Research Article

S. Sumaryanto, Sri Hery Susilowati, S. Saptana, Bambang Sayaka, Erma Suryani, Adang Agustian, A. Ashari, Helena Juliani Purba*, S. Sumedi, Saktyanu Kristyantoadi Dermoredjo, Tri Bastuti Purwantini, Rangga Ditya Yofa, Sahat Marulitua Pasaribu

Technical efficiency changes of rice farming in the favorable irrigated areas of Indonesia

https://doi.org/10.1515/opag-2022-0207
received February 20, 2023; accepted May 9, 2023

Abstract: The main sources of rice production growth are increases in the yield and area harvested. Yield improvement is carried out through intensification, mainly using more inputs and better irrigation, while increasing the harvested area is associated with increasing the cropping intensity. Unfortunately, even in favorable irrigated areas, outcomes of the coupled approach are not always synergistic. This study aims to assess technical efficiency (TE), its changes in direction, and the factors responsible for inefficiency during the last 10 years. The data analyzed were those of rice farming through a panel survey of farmer households in several villages with favorable irrigation. The survey was conducted in 2010, 2016, and 2021. The results showed that the use of higher seed quality and inorganic fertilizers positively affected the yield. The TE level was relatively high but tended to degrade in these 3 years. The farmers' TE in Java Island was higher than that outside Java. The older the farmer, the more inefficient the farmer was. The number of family members working in rice farming negatively affected efficiency. TE increased as the agricultural contribution to household income increased. On the other hand, the farmers' educational background did not significantly affect TE. Based on these findings, it is recommended to encourage farmers to adopt higher quality seeds of improved rice varieties. It is also urgent to encourage young farmers to pursue rice farming as their main profession. In the middle and long term, breeding improved rice varieties adapted to climate stress will become a pressing need.

Keywords: rice farming, panel data, rice productivity, technical efficiency, inefficiency factor

1 Introduction

Indonesian's staple food as the most vital source of carbohydrates is rice. The commodity is the main component of the food supply for national food security along with its relatively significant household consumption expenditure [1–3]. Indonesian per capita rice consumption is relatively high, i.e., 104 kg/year in 2019 [4]. Meanwhile, rice farming remains one of the main income sources for Indonesian farm households [5,6].

Rice crop is grown on various agroecosystems, either in lowland, upland, or swampland areas [7]. Most of the rice is produced in lowland areas so it is considered a determining factor for national rice availability. Among the lowland areas, irrigated land contributes the most share of rice production (67.5%) and rainfed lowland (27.5%). Both types of lowland areas (43% of the total area) are found on Java Island [8]. Irrigated land also plays an important role in the national rice production in some countries, such as Thailand [9], the Philippines [10], and Brazil [11].

* **Corresponding author: Helena Juliani Purba,** Research Center for Behavioral and Circular Economics, National Research and Innovation Agency, Jl. Gatot Subroto No. 10, Jakarta, Indonesia, e-mail: helenajulianipurba@gmail.com
S. Sumaryanto, Sri Hery Susilowati, Adang Agustian, A. Ashari: Research Center for Behavioral and Circular Economics, National Research and Innovation Agency, Jl. Gatot Subroto No. 10, Jakarta, Indonesia
S. Saptana: Research Center for Cooperative, Corporation, and People's Economy, National Research and Innovation Agency, Jl. Gatot Subroto No. 10, Jakarta, Indonesia
Bambang Sayaka, Saktyanu Kristyantoadi Dermoredjo, Sahat Marulitua Pasaribu: Research Center for Economics of Industry, Services, and Trade, National Research and Innovation Agency, Jl. Gatot Subroto No. 10, Jakarta, Indonesia
Erma Suryani, S. Sumedi, Rangga Ditya Yofa: Indonesian Center for Agricultural Socio-Economics and Policy Studies, Jl. Tentara Pelajar No. 3B, Bogor, Indonesia
Tri Bastuti Purwantini: Research Center for Social Welfare, Village, and Connectivity, National Research and Innovation Agency, Jl. Gatot Subroto No.10, Jakarta, Indonesia

The role of rice as the staple food of the majority of Indonesian is irreplaceable. On the one hand, Indonesia's total population is quite large, and thus, sustainable food security through rice production growth should at least meet its consumption demand. On the other hand, production growth is an outcome of those harvested area and yield and the country's ability to enhance agricultural land, especially for rice, is limited as the irrigation investment gets more expensive. This implies that the rice production growth will rely on enhanced cropping intensity and improved yield in the future. Consequently, rice farming's technical efficiency (TE) is essential. Rice production from irrigated lowlands will contribute more to the national food supply if it has high TE. Some studies showed that rice farming technical efficiencies in Indonesia varied among region, season, and year [12–16].

