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Technical Efficiency of Rice Production in Tidal Swampland: A Stochastic Model Approach

Muhamad Sabran[1*], Yanti Rina Darsani[2], Retna Qomariah[2], Susilawati[1], Fachrur Rozi[3], Susi Lesmayati[4], Eni Maftu'ah[1], Izhar Khairullah[1], Twenty Liana[1]

[1] Research Center for Food Crops, Research Organization for Agricultural and Food, National Research and Innovation Agency, Cibinong 16911, Indonesia
[2] Research Center for Behavioral and Circular Economics, Research Organization for Governance, Economy and Community Welfare, National Research and Innovation Agency, Jakarta 12710, Indonesia
[3] Research Center for Macroeconomics and Finance, Research Organization for Governance, Economy and Community Welfare, National Research and Innovation Agency, Jakarta 12710, Indonesia
[4] Research Center for Agroindustry, Research Organization for Agricultural and Food, National Research and Innovation Agency, Cibinong 16911, Indonesia

Corresponding Author Email: muha329@brin.go.id

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ABSTRACT

Tidal swamplands have great potential for rice production, but their contribution to rice production in Indonesia could be more significant. This study aimed to identify factors that could significantly increase rice yield in tidal swamplands, measure technical efficiency (TE), and determine the factors influencing efficiency. The survey was carried out in two districts of Central Kalimantan Province, Indonesia: Kapuas and Pulang Pisau. The stochastic frontier model was used to estimate TE, defined as the ratio of actual output to the maximum possible output given the input levels, while accounting for random shocks beyond the farmers' control. The TE estimates provide suggestions for farmer-targeted interventions and for optimizing input allocation to enhance rice production. The study found that expanding the area under rice cultivation and applying NPK fertilizers significantly increased rice yields. Farmers' efficiency levels ranged widely, from 0.24 to 1.0, with an average of 0.755, depending on the estimation method. Age and experience are important variables in determining efficiency. Relaxing the assumption of independence between the two error components in stochastic frontier models had no meaningful effect on estimated efficiency. The conventional model outperformed three copula-based models based on the Akaike and Bayesian Information Criterion, neither overestimating nor underestimating efficiency. It is proposed to encourage new generation participation in farming and upgrading their expertise through training to boost efficiency. Expanding the cultivated area and implementing intensive fertilization strategies are also proposed to increase rice production in tidal swamplands.

1. INTRODUCTION

Swamplands will play essential roles in future agriculture, particularly for rice (*Oryza sativa* L.) production to feed the ever-growing population in Indonesia. Swamplands are low-lying lands that are regularly flooded and can be categorized into tidal and inland swamps. Sea tides influence tidal swamps, while inland swamps are formed in inland valleys where water comes from upstream rivers or rain. Inland swamps are further categorized based on the depth and duration of flooding, including deep, medium, and shallow inland swamps.

Rice is a traditional crop cultivated in tidal swamplands. However, due to biophysical and socio-economic constraints, rice productivity in tidal swamplands is lower (2-3 tons/ha) compared to other agroecosystems, which can reach 6-7 tons/ha with a national average of 5.29 t/ha [1]. Biophysical constraints include iron toxicity, salinity, flooding, low fertility, and pest and disease infestation. Socio-economic constraints such as limited labour, poor infrastructure, low education, poor skills, and low farmers' capital also hinder crop production in tidal swamplands. The adoption of new technologies is limited by high input requirements, insufficient capital, inadequate farmer skills, and a lack of effective government intervention in infrastructure and water management systems.

In Indonesia, swampy land covers 32.67 million hectares, with 12.41 million hectares of tidal swampland and 20.26 million hectares of inland swamps. Only 0.7 million hectares of the 2.801 million hectares of swampy land suitable for rice cultivation are currently cultivated [2]. The main reason for the poor contribution of rice production in tidal swamplands, which accounts for approximately 5% of total rice production in Indonesia, is limited cultivated area and low technical efficiency. The Indonesian government prioritized expanding agricultural acreage in tidal swamplands to increase rice production and strengthen national food security. Increasing efficiency is one way to support the program. This condition emphasizes the importance of studying input efficiency in rice cultivation in tidal swamplands.

Technical efficiency (TE) in rice production refers to farmers' ability to maximize production (rice yield) from a given set of inputs while minimizing waste. It measures how effectively resources are utilized compared to the best practice or production frontier. The stochastic frontier model (SFM) is commonly used to estimate TE by comparing the efficiency of each farm relative to the best-performing farms on the production frontier. Analysing efficiency enables the development of targeted interventions to improve farmer performance and optimize input allocation for higher rice output in tidal swamplands.

