efficiently farmers convert inputs into outputs and how much of the yield gap is due to inefficiency versus environmental limitations. This is particularly important in semi-arid zones, such as West Timor, where low yields may reflect structural constraints rather than poor management. By identifying the sources of inefficiency, SFA can inform targeted interventions that improve productivity without requiring uniform solutions.

This study employs the Cobb-Douglas production function because it offers simplicity, interpretability, and suitability for small to moderate sample sizes. It directly estimates the elasticity of each input, making it easier to understand the relationships between inputs (labor, capital, land, and technology adoption) and outputs (rice yield). Compared to the more flexible Translog model, the Cobb-Douglas model is more straightforward, reducing the likelihood of overfitting, which is especially important when working with limited data or when there is multicollinearity among inputs (Mahaboob et al. 2019).

Unlike deterministic models, such as Data Envelopment Analysis (DEA), which attribute all deviations from optimal output to inefficiency, SFA distinguishes between inefficiency and statistical noise, a critical distinction in dryland systems, where yield fluctuations often result from factors like rainfall variability, soil degradation, and pest outbreaks. This feature makes SFA particularly suitable for semi-arid and climate-vulnerable regions, where production outcomes are not solely determined by farmer effort or input use (Kumbhakar et al. 2020).

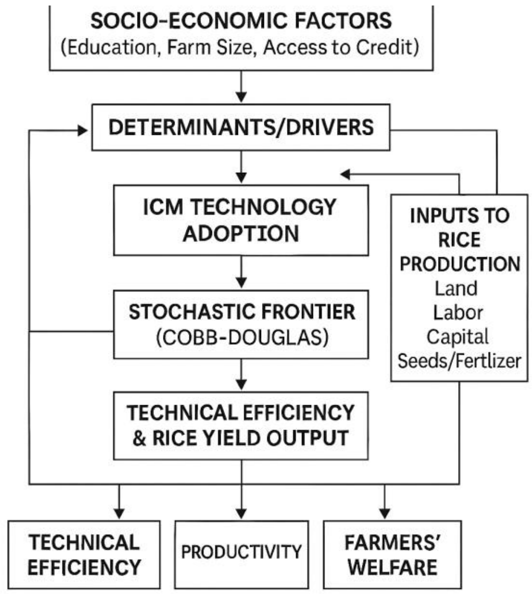

Figure 2. Conceptual framework. Source: Author's own conceptualization based on SFA literature (Aigner et al. 1977; Meeusen and van Den Broeck 1977) and technology adoption studies

The stochastic frontier model is represented as:

$$Y_i = X_i;\beta + \varepsilon_i \quad [1]$$

The Cobb-Douglas type's stochastic production frontier function model is the empirical model to estimate technical efficiency. Which is given below:

$$\ln Yi = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 \ln X_{3i} + \beta_4 \ln X_{4i} + \beta_5 \ln X_{5i} + \beta_6 \ln X_{6i} + \varepsilon_i \quad [2]$$

Specify a production function (Cobb-Douglas) that relates output to inputs:

$$y_i = f(x_i;\, \beta) + v_i - u_i \quad [3]$$

In dryland contexts, such as West Timor, where farming is shaped by environmental variability and resource constraints, SFA provides a robust method for assessing how efficiently farmers (i^{th}) convert inputs (x_i) into outputs (y_i). It distinguishes between inefficiency (u_i) and random shocks (v_i), such as drought or poor soil, making it especially relevant where low yields may reflect structural limitations rather than poor management. Assume v_i follows a normal distribution N (0, σ^2), and u_i follows a non-negative distribution such as half-normal. The study also incorporates the model from Battese and Coelli (1995), which expresses the technical inefficiency effect as follows:

$$u_i = Z_i\, \delta + w_i \quad [4]$$

Z_i is a (1 × m) vector of explanatory variables linked to the TI (Technical Inefficiency) effects; δ is a (m × 1) vector of unknown parameters to be estimated; and w_i represents an unobservable random variable. These parameters reflect the influence of variables in Z on TE, where a negative value indicates a positive effect on TE, and vice versa. The inefficiency model has been adopted, as shown below.

$$u_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6 + \delta_7 Z_7 + w_i \quad [5]$$

The model's parameters are estimated using the Maximum Likelihood Estimation (MLE) method. Technical Efficiency scores for each farmer can then be calculated based on:

$$TE = \frac{f(Xi;\beta)\exp(vi-ui)}{f(Xi;\beta)\exp vi} = \exp(-u_i) \quad [6]$$

The theoretical basis (Table 1) for variable selection is grounded in production economics and empirical studies on technical efficiency (Battese and Coelli 1995; Bravo-Ureta et al. 2007).