Referring to the empirical conditions, favorable irrigated areas are the lowland of rice-producing centers with satisfactory water irrigation availability, which encourage farmers to grow paddy at least twice or two growing seasons in 1 year. This is consistent with the fact that rice is the crop most chosen by farmers in the cropping pattern of the lowland areas. Rice is among the selected food crops because (i) rice price is the most stable among those of food commodities in Indonesia and (ii) the irrigation water system in the tertiary lowland blocks is water flow from one plot to another based on gravitation and technically the condition is suitable for paddy wetland cultivation but less suitable for other food commodities.

Most studies on TE were based on cross-sectional data, and it was rarely found any study using the panel data for evaluating the dynamics of TE in Indonesia. One that could be well noted is a study on National Farmers Panel (*Patanas*) in some villages including those favorable irrigated lowlands conducted by the Indonesian Center for Agricultural Socio-Economic and Policy Studies (ICASEPS) over several decades. The frontier production functions were applied to estimate the TE of the dairy industries in New South Wales and Victoria, Australia [17]. TE was estimated using panel data of dairy farms in New England by employing the stochastic production frontiers (SPFs) [18]. Estimations of a stochastic frontier production (SFP) function model to find the technical efficiencies were carried out using the panel data of the US domestic airline industry. The quarterly data of 12 airlines were used in this study from quarter I in 1970 to quarter II in 1978 [19]. Using the parametric production function and cost minimization hypothesis, it was possible to estimate firm-specific technical inefficiency based on the panel-data framework, which is allowed to vary over time [20]. The novelty of this study is the use of the panel data of rice farming yields in favorable irrigated areas for evaluating its TE in Indonesia. Using the unbalanced panel data, this study aims to (1) assess trends in the rice yield and TE on favorable irrigated rice fields, and (2) identify the technical inefficiency determinants.

2 Methods

2.1 Conceptual framework

The attainable yield is the result of various factors, which are internal or controllable and external or off-farmers' control. The other influencing factors are the input use intensity and relative prices [21]. Enhancement in economic efficiency and farming sustainability could be carried out through yield improvement and efficient resource allocation.

Technical inefficiency exists basically due to the gap between the actual yield of a firm compared to its potential yield. The firm could not achieve its potential yield because it may cope with best practices or organizational factors. If the firms apply input I_2, it operates at C and its yield is Q_4 on AA's actual production frontier and it is not technically efficient (Figure 1). To maximize its profit, the firm has to apply an input I_3 operating at D with output Q_3. However, to be technically efficient, the firm has to operate at the FF's production frontier, i.e., at B with output Q_1. Applying input I_2, the firm's TE is Q_2/Q_1. Thus, the firm's technical inefficiency is $(Q_1 - Q_2)/Q_1$.

Experienced rice farmers do not always achieve the expected yield and TE. Variation arises when farmers in the same land, ecosystem, and cropping season apply the same technology. Farmers' training, technical guidance, and credit access are among the actions to be taken [22]. Daily practice of rice farmers in homogenous regions and ecosystems tends to improve TE through maximizing yield efforts [23].

Factors affecting technical inefficiency varied among locations and seasons. Heriqbaldi et al. [24] used the SPF method and found a large inefficiency variation in the 15 provinces of study. The area size, income, and source of finance were the determining variables of TE. The farmers' participation in field schools, farmers' groups, crop spacing, seed quality, and cropping season affected significantly the TE. Kea et al. [25] showed that rice production in Cambodia depended on capital value and agricultural machinery adoption. They showed that the overall TE was 78.4%, indicating the possibility to improve TE due to relatively the same input and technology levels.

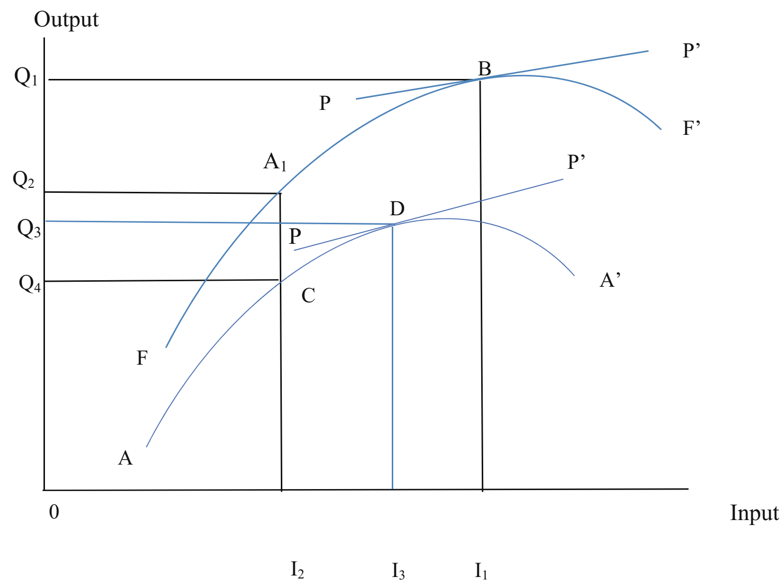

Figure 1: TE framework [26].