The SFM is like the regression model except for its two error terms: random noise and inefficiency. It improves the deterministic frontier by incorporating random errors or noise. The random noise is a two-sided symmetric error representing random effects beyond the farmers' control, such as measurement error, soil fertility, climatic variance, and other standard statistical noises in regression modelling. The one-sided error component represents inefficiency. Conventional SFM assumes independence between the two components [3, 4]. A copula-based stochastic model is employed when the assumption of independence of the two error components is relaxed [5-7]. The copula-based stochastic frontier is one where the copula function connects the two error components in their joint probability density function.

Several studies have investigated TEs in rice production in Indonesia and their determinants. Variations in these studies include differences in the agroecosystem, input factors, farmer conditions influencing TE, and the method used to evaluate TE. The agroecosystem includes tidal swampland [8-10], flood-prone locations [11], and irrigated areas [12]. Input variables generally comprise cultivated land, fertilizer, and labour, while some studies also include farm machinery [8, 13]. The average TE ranges between 56% and 86%. Studies on the determinants of efficiencies have revealed that factors such as age, farmers' experience, government intervention [13], or the ease of gathering information on technologies [14, 15] affect efficiency. While most studies used the conventional SFM model, some researchers used copula-based SFM to estimate TE [7, 16].

This study aims to discover factors influencing rice production in tidal swamplands and estimate TE and its determinants. It will also evaluate TE estimation techniques by comparing the conventional and copula-based SFM for TE.

2. METHODOLOGY

2.1 Location and methods of data gathering

The survey was conducted during the dry season in 2021 in two districts in Central Kalimantan, Indonesia: Kapuas and Pulang Pisau. The Terusan Karya village of Bataguh subdistrict and Sidomulyo village of Tamban Catur subdistrict in Kapuas, while Belanti Siam village of Pandih Batu subdistrict in Pulang Pisau was chosen as a sampling area because they are rice-producing centres and are predominantly covered by tidal swampland. The three villages in the two districts were purposively sampled.

Respondents were randomly drawn from each of the three villages in proportion (unbalanced sample size). The villages were purposefully selected, and the number of farmers is proportional to the number of farmers in each village. The poll received responses from 94 farmers in total. The following data was acquired using structured surveys and interviews: (1) farmer characteristics, such as age, education, and years of farming experience; (2) land area; and (3) farming inputs, which include seed quantity (kg), lime, urea, KCl (kg), TSP (kg), and pesticide cost. (4) labour: total labour (person-days) and family labour (person-days). Due to the traditional nature of rice production in tidal swamplands, three characteristics, such as age, education, and experience, should be determinants of efficiency, whereas land ownership will dictate farmers' focus on rice cultivation.

2.2 Stochastic frontier model

The general form of a Stochastic frontier model is

$$Y_i = f(x_i;\beta)exp(v_i - u_i) \tag{1}$$

where, Y is the maximum achievable output, X is the input vector, β is the vector of parameters, v is the noise error component assumed to be a symmetric distribution random variable, and u is a positive (one-sided) random variable. For simplicity, we dropped the index in (1). On a logarithmic scale, we can write the model (1) as

$$Ln\ Y = Ln\ f(X,\beta) + v - u \tag{2}$$

In our particular case of rice production, the stochastic frontier model in Eq. (1) can be written as

$$\begin{aligned} Ln\ Y_i = \beta_0 + A_i + D\ (X_{ik}) \\ + \beta_1 \ln \max\big(X_{ik}\ , D\ (X_{ik})\big) \\ + \sum_{\substack{j=1,\\ j\neq k}}^{7} \beta_j \ln\big(X_{ij}\big) + v_i - u_i \end{aligned} \tag{3}$$

Y_i	The production of rice by the i-th farmer (ton)
X_{i1}	Cultivated area (ha)
X_{i2}	The weight of seeds the i-th farmer uses (kg)
X_{i3}	The weight of lime (dolomite) the i-th farmer(kg) applied
X_{i4}	The weight of fertilizer applied by the i-th farmer (kg; NPK-equivalent)
X_{i5}	Total labour (person-days)
X_{i6}	Pesticide cost (IDR)
A_i	Dummy variable for a system of planting, equal to 1 for direct seeding and 0 for transplanting
$D\ (X_{ik})$	Dummy variable, equal to 1 if $X_{ik} = 0$ and 0 if $X_{ik} > 0$
v_i	Random noise is assumed to be a normal random variable with E(V)=0 and var (v)=σ_v^2
u_i	Inefficiency error, assumed to half-normal random variable, with E(U)>0, var (u)=σ_u^2

The dummy variable was introduced to tackle when inputs like lime or fertilizers vary and may be zero (where no lime or fertilizer is applied). The technological framework for positive and zero fertilizer or lime is different, so the elasticity concerning the input, such as X_{ik}, for example, might not be the same value β_i for the observations involving the positive and zero values of X_{ik}, and the variance of the errors may be different [17]. Consequently, we adhere to the model presented by setting dummy variable $D(X_{ik})$ and then transforming X_{ik} to max ($D(X_{ik})$, X_{ij}). Some farmers did not apply lime (dolomite) on their cultivated fields. Therefore, we introduced $D(X_{ik}) = D(X_{i3})$ and X_{i3}=max($D(X_{i3})$, X_{i3}).