Software used

The analysis used Frontier 4.1, a specialized software for estimating stochastic frontier models through Maximum Likelihood Estimation (MLE). Frontier 4.1 provides flexible options for specifying inefficiency effects and supports various distributions, including the half-normal distribution, for the inefficiency term.

RESULTS AND DISCUSSION

Socio-economic characteristics of the respondent

Table 2 shows the socio-economic profile of farmers in the research site (Kupang and North Central Timor District). It reveals a predominantly mature farming population, with most individuals falling within the 40–59 age bracket.

This age distribution suggests a workforce with considerable life and field experience, consistent with findings from Southeast Asia, where older farmers dominate rural agricultural communities (Mekonnen et al. 2021; Woh et al. 2025). Educational attainment among these farmers is generally low to moderate, with the majority having completed only primary or secondary education, and relatively few reaching tertiary levels. This pattern aligns with broader trends in developing countries, where limited access to higher education constrains human capital development in rural areas (FAO 2020). Farming experience is notably high, with many farmers having over a decade of experience, indicating a deep-rooted knowledge and skill in agriculture. Such experience is a critical factor influencing the adoption of sustainable agricultural practices (Abdulai and Huffman 2014; Xayavong et al. 2016; Zhou and Li 2022).

Table 1. Variable, unit, type, and theoretical basis

Variable	Unit	Type	Theoretical basis
Rice output (Y)	Kilograms	Dependent	Farm productivity (Gautam 2024)
Farm size (X_1)	Hectares	Input	Scale of operation (Gautam 2024)
Seed input (X_2)	Kilograms	Input	Genetic potential (Senapati and Semenov 2020; Aziz et al. 2022)
Urea fertilizer (X_3)	Kilograms	Input	Nitrogen supply (Motasim et al. 2024)
NPK fertilizer (X_4)	Kilograms	Input	Balanced nutrients (Nabayi et al. 2021)
Pesticide (X_5)	Liters	Input	Pest control (Fahad and Wang 2018)
Labor (X_6)	Man-days	Input	Human capital (Abidin et al. 2022)
Extension access (Z_1)	Frequency	Inefficiency	Knowledge transfer (Danjumah et al. 2024)
Education (Z_2)	Years	Inefficiency	Decision-making ability (Paltasingh and Goyari 2018; Taramuel-Taramuel et al. 2023)
Age (Z_3)	Years	Inefficiency	Experience vs inertia (Woh et al. 2025)
Farming experience (Z_4)	Years	Inefficiency	Skill accumulation (Xayavong et al. 2016; Zhou and Li 2022)
ICM adoption (Z_5)	Dummy (1/0)	Inefficiency	Technology use (Wang et al. 2017; Ambong 2022)
Land ownership (Z_6)	Dummy (1/0)	Inefficiency	Investment incentive (Ardiansyah and Hartono 2014; Akber et al. 2024)
Occupation (Z_7)	Dummy (1/0)	Inefficiency	Time commitment (Hoang-Khac et al. 2022)

Table 2. Socio-economic attributes of farmers

Variable	Frequency
Age in years	
20-39	35
40-59	88
60+	27
Educational level (years)	
Non-formal education (0)	2
Primary education (1-6)	96
Secondary education (7-12)	41
Tertiary education (>12)	11
Farming experience (years)	
1-5	13
6-10	22
11+	115
Farm Size (hectare)	
0.1-0.9	129
1.0-2.0	19
2.1-3.0	2
Land Ownership	
Tenant	4
Landlord	146
Occupation	
Farmers	101
Civil Servant	44
Traders	5

Regarding landholding, most farmers operate on small to medium-sized plots, reflecting the region's typical structure of smallholder agriculture. Land ownership is widespread, supporting long-term investment and stewardship of agricultural resources (Deininger and Jin 2006; Ardiansyah and Hartono 2014; Akber et al. 2024). Finally, farming remains the primary occupation for most individuals, although a minority are engaged in civil service or trade, highlighting the mixed livelihood strategies often employed in rural economies (Hoang-Khac et al. 2022; Race et al. 2022).