Applying panel data, it was found that the TE of rice production in Thailand was decreasing [27]. It was found that the TE decreased from the 1987/1988 cropping season to the 2007/2008 cropping season. A study by Alam et al. [28] in Bangladesh, applying an SPF, also indicated that there was a decrease in technical change from 1987 to 2004. Using the data envelopment analysis (DEA) approach, Pradhan [29] estimated that the average rice TE in Odisha, India, was 79.10%, which indicated that the input was overused up to 20.90%. Meanwhile, a study in Malaysia stated that rice farming had not been efficient but there was still potential for improvement with input rationalization [30]. Using the total factor productivity approach, rice farming in Indonesia tended to decrease due to relatively low TE [31].

The producers try their best to produce goods efficiently. In production economics, economic efficiency is realized if both technical and allocative efficiencies are attainable simultaneously. Empirically, the output market structure is oligopolistic resulting in the unpredictability of the farmers' commodity. Accordingly, most Indonesian rice farmers try to improve only their TE [27,28].

The rice farmers in Indonesia try their best practices to achieve the best yield. However, most of them do not operate at the frontier production function. Some factors affecting this are an inappropriate time of input application, lack of input quantity and quality, weather disturbance, etc. Water supply for irrigating rice crops is a crucial issue as competing water use with the non-agricultural sector is more intense [29,30].

This study explored an econometric approach to estimate rice farming TE, its changes, and factors affecting inefficiency. Using unbalanced panel data, two approaches were employed, namely (i) TE estimation using a time-varying decay model (truncated-normal; random effect), and (ii) the Tobit model to describe factors affecting technical inefficiency.

2.2 Analytical methods

The most popular approaches to calculate efficiency are (1) the non-parametric techniques [32], the DEA based on the linear programming tools; and (2) parametric techniques [33,34], the stochastic frontier analysis (SFA) – SFP – based on econometric tools. DEA does not require a functional form and SFA does. The DEA (deterministic) approach ignores the random effects (noise) but the SFA approach takes it into account. Therefore, in the DEA model, any deviation is considered inefficiency but in SFA noise and inefficiency are considered. Both approaches seem to be useful and their use will depend on the objectives of the analysis [35].

According to Silva and Azurbi [36], the DEA approach has the advantage of considering many inputs and many outputs simultaneously. It also does not require a parametric specification of a functional form to construct the frontier. The major limitations of DEA are that it is difficult, conceptually, to separate the effects of uncontrollable environmental variables and the measurement error from the effect of differences in farm management and the presence of outliers. Coelli and Perelman [37] stated that the main disadvantage of DEA is that when the calculation of shadow prices is desired, only a range of prices can be derived for efficient firms.

One advantage of parametric methods is that they allow the testing of hypotheses such as those relating to the significance of included inputs and/or outputs, returns to scale, and so on [37]. Coelli [38] and Coelli et al. [39] stated that estimating a frontier production function had two advantages compared to that of an average production function. First, the average production function estimate indicates an average technology function achieved by farmers, while the frontier production function estimate is significantly affected by the farmers with the best farming practices revealing their adopted technology. Second, the frontier production function represents the best practice method results in which farming efficiency is measurable. According to Reinhard et al. [40], one of the most important characteristics of econometric models (SFA) is that it allows a specification in the case of panel data and the construction of confidence intervals. The literature review shows that SPF taking error term into the model is relevant to estimate rice farming efficiency.

Random effect modeling was initiated by Pitt and Lee [41]. They proposed a model with distributional assumptions about the error term, $v_{it} \cap$ i.d. $N(0, \sigma_r^2)$, which represents noise, and $u_{it} \cap$ i.d. $N^{+}(0, \sigma_u^2)$ reflects the distribution of the non-negative component, which translates the inefficiency of the model. The estimate method applied was a maximum likelihood. Some years later, Battese and Coelli [17] adopted this formula and developed it by proposing truncated-normal distribution for modeling technical inefficiency components with maximum likelihood as the estimate method. This study employed a maximum likelihood estimator (MLE) to estimate the yield function of panel stochastic frontier time-varying decay (PSF-TVD).