Conventional SFM assumes that v and u are independent variables distributed as Normal and half-normal distributions with mean μ and variance σ^2 . If the assumption of independence is relaxed, then we face the problem of defining the joint distribution of v and u. Smith [18] proposed using the copula function to connect the distribution of v and u.

2.3 Copula function

The copula function was commonly used to connect two distribution functions. Saklar's theorem states that any cumulative distribution of a two-dimensional random vector (X_1, X_2) can be written as

$$F(X_1, X_2) = C(F_1(X_1), F_2(X_2)) \quad (4)$$

where, $F_1(.)$ and $F_2(.)$ are the marginal cumulative distribution functions of X_1 and X_2, respectively, and $C(.)$ is a copula function. There are many forms of copula functions, and we will use three of those Copulas as follows:

1. Gaussian Copula:

$$C_{ga}(u_1, u_2; \rho) = \int_{-\infty}^{\phi^{-1}(u_1)} \int_{-\infty}^{\phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-r^2}} \exp\left[-\frac{x_1^2 + x_2^2 - 2rx_1x_2}{2(1-r^2)}\right] dx_1 dx_2 \quad (5)$$

where, -1< r <1 is Pearson's correlation coefficient, and ϕ is the cdf of the standard normal distribution.

2. Clayton Copula

$$C_{cl}(u_1, u_2 | \Theta) = (u_1^{\theta} + u_2^{\theta} - 1)^{-\frac{1}{\theta}} \quad (6)$$

where, Θ>0.

3. Frank Copula

$$C_{fr}(u_1, u_2) = -\frac{1}{\theta} \ln\left(1 + \frac{(\exp(-\theta u_1) - 1))(\exp((-\theta u_2) - 1)}{\exp((-\theta) - 1)}\right) \quad (7)$$

where, $\Theta \in (-\infty, \infty) \backslash \{0\}$. Positive (resp., negative) values of Θ correspond to positive (resp., negative) dependence.

The probability density function of the random vector (X_1, X_2) is

$$f(x_1, x_2) = \frac{\delta^2 F(x_1, x_2)}{\delta x_1 \delta x_2} = \frac{\delta^2 C(u_1, u_2)}{\delta u_1 \delta u_2} \frac{\delta F_1(x_1)}{\delta x_1} \frac{\delta F_2(x_2)}{\delta x_2} = c(u_1, u_2) f_1(x_1) f_2(x_2) \quad (8)$$

where, $f_1(x_1)$ and $f_2(x_2)$ are the marginal pdf of X_1 and X_2, respectively, and $c(.)$ is the derivative of copula function C.

2.4 Copula-based stochastic frontier

By relaxing the independent assumption on our model in Eq. (1), we will face the problem of determining the joint probability density function of u and v. Writing ϵ=v-u and applying Eq. (8), the pdf of u and v can be expressed as:

$$f_{uv}(u, v) = f_{uv}(u, u+\epsilon) = c(F_u(u), F_V(u+\epsilon)) f_u(u) . f_v(u+\epsilon) \quad (9)$$

where, $f_{uv}(.)$ is the joint pdf of u and v, $f_u(.)$ and $f_v(.)$ are the marginal pdfs of u and v, respectively. F_u and F_v are the cumulative distribution functions of u and v, while $c(.)$ is the derivative of the copula function C. The pdf of ϵ could be expressed as:

$$f(\epsilon) = \int_0^{\infty} (f_u(u) . f_v(u+\epsilon)\, c((F_u(u), (F_V(u+\epsilon)) du \quad (10)$$

$$f(u|\epsilon) = \frac{f_{uv}(u, u+\epsilon)}{f(\epsilon)} \quad (11)$$

Therefore, the conditional technical efficiency is given as

$$TE = E(e^{-u}|\epsilon) = \int_0^{\infty} e^{-u} \frac{f_{uv}(u, u+\epsilon)}{f_{\epsilon}(\epsilon)} du = \frac{\int_0^{\infty} \boldsymbol{e^{-u}} f_u(u) f_v(u+\epsilon) c(F_u(u), F_V(u+\epsilon))) du}{\int_0^{\infty} f_u(u) . f_v(u+\epsilon)\, c(F_u(u), F_V(u+\epsilon)) du} \quad (12)$$

Assuming that f_u is a pdf of a half-normal distribution N (0, σ_u) and $f_v(.)$ a pdf of normal distribution N (0, σ_v), and writing $u=u_0\sigma_u$, the numerator of Eq. (12) can be written as

$$\int_0^{\infty} e^{-u_0\sigma_0}\, 2\phi(u_0) f_v(u_0\sigma_u + \epsilon) c(F_u(u_0\sigma_u), F_V(u_0\sigma_u + \epsilon)) du_0 \quad (13)$$