The socio-economic characteristics of farmers in North Central Timor and Kupang District provide valuable insights into the structure and potential of rural agricultural communities. The average education level is 7.66 years, mostly completing primary or early secondary school, typical for rural areas and influential in technology adoption and decision-making (Paltasingh and Goyari 2018; Ruzzante et al. 2021; Taramuel-Taramuel et al. 2023). The average age of farmers is 47.1 years, indicating a mature farming population, with older farmers often relying on traditional methods (Han et al. 2022). With 20.19 years of farming experience, most possess deep agricultural knowledge and resilience (Bhatnagar et al. 2024; Chao 2024). Farm sizes average 1.24 hectares, highlighting the prevalence of smallholder farming and resource constraints (FAO 2020). Access to extension services is limited, averaging just 0.36 contacts, indicating a lack of institutional support, despite its importance for improving productivity (Yanfika et al. 2024).

OLS and Maximum Likelihood Estimates (MLE) of the Stochastic Frontier Cobb-Douglas production function

The Stochastic Frontier Analysis (SFA) is commonly used to measure technical efficiency by modeling the production function, often in the Cobb-Douglas form, with a composite error term that separates statistical noise from inefficiency (Aigner and Schmidt 1977). This method is ideal for agriculture, like rice farming, due to environmental variability and input differences. SFA provides more accurate efficiency estimates than traditional regression models. The Cobb-Douglas function helps analyze input-output relationships and resource allocation efficiency (Başeğmez 2021; Gautam 2024).

In SFA, the Maximum Likelihood Estimation (MLE) method is usually used to estimate the production function parameters and separate the error term into its noise and inefficiency components (e.g., half-normal, exponential, gamma, Nakagami), which allows for the calculation of firm-specific efficiency scores (Greene 1990; Papadopoulos 2024).

Table 3 presents the Stochastic Frontier Analysis (SFA) results for rice farmers in the Indonesia-Timor Leste border area. The estimates show that seed input has a strong, positive, and statistically significant effect on output in both OLS and Maximum Likelihood models, highlighting its key role in productivity. Labor also shows a positive coefficient and nears statistical significance, indicating its importance. However, land size, fertilizer (urea, NPK), and pesticide use have limited impact in the sample. Seed use and labor are the main factors affecting rice output, while land size, urea, and NPK fertilizers are not significant. The ICM coefficient's insignificance suggests partial or inconsistent implementation among farmers, rather than a lack of agronomic benefits, primarily in terms of dose and timing, which contradicts the extension agent's suggestion.

The sigma squared (σ^2) value indicates the total variance in the combined error term of the stochastic production frontier, capturing both random noise (v_i), such as weather conditions beyond farmers' control, and technical inefficiency (farmer-specific management capacity). The sigma square value from MLE (1.22) surpasses that from OLS (0.42), indicating greater variability captured by the stochastic frontier model. This suggests that the variation in rice farmers' output is due to both inefficiency (u_i) and random effects (v_i), or total error variance (Adinya et al. 2012; Ho et al. 2022; Okoh et al. 2022). The gamma (γ) value of 0.82, meaning 82% of output variation is due to technical efficiency, while 18% results from random shocks (Samat et al. 2023; Baruah and Saha 2024; Akinsulu 2025). This aligns with findings from Nigeria and Bangladesh by Chikezie et al. (2020) and Regmi (2016), who indicated that inefficiency is the leading cause of output loss among rice farmers. The log-likelihood for MLE (-135.93) is better than for OLS (-145.4), and the Likelihood Ratio (LR) test value 19.03 confirms that the stochastic frontier model is statistically superior to the OLS model (Greene 2001; Simar et al. 2017; Wang et al. 2025).