The model of Pitt and Lee [41] was also improved by Schmidt and Sickles [19] using a random effect model by the assumption of a particular distribution for the inefficiency component and regressors variable over time. The random effect model is expressed as follows:

$$\ln Y_i = \beta_0^{\star} + \sum_{n=1}^{N} \beta_n \ln X_{nit} + v_{it} - u_i^{*}, \tag{1}$$

where $\beta_0^{*} = \beta_0 - E(u_i)$, $u_i^{*} = u_i - E(u_i)$, and zero mean for u_i^{*} and v_i. With the introduction of this transformation, the zero mean for the error term, the GLS (generalized least squares) technique, can be applied to estimate the model. The random effect model operates in the same way as the error component (one-way) model described in the literature on panel data. To estimate this model, the GLS technique is used in two steps.

For the time-varying decay model, the log-likelihood function is derived as

$$\begin{aligned}\ln L = &-\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\{\ln(2\pi) + \ln(\sigma_S^2)\}\\ &-\frac{1}{2}\sum_{i=1}^{N}(T_i - 1)\ln(1-\gamma) - \frac{1}{2}\sum_{i=1}^{N}\ln\left\{1 + \left(\sum_{i=1}^{N}\eta_{it}^2 - 1\right)\gamma\right\}\\ &- N\ln\{1-\Phi(\tilde{z})\} - \frac{1}{2}N\tilde{z}^2 + \sum_{i=1}^{N}\ln\{1-\Phi(-z_i^{*})\}\\ &+\frac{1}{2}\sum_{i=1}^{N} z_i^{*2} - \frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\frac{\varepsilon_{it}^2}{(1-\gamma)\sigma_S^2},\end{aligned} \tag{2}$$

where

$$\begin{aligned}&\sigma = (\sigma_u^2 + \sigma_v^2)^{\frac{1}{2}},\ \gamma = \sigma_u^2/\sigma^2,\ \varepsilon_{it} = y_{it} - \mathbf{x}_{it}\beta,\\ &\eta_{it} = \exp\{-\eta(t-T)\},\\ &\tilde{z} = \mu/(\gamma\sigma^2)^{1/2},\ \ \Phi(\,),\end{aligned} \tag{3}$$

is the cumulative distribution function of the standard normal distribution, and

$$z_i^{*} = \frac{\mu(1-\gamma) - s\gamma\sum_{t=1}^{T_i}\eta_{it}\varepsilon_{it}}{\left[\gamma(1-\gamma)\sigma_S^2\{1 + (\sum_{t=1}^{T_i}\eta_{it}^2 - 1)\gamma\}\right]^{1/2}}. \tag{4}$$

Social interaction among individuals in the intra-region in the country is more intense due to their homogeneity than that in the inter-region. Thus, it is common to report standard errors that account for the clustering of units. Typically, the motivation given for clustering adjustments is that unobserved components in outcomes for units within clusters are correlated. However, because correlation may take place across more than one dimension, this motivation makes it difficult to justify why researchers use clustering in some dimensions, such as geographic [42]. The better parameter estimate method is maximum likelihood with clustered-robust standard errors.

Cluster-robust standard errors are now widely used, popularized in part by Reinhard et al. [40] and Bertrand et al. [43], who incorporated the method in Stata. Cameron and Miller [44] and Wooldridge [45] provide surveys, and lengthy expositions are given in Wooldridge [45]. Based on those arguments, the estimate method applied is a likelihood with clustered-robust standard errors, as its parameter estimates are the most efficient and consistent. The cluster approach is islands, i.e., Java and off-Java.

2.3 Empirical model

2.3.1 Estimating TE

TE can be measured using either the total production or yield. The yield function approach requires outputs, and all inputs are measured per hectare. This study applied a yield approach. Production inputs presumably affecting yields are inputs used per hectare consisting of seed, fertilizer, labor, and other expenses. There are also other factors affecting the yield hypothesized. First, water adequacy for rice farming. Second, the variables related to regional characteristics represent some factors such as agricultural development, population density and its implications on socio-cultural aspects and general condition of infrastructure, and farm-level water management.

Some rice farmers used their seed production and some of them adopted certified seed. The viability of certified seed is relatively higher resulting in a lower volume of seed grown for the same area than that of farmers' seeds. The yield potential of the certified seed is also higher. In addition to the seed volume as one of the independent variables, the seed dummy was also introduced, i.e., (a) certified seed and (b) the farmers' seed.