Following Wiboonpongse et al. [5], Eq. (13) can be approximated by

$$\frac{1}{N} \sum_{r=1}^{N} e^{-u_{0r}\sigma_u}\, fv(u_{0r}\sigma_u + \epsilon) c(F_u(u_{0r}\sigma_u), (F_V(u_{0r}\sigma_u + \epsilon)) \quad (14)$$

where, $\phi(.)$ is a standard normal pdf and u_{0r}, r=1,2…N is a sequence of a random draw from a half-normal distribution. Similarly, the denominator in Eq. (12) can be approximated by

$$\frac{1}{N} \sum_{r=1}^{N} f_v(u_{0r}\sigma_u + \epsilon) c(F_u(u_{0r}\sigma_u), (F_V(u_{0r}\sigma_u + \epsilon)) \quad (15)$$

Hence, the TE can be approximated by

$$TE = \frac{\sum_{r=1}^{N} e^{-u_{0r}\sigma_u} f_v(u_{0r}\sigma_u + \epsilon) c(F_u(u_{0r}\sigma_u), F_v(u_{0r}\sigma_u + \epsilon))}{\sum_{r=1}^{N} f_v(u_{0r}\sigma_u + \epsilon) c(F_u(u_0\sigma_u), F_v(u_{or}\sigma_u + \epsilon))} \quad (16)$$

Technical efficiency in Eq. (16) depends on the copula function C since $f_{\epsilon}(\epsilon)$ and $f_{uv}(u, u+\epsilon)$ depend on c. Monte Carlo Simulation can estimate the TE. An R software program, "CopSfm," [19] can be used for such estimation.

When v and u are independent, C=π, and c=1, since C (u_1, u_2) = $\pi(u_1, u_2)$ =u_1u_2, and

$$\frac{\delta^2 \pi(u_1, u_2)}{\delta u_1 \delta u_2} = 1 \quad (17)$$

If the distributions of v and u are normal $N(0, \sigma_v^2)$ and half normal $N_+(0, \sigma_u^2)$, respectively, then

$$f_{uv}(u,u+\epsilon) = f_u(u)f_v(u+\epsilon) = \frac{2}{\sigma_u} \emptyset(\frac{u}{\sigma_u}) \frac{1}{\sigma_v} \emptyset(\frac{u+\epsilon}{\sigma_v}) \quad (18)$$

where, $\emptyset(.)$ is a standard normal. The pdf of ϵ is

$$f(\epsilon)=\int_0^\infty \frac{2}{\sigma_u} \emptyset\left(\frac{u}{\sigma_u}\right) \frac{1}{\sigma_v} \emptyset(\frac{u+\epsilon}{\sigma_v}) du \quad (19)$$

Aigner et al. [3] has derived that f(ϵ) in Eq. (19) is equal to

$$f(\epsilon)=\frac{2}{\sigma\sqrt{2\pi}} \left(1 - \phi\left(\frac{\epsilon\lambda}{\sigma}\right)\right) \exp\left(-\frac{1}{2\sigma^2}\epsilon^2\right) \quad (20)$$

where, $\lambda = \frac{\sigma_u}{\sigma_v}$. The pdf of u conditional on ϵ is a normal distribution with mean u_* and variance σ_*^2, N(u_*, σ_*^2) truncated at 0 is [4]

$$f(u|\epsilon) = (1 - \phi(\frac{u_*}{\sigma_*^2}))^{-1} \frac{1}{\sqrt{2\pi}}\, exp\left[\frac{-1}{2\sigma_*}(u - u_*)^2\right] \quad (21)$$

where,

$$u_* = \frac{-\epsilon\sigma_u^2}{\sigma_u^2 + \sigma_v^2} \quad (22)$$

And

$$\sigma_*^2 = \frac{\sigma_u^2\, \sigma_v^2}{\sigma_u^2 + \sigma_v^2} \quad (23)$$

The technical efficiency, if u and v are independent, given the value of ϵ, is

$$E(e^{-u}|\epsilon) = \int_0^\infty e^{-u}(1 - \phi(\frac{\boldsymbol{u}_*}{\sigma_*}))^{-1} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2\sigma_*^2}(u - u_*)^2\right) du = \int_0^\infty (1 - \phi(\frac{\boldsymbol{u}_*}{\sigma_*}))^{-1} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2\sigma_*^2}(u - u_*)^2 - u\right) du \quad (24)$$

The exponential argument in Eq. (24) can be written as

$$-\frac{1}{2\sigma_*^2}(\mathrm{u} - \mathrm{u}_*)^2 - \mathrm{u} = -\frac{1}{2}\left(\frac{\mathrm{u}}{\sigma_*} - \left(\frac{\mathrm{u}_*}{\sigma_*} - \sigma_*\right)\right)^2 - \mathrm{u}_* + \frac{1}{2}\sigma_*^2 \quad (25)$$