Table 3. Descriptive statistics of the socio-economic characteristics

Socio-economic variables	Measurement unit	Observation	Mean	Standard deviation	Minimum	Maximum
Education level	Year	150	7.66	3.26	0	17
Age	Year	150	47.1	11.6	25	79
Farming experience	Year	150	20.19	10.62	2	54
Farm size	Ha	150	1.24	6.85	0.02	8
Extension service	Frequency	150	0.36	0.73	0	4

Table 4. The results of the estimated average production function using the MLE Method

Variables		OLS estimates			Maximum Likelihood Estimates		
	Parameters	Coefficients (SE)	t-ratios	p-value	Coefficients (SE)	t-ratios	p-value
Production function							
Intercept	β_0	5.84 (0.52)	11.15		6.30 (0.54)	11.54	
Land Size	β_1	-0.10 (0.063)	-1.7	0.08	-0.045 (0.06)	-0.75	0.33
Seeds	β_2	0.34 (0.07)	4.45	0.00*	0.32 (0.06)	4.72	0.00*
Urea	β_3	0.062 (0.064)	0.96	0.33	0.04 (0.05)	0.78	0.45
NPK	β_4	0.018 (0.05)	0.33	0.73	0.014 (0.05)	0.27	0.76
Pesticide	β_5	0.04 (0.042)	1	0.31	0.05(0.03)	1.30	0.15*
Labor	β_6	0.13 (0.081)	1.65	0.09	0.15 (0.09)	1.67	0.05**
Technical inefficiency							
Intercept	δ_0				-3.02 (3.86)	-0.78	
Extension	δ_1				-1.47 (1.08)	-1.35	0.07
Education	δ_2				-0.19 (0.12)	-1.61	0.03**
Age	δ_3				0.018 (0.02)	0.89	0.14
Experience	δ_4				-0.02 (0.02)	-1.02	0.05**
ICM	δ_5				-1.30 (1.18)	-1.09	0.30
Dummy land ownership	δ_6				3.99 (3.83)	1.03	0.11
Dummy occupations	δ_7				-0.66 (0.55)	-1.88	0.19
Sigma square	σ^2	0.42			1.22 (0.53)	2.30	
Gamma	γ				0.821 (0.079)	10.28	
Log likelihood		-145.4			-135.93		
LR test					19.03		

Note: Numbers of observation: 150, significance *: 1% level, **: 5% level. Source: Field work survey (2024)

The production function model reveals that in semi-arid dryland rice systems, particularly in Indonesia's eastern border regions, seed and labor are significant drivers of productivity (Senapati and Semenov 2020; Abidin et al. 2022; Aziz et al. 2022), while education and full-time farming reduce inefficiency. Education (δ2) and full-time farming (δ7) reduce inefficiency, as educated farmers utilize resources effectively and adopt innovations more quickly. In contrast, full-time farmers enhance yields through greater labor and technology adoption (Njeru 2010; Paltasingh and Goyari 2018; Kumbhakar et al. 2020; Andrianarison et al. 2021). Access to extension services (δ1) and Integrated Crop Management (ICM) adoption (δ5) show potential to improve efficiency further, supporting resilience and productivity in these border agricultural economies (Acevedo et al. 2020; Jabbar et al. 2022).

Table 3 shows that rice farmers in Kupang and North Central Timor District, on average, achieve a technical efficiency of 0.708, indicating they produce approximately 70.8%, which is consistent with Indonesia's national average for smallholder rice farms, typically between 65% and 75% (Oelviani et al. 2024; Rachmina et al. 2025), implying a significant efficiency gap, where farmers could increase output by nearly 29%, without needing additional inputs (Acharya et al. 2020).

This degree of efficiency is commonly observed in traditional or non-mechanized rice systems across Asia and Africa, as highlighted by Chandel et al. (2022) and Ho et al. (2022), who found average technical efficiency levels ranging from 62% to 76%. For instance, a study of traditional rice farms in Nepal found a mean technical efficiency of 70.11% (Acharya et al. 2020). In comparison, fully mechanized or highly sustainable rice farms can reach 80-90% efficiency, indicating significant room for improvement through technology adoption, input optimization, or enhanced training and extension services (Min et al. 2021; Hien et al. 2023).

As the result in Table 5 did not include any farmers with an ICM score of zero, a binary classification distinguishing between "adopters" and "non-adopters" was not feasible. Instead, Table 6 presents a comparative analysis between low-level adopters (ICM score ≤ 0.625) and high-level adopters (ICM score ≥ 0.625), enabling a nuanced examination of adoption intensity and its associated outcomes.