So that Eq. (24) becomes

$$exp(-u_* + \frac{1}{2}\sigma_*^2)(-\frac{1}{2}\left(1 - \phi\left(\frac{u_*}{\sigma_*}\right))^{-1}\right) \int_0^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{u}{\sigma_*} - (\frac{u_*}{\sigma_*} - \sigma_*))^2} du \quad (26)$$

Which can be written as

$$exp(-u_* + \frac{1}{2}\sigma_*^2)(-\frac{1}{2}\left(1 - \phi\left(\frac{u_*}{\sigma_*}\right)\right)^{-1})\phi\left(-\left(\frac{u_*}{\sigma_*} - \sigma_*\right)\right) \quad (27)$$

Hence, the TE becomes

$$\mathrm{TE} = \mathrm{E}(\mathrm{e}^{-\mathrm{u}}|\epsilon) = \exp(-\mathrm{u}_* + \frac{1}{2}\sigma_*^2)(-\frac{1}{2}\left(1 - \phi\left(\frac{\mathrm{u}_*}{\sigma_*}\right)\right)^{-1})\phi\left(-\left(\frac{\mathrm{u}_*}{\sigma_*} - \sigma_*\right)\right) \quad (28)$$

Which is equal to the TE of Battese and Coelli [20].

2.5 Model selection

To select among the four models (conventional and three copula-based SFM), we use Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) as follows:

$$AIC = 2k - 2\ln(L) \quad (29)$$

$$BIC = k\ln(n) - 2\ln(L) \quad (30)$$

where, k is the number of parameters in the model, L is the loglikelihood, and n is the number of observations. The best-fitted model has the lowest AIC and BIC.

2.6 Driver of efficiency

We consider four exogenous variables associated with the farmers' profile as drivers of efficiency and regress those variables on the efficiency ($E(exp(-u_i)|\epsilon)$). The four exogenous variables are age (Z_1), Education (Z_2), experience in farming (Z_3) of farmers' family heads, and land ownership (Z_4), with the following model.

$$E(exp(-U_i)|\epsilon) = \delta_1 Z_{1i} + \delta_2 Z_{2i} + \delta_3 Z_{3i} + \delta_4 Z_{4i} + \epsilon_i \quad (31)$$

3. RESULT AND DISCUSSION

3.1 Profile of respondent farmers

Table 1. Summary statistics of the data

Variables	Mean	Std Dev	Min	Max
Rice prod (t)	8.94	1.80	6.72	35.00
Area (ha)	2.49	1.74	0.50	10.00
Fertilizer (-kg) NPK	140.58	123.08	23.33	692.33
Lime/dolomite (kg)	1289.21	1410.48	0	10,000
Seed (kg)	69.47	65.72	7.00	400.00
Labour (person-days)	76.29	62.25	17.00	430.00
Pesticide cost (IDR)	2097.76	1810.8	140.0	9120.00

Despite having a lot of farming experience and being at productive ages, most of the farmers who participated in the study also needed more land and more education. Of the 94 farmers that responded to the survey, 81% were of productive age, and only 19% were of less productive age. Farmers are most productive between the ages of fifteen and forty-four. According to educational attainment, 48.94% of farmers have completed elementary school or less (0–6 years), 29.79% have completed junior high school (7-9 years), 23.85% have completed senior high school (10–12 years), and 2.75% have a college degree. Most farmers have been in the rice farming business for two to eighteen years (46.82%), followed by those who have been in it for 18 to 34 years (41.49%) and those who have been in it for more than 34 years. Regarding holding land, 32.98% of farmers owned between 3.0 and 5.6 ha, 54.25% owned between 0.5 and 3.0 hectares, and the rest owned more than 5.6 ha. Summary statistics of the data are presented in Table 1.

3.2 Model selection

The independence model, also known as Battese and Coelli's conventional model, is the most reliable as it has the lowest AIC (42.53793) and (70.51417) among the four models. AIC focuses on finding the best model to describe the data while penalizing complexity, and BIC also penalizes complexity with a higher penalty for the number of parameters. Despite all four models having the same production frontier and an identical number of parameters (k), the conventional model has the highest loglikelihood (ln L), resulting in the lowest AIC and BIC as determined by Eqs. (29)-(30). The Clayton copula-based SFM outperforms the other two models due to its low AIC and BIC (Table 2).

Table 2. Information Criterion and loglikelihood of SFMs

Copula	AIC	BIC	Loglikelihood
Independent	42.53793	70.51417	-10.26896
Gaussian	47.56879	78.08832	-11.78439
Clayton	46.72403	77.24356	-11.36201
Frank	49.09682	79.5484	-12.51443

3.3 Technical efficiency

The average technical efficiency (TE) of rice production in this study, calculated using the conventional SFM, is 0.75534, while Gaussian, Clayton, and Frank copula-based SFMs estimate 0.5583388, 0.6863300, and 0.7764366, respectively. Figure 1 shows that although most high efficiencies were estimated by conventional SFM, some farmers' estimations of TE were lower by the conventional model than those of the three copula SFM. This result indicates that the conventional SFM does not overestimate or underestimate average efficiency, as it falls between the values estimated by the Gaussian and Clayton copula-based SFMs but is lower than the Frank copula-based SFM. Therefore, using the conventional SFM for efficiency prediction is reliable.

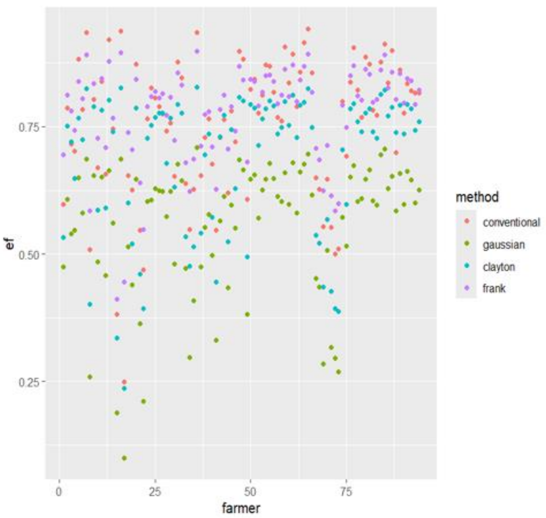

Figure 1. Farmer-wise distribution of TE estimated by the four methods

The estimated average efficiency suggests that farmers in tidal swampland achieve 75.5% of the maximum rice production with the available inputs. This finding aligns with similar studies in the same agroecosystem [8-10], which reported an estimated efficiency of 78.2%. However, the average efficiency for local varieties is lower at 58%. If we define efficient farmers as those with an efficiency greater than 0.70, then 70.21% of farmers on tidal swampland were efficient. This percentage varies when using different copula-based SFMs: 2.12% with Gaussian, 67% with Clayton, and 82.97% with Frank (Table 3). Therefore, the choice of SFM can impact the percentage of efficient farmers identified.

Table 3. Average efficiency and percentage of farmers having an efficiency score > 70%

Copula	Average TE	TE > 70%
Independent	0.7543541	70.21277
Gaussian	0.5583388	2.12766
Clayton	0.6863300	67.02128
Frank	0.7764366	82.97872

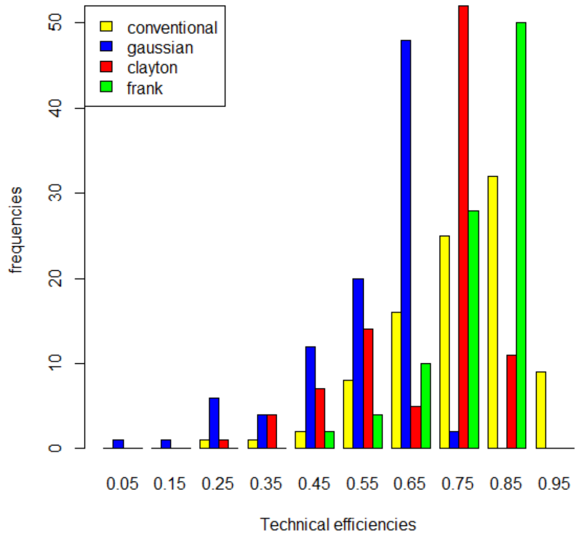

Figure 2. Histogram of TE based on some SFMs

According to Figure 2, most farmers have efficiencies of approximately 80-90% when estimated using the Frank copula SFM (green bar), 70-80% when estimated using the Clayton copula-based SFM (red bar), and 60-70% when estimated using the Gaussian copula-based SFM (blue bar). The efficiencies estimated using the conventional SFM (yellow bar) ranged evenly from 60% to 100%. While a few farmers assessed their efficiencies using the conventional model, which may reach 100%, the conventional model estimation in this study did not overestimate the efficiencies. Therefore, the output of the conventional model is suitable for providing recommendations.

3.4 Factors driving efficiency

Table 4 shows the impact of external variables on efficiency. Among the external variables considered, age and experience of the farmer's family heads had a notable influence on efficiency. The results indicated that farmers with more experience tend to have higher efficiency levels, as shown by the positive coefficient estimate. Conversely, the negative coefficient estimate indicated that older farmers were associated with lower efficiencies. Experienced farmers enhance efficiency through the Knowledge and skills they acquire over time. Rice farming in tidal swamps has been a traditional practice, leading to the accumulation of expertise among farmers. Research has also shown that farmers' experience plays a crucial role in improving technological efficiencies [21-23].