Table 5. Farm level technical efficiency index in the study area

Frequency distribution (technical efficiency)	Number of farms	Percent
0.00-0.10	0	0.00
0.10-0.20	1	0.67
0.20-0.30	2	1.33
0.30-0.40	6	4.00
0.40-0.50	3	2.00
0.50-0.60	9	6.00
0.60-0.70	23	15.33
0.70-0.80	51	34.00
0.80-0.90	54	36.00
0.90-1.00	1	0.67
Total	150	100
Descriptive statistics		
Number of observations: 150		
Mean: 0.70		
Minimum: 0.09		
Maximum: 0.89		
Standard deviation:0.14		

Table 6. Efficiency across ICM adopters

Category	Number of farmers	Average ICM score	Average efficiency score	Average yield (kg/ha)
High adopters	79	0.707	0.717	6,502
Low adopters	71	0.386	0.697	5,664

Note: Source: Compilations based on data processing

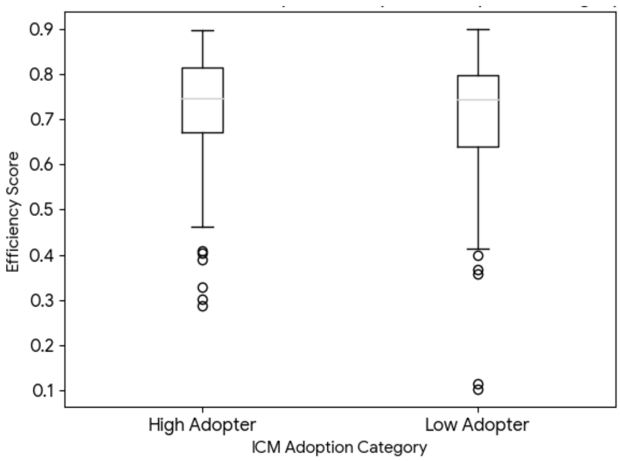

Figure 3. Distribution of efficiency scores by ICM adoption category

A growing body of evidence indicates a positive relationship between the level of ICM adoption and both technical efficiency and crop yields within agricultural systems. Concerning technical efficiency, a comparative analysis reveals that high ICM adopters demonstrate an average efficiency score of 0.717 compared to 0.697 for low adopters. This suggests that farmers integrating a broader spectrum of ICM practices are more effective in converting inputs into outputs. This is consistent with other studies showing that adopting environmentally friendly and control-intensive agricultural technologies is associated with improved technical efficiency scores among crop producers (Lampach et al. 2021; Esuh-Nnoko et al. 2022; Biswakarma et al. 2025).

The effect on crop yield is even more pronounced. High ICM adopters achieve an average yield of 6,502kg/ha, approximately 14.8% higher than the 5,664kg/ha recorded among low adopters, despite pervasive constraints like water scarcity, insecure land tenure, and labor migration. This substantial difference underscores how enhanced ICM practices, including water-efficient techniques, Alternate Wetting and Drying (AWD), and drought-tolerant varieties, directly bolster productivity and resilience by mitigating water scarcity in West Timor's rainfed lowlands, where droughts intensify during the dry season (May-October) and disrupt planting cycles in non-irrigated areas (Singh et al. 2021). Land tenure issues, such as rapid conversion of agricultural land to urban uses and insecure ownership, further hinder long-term investments in adaptive practices, reducing farmers' ability to sustain yields amid soil degradation and limited access to irrigation infrastructure (Lulan et al. 2017). Labor migration, driven by the aging of rural workforces and urban opportunities, exacerbates labor scarcity, thereby lowering technical efficiency in rice production (Ngadi et al. 2023). However, remittances provide partial economic buffers. In contrast, ICM adoption counters this by optimizing labor through mechanization and site-specific management, thereby enhancing household resilience to economic shocks.