Table 4. Effect of exogenous variable on TE

Exogenous Variables	Copula			
	Independent	Gaussian	Clayton	Frank
Age	-0.0042*	-0.0029	0.0030	-0.0020
Education	0.00347	0.0023	0.0028	0.0010
Experience	0.0047**	0.0033	0.0030	0.0022
Land ownership	0.0046	0.0021	0.0023	0.0021

Note: 1. **) significant at 0.01; 2. *) significant at 0.05

Table 5. The relation between education (years in school) with TE

Education (yrs)	Education Level	TE
4	elementary	0.653
5	elementary	0.790
6	elementary	0.755
7	Junior high	0.650
9	Junior high	0.765
12	Senior high	0.721
15	University	0.899
16	University	0.883
17	University	0.905

Education and land ownership had little effect on efficiency. Aside from the lack of variation in education and land ownership, which may account for the two factors' nonsignificant effects on efficiencies, the less intensive extension, training, and supply of information and technology may explain why education does not affect efficiency. If the information and technology are given to them, farmers with higher levels of education will be more receptive to and capable of embracing new technology than those with lower levels of education. With a few exceptions for non-university education farmers (less than or equal to 12 years in school), Table 5 demonstrated that farmers with university education (15 to 17 years in school) had higher efficiency.

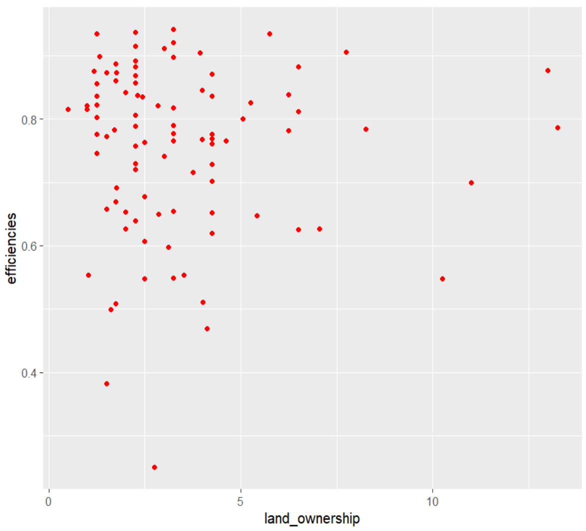

Figure 3. Distribution of efficiencies on land ownership

Figure 3 shows that at low land ownership, the efficiencies vary greatly from the lowest to the highest, while at high land ownership, efficiencies range from medium to high. Most of the land ownership is low, which causes nonsignificant effects of land ownership on efficiencies. However, the figure also indicated that the increase in land ownership will increase the TE.

3.5 Factors affecting rice production

The focus of the models under investigation is inference, i.e., determining which input variable has the most impact on rice production rather than predicting rice production accuracy based on input quantity and technical efficiency. Table 6 displays the production frontier estimates based on conventional SFM. The calculated coefficients indicate the elasticity of each variable in rice production. The area of rice cultivation and the amount of fertilizer applied, measured in kg of NPK fertilizers, significantly influence rice production. The elasticity of the cultivated area is 0.8892, while for fertilizers, it is 0.1583. This elasticity suggests that a 1% increase in the rice growing area in tidal swampland increases rice yield by 0.89%. Similarly, a 1% increase in fertilizer application enhances rice output by 0.16%, regardless of the increase in cultivation area.

Table 6. Factors affecting rice production in tidal swampland

Variables	Coeff.	Std Error	Z-Values	Pr (>Z)
Intercept	0.7820	0.4312	1.8136	0.0697
Area	0.8892	0.0965	9.2184	<2.2e-16***
Fertilizer	0.1583	0.0576	2.4782	0.0060**
Seed	-0.0755	0.0567	0.0467	0.1062
Lime	0.0228	0.0440	0.5195	0.6034
Labour	0.0266	0.0683	0.3891	0.6972
Pest.cost	0.0142	0.0342	0.4148	0.6783
P.system[a]	0.0404	0.0710	0.5689	0.6984
DX3[b]	0.0835	0.3205	0.2606	0.7944

Notes: 1. ***) significant at 0.01; 2. **) significant at 0.05; 3. [a]) planting system; 4. [b]) dummy variable.

Tidal swampland has limited soil nutrient availability, necessitating fertilization for practical farming and increased crop output. The production of improved rice varieties can lead to increased nutrient depletion, particularly of N, P, and K, as these nutrients are extracted in more significant quantities after harvest. This condition is due to the higher nutrient requirements of improved rice for optimal growth. Plant growth and yield follow the law of diminishing returns, meaning optimal output is achieved only under specific nutrient-balancing conditions. The nutrient balance of the soil is dynamic and constantly changing. Fertilization efficiency can be improved using fertilizers compatible with the soil's nutrient availability and the variety of crops grown.