Numerous Indonesian and global studies align with these findings, providing further context for the observed efficiency and yield gaps. In the Indonesian context, recent studies report an average technical efficiency of rice farms of 0.82 from 2018 to 2021. Nonetheless, considerable regional disparities remain, with Java demonstrating higher efficiency levels than provinces outside Java, suggesting institutional and resource-based disparities. Research conducted in East Java further identifies technical efficiency as a key constraint to productivity, with significant contributions from extension services, access to irrigation, and practical government assistance. Interestingly, membership in farmer organizations, which typically enhances technology transfer and collective action, was not always linked to improved efficiency in that region (Hakim et al. 2021; Sinuraya et al. 2024). On the global stage, ICM has consistently yielded gains of 10–19% in rice across diverse environments, including China, India, and Bangladesh, reflecting the universal benefits of comprehensive, resource-optimized practices. Adopting digital and precision agriculture tools, as seen in Vietnam, also leads to significant annual yield increases, further reinforcing the notion that multifaceted, informed management is crucial for productivity growth (Wang et al. 2017; Yamini et al. 2025).

The box plot in Figure 3 below illustrates the distribution of technical efficiency scores among rice farmers, stratified by their level of adoption of Integrated Crop Management (ICM). Partitioning the dataset at the median ICM score of 0.625 resulted in two distinct groups: "low adopters" (ICM score < 0.625) and "high adopters" (ICM score ≥ 0.625).

As illustrated in Figure 3, the median efficiency score (shown by the line within each box) for high adopters is notably greater than that for low adopters, indicating a positive association between the intensity of ICM adoption and efficiency. Moreover, the interquartile range is narrower for high adopters, indicating reduced variability and a more concentrated distribution of efficiency among this group. This finding aligns with the literature, which demonstrates that the consistent and comprehensive implementation of ICM practices, often facilitated by field school programs or strategic management, contributes to higher and more consistent technical efficiency outcomes in rice production. Such programs have been shown to promote the adoption of best practices, enabling farmers to optimize input use and production processes, thereby reducing the risk of low-efficiency results (Rasyid et al. 2016; Deng et al. 2022).

Conversely, the broader spread of efficiency scores among low adopters reflects greater heterogeneity, with a significant portion of farmers operating at lower efficiency levels. This disparity may be attributed to the partial or inconsistent application of key ICM components, resulting in unpredictable efficiency outcomes. Prior research has noted that variability in management practices, such as fertilizer strategies, water management, and knowledge transfer, directly influences technical efficiency heterogeneity among rice producers. These outcomes collectively suggest that a comprehensive and sustained approach to ICM adoption is essential for increasing and stabilizing technical efficiency within rice-based agricultural systems (Deng et al. 2022).

Practical implication

Policies to improve technical efficiency in rice farming should prioritize expanding educational and training opportunities via formal schooling and informal agricultural education. Extension services and training programs should specifically target older farmers, who may be less inclined or physically less able to adopt new technologies, while encouraging knowledge transfer from experienced to less experienced farmers through farmer field schools, mentoring, or demonstration plots (Ndubueze-Ogaraku and Ogbonna 2016; Acharya et al. 2020). Facilitating greater access to ICM training and resources, and promoting comprehensive ICM adoption, can further enhance efficiency and productivity, consistent with existing evidence from multiple rice-producing regions (Novitaningrum et al. 2020; Biswas et al. 2021). Additionally, land tenure reforms, effective land management education, and incentive structures for landowners have been shown to influence technical efficiency by addressing inefficiencies linked to land ownership (Koirala et al. 2016; Ganiyu et al. 2024). Finally, supporting rice farmers in engaging in full-time, professional farming through improved market access, training, and social protections can substantially raise technical efficiency, in line with studies highlighting the benefits of dedicated labor and occupation focus (Darmawan et al. 2024; Raghua et al. 2025).

Conclusion, this study identifies a significant efficiency gap among rice farmers in West Timor's dryland border regions, with average output reaching only 70% of potential. It highlights the role of Integrated Crop Management (ICM) in improving productivity, though its effectiveness depends on enabling conditions. Key factors such as education, labor, and full-time farming are shown to reduce inefficiency, underscoring the importance of human capital and institutional support. The findings contribute to dryland agricultural research by demonstrating that context-specific ICM adaptation, combined with strengthened extension services and policy support, can enhance resilience and resource-use efficiency. This research is limited by its cross-sectional design, reliance on self-reported data, and focus solely on technical efficiency. Future studies should use multi-season or panel data, incorporate allocative and economic efficiency, and assess the long-term impacts of ICM under variable climate and market conditions. Evaluating targeted interventions, such as water-saving technologies, improved land tenure security, and farmer field schools, would further guide scalable strategies for sustainable intensification in semi-arid rice ecosystems.

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