KCl fertilizer enhances rice tolerance to iron toxicity, increases tiller number, and boosts yield. These benefits may be related to the potassium (K) nutrient deficiency in tidal swampland. Potassium is a macronutrient that stimulates various enzymes involved in photosynthesis and respiration. It also aids in protein and starch synthesis, cell growth, stomatal movement, and stress mitigation. Potassium also plays a role in maintaining anion-cation balance and regulating the electric charge. Studies have shown that potassium can increase root exclusion of iron and inhibit iron absorption [24, 25], beneficial in environments with iron toxicity.

Tidal swamplands often have low nitrogen and phosphorus levels, leading to deficiency symptoms such as pale leaf colour, reduced tillers, and lower yields. Inadequate phosphate levels can result in stunted plant growth and empty grains.

3.6 Discussion

Relaxing the independence assumption between the two error components in the stochastic frontier is intended to prevent the overestimation of technical efficiencies in rice production. However, such overestimation does not always happen and could be negligible. A specific no-independence model, namely the Frank copula-based SFM, produced a greater estimate of average efficiency and the percentage of farmers who practice efficient farming. What causes the few discrepancies and inconsistencies with the general theory of overestimation is left to be explained.

Conventional SFM and Copula-based SFM have significantly different methodologies and applications, and comparing their technical efficiency estimates requires an awareness of their respective strengths and limits. Conventional SFM depends on distributional assumptions for the inefficiency component (e.g., half-normal, truncated-normal) and the noise term (e.g., normal distribution). It is easier to implement, with fewer assumptions regarding the dependence structure of error terms, and is more computationally efficient. However, if these assumptions are not followed, strong assumptions regarding error term distributions can result in erroneous estimations. The independence of inefficiency and noise terms may not be maintained in practice.

Copula-based SFM, which makes use of copula functions, has the potential to improve the accuracy and resilience of efficiency estimations, apply less restrictive distribution assumptions, and capture complex relationships between inefficiency and noise sources. However, it is computationally more difficult since copula parameters must be estimated, the copula function must be carefully chosen, and practitioners must be better knowledgeable.

Although 70.21% of farmers are classified as efficient (efficiency score > 70%), there is still room to improve efficiency. Thirty per cent of farmers still need to become more efficient. Increased efficiency can be achieved by encouraging younger individuals to enter the farming industry, enhancing and expanding farmer education and training, and boosting land ownership.

Encouraging young people to start farming in tidal swampland areas is critical for guaranteeing food security, lowering unemployment, and encouraging sustainable development. to encourage and enable the next generation to pursue agriculture as a lucrative and dynamic economic endeavour and a source of income. Young farmers should be given subsidized loans or grants, encouraged to sell directly to customers through apps and online marketplaces, and given the opportunity to collaborate with one another through online forums or cooperatives.

Strengthening and expanding farmer education and training is critical for increasing agricultural output, assuring sustainable practices, and improving farmers' livelihoods. It will better prepare them to face difficulties, implement innovations, and succeed in a competitive agricultural landscape. Increasing farmer land ownership in tidal swampland is vital for increasing agricultural productivity, lowering poverty, and ensuring equitable development. Farmers cultivated rice fields in tidal swamplands ranging from 0.50 ha to 10 ha, with an average of 2.5 ha. However, most farmers in tidal swampland have a modest rice cultivation area.

Tidal swampland's contribution to national rice production is limited due to the low rice productivity in this agroecosystem, and only a tiny portion of tidal swampland has been planted with rice. Most tidal swampland is either abandoned or not yet ready for agriculture. To boost rice production in tidal swamplands and improve national food security, the Indonesian government has started a "food estate project."

This study's findings suggest that increasing the rice cultivated area and utilizing more NPK fertilizer can boost rice yield in tidal swampland. Large swamplands that are exposed to agriculture, however, may lose biodiversity, alter the hydrological cycle, emit greenhouse gases, degrade soil, pollute water, raise the danger of floods, and affect nearby communities. Additionally, because swamplands have special characteristics such as water pollution, soil acidification, the bioaccumulation of hazardous substances, and changed plant communities, the use of NPK (nitrogen, phosphorus, and potassium) fertilizers there may have detrimental effects.

As a result, while converting swampland to farmland may provide immediate economic benefits and NPK fertilizers might boost agricultural productivity, the long-term environmental costs are enormous and may compromise the ecosystem's health. Increasing technical efficiency could be a less harmful option to increase rice production in tidal swamplands.

4. CONCLUSION

Expanding cultivated land and using more fertilizers will boost rice production in tidal swamplands. However, increasing efficiency, which varies considerably across farmers, can still enhance rice production.

The conventional SFM is still the best appropriate model compared to copula SFM based on AIC and BIC criteria. It delivers more precise estimations of technological efficiency.

To further enhance technical efficiency, promoting the involvement of younger individuals in farming, providing additional training for farmers, and increasing land ownership in tidal swampland are recommended strategies.

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