Besides seed, fertilizer, and labor, the model also incorporated expenses for herbicides, pesticides, liquid fertilizers, organic fertilizers, and irrigation fees. It was aimed to accommodate farmers' recall on expense values but not their accurate volume of purchase for respected inputs due to the various brands of those inputs. Few farmers applied organic fertilizer, i.e., less than 3%, and it was incorporated into part of other expenses for simplifying purposes.

All of the sample rice farmers adopted inorganic fertilizers for their rice farming. The types and volumes of inorganic fertilizers varied depending on preference, price, and availability. There were three popular single inorganic fertilizers, i.e., urea, SP36, KCl, and one compound fertilizer, i.e., NPK (15:15:15). The farmers obtained information from the agricultural extension workers that inorganic fertilizers contained three nutrients most required by the rice crop, i.e., nitrogen, phosphorus, and potash. The main sources of nitrogen are urea, ZA, and NPK. Phosphorus comes from SP36 and NPK, while sources of potash are KCl and NPK fertilizers. ZA fertilizer is less popular with farmers. Most farmers well recognize urea and NPK fertilizers for rice farming application. However, only some farmers adopted SP36 and KCl fertilizers. The measurement unit for fertilizers used by the farmers in this study was based on their nutrient content. Assuming that Q_{Urea}, Q_{ZA}, Q_{SP36}, Q_{KCl}, and Q_{NPK} represent the volume of urea, ZA, SP36, and NPK applied, and based on the label on its package, the contents of N, P, and K used in the rice farming are as follows:

$$\mathrm{N} = 0.46 \times Q_{\mathrm{Urea}} + 0.21 \times Q_{\mathrm{ZA}} + 0.15 \times Q_{\mathrm{NPK}},$$

$$\mathrm{P} = 0.36 \times Q_{\mathrm{SP36}} + 0.15 \times Q_{\mathrm{NPK}},$$

$$\mathrm{K} = 0.60 \times Q_{\mathrm{KCl}} + 0.15 \times Q_{\mathrm{NPK}}. \tag{5}$$

The model applied is the stochastic Frontier production function using unbalanced panel data with the time-varying decay model:

$$\ln y_{it} = \ln \beta_0 \sum_{k=1}^{6} \beta_k \ln x_{kit} + \sum_{l=1}^{4} \delta_l \ln D_{lit} + v_{it} - u_{it}, \tag{6}$$

where y and $x_1, x_2, \cdots x_6$ variables in the model above were expressed per hectare per cropping season. The subscript i refers to the farming carried out each cropping season by the corresponding farmer, while t denotes the observed year, i.e., 2010, 2016, and 2021. The description of each variable is as follows:

(a) y = yield (kg/hectare).
(b) x_1 is the seed used, x_2, x_3, and x_4 are nutrient contents of nitrogen, phosphorous, and potash in the urea, ZA, SP36, and NPK fertilizers applied (kg/hectare).
(c) x_5 is the labor used (man-days equivalent/hectare).
(d) x_6 is another input outside $x_1, \ldots, x_5$. Formerly, the measurement was in IDR in accordance with the year of survey conducted (2010, 2016, 2021). To get a suitable measurement, the value was deflated by the average price of the output (rice) in the village corresponding to its year and season. So, the new measurement is in kg rice equivalent per hectare.

The farmers could control only some factors affecting the rice yield in rice farming. Those external factors were not easily measured using ratios but they could be categorized and were represented in dummy variables. There are four dummy variables, namely:

D_1 = seed quality; 0 = low (uncertified seed), 1 = high (certified seed); base: 0.

D_2 = cropping season (I = rainy season, II = first dry season, and III = second dry season); base: cropping season I.

D_3 = rainfall regime (RR) and refers to the Walsh and Lawler approach (1981). There are three rainfall regimes in this study, namely RR_2, RR_3, RR_4 base: RR_2.

D_4 = region; 0 = Java Island, 1 = off-Java Island; base: Java Island.

The following are justifications for the dummy variables above. First, the effect of seeds on the yield is not only by their volume applied but also their quality. Theoretically, higher quality will give a higher yield. Second, the rice yield will be higher if the rice crop during certain periods gets sufficient inundation [46]. Water supply for rice farming comes from irrigation and rainfall. Rainfall among seasons and rainfall regimes is different. In the same rainfall regimes, the rainfall in season I > season II > season III. For the same seasons, the rainfall in RR_2 > RR_3 > RR_4. Third, the social economic conditions of rural Java are different from those in off-Java. Those factors were presumably affecting the achieved TE.

Based on SPF, it was possible to estimate the TE for each observation [17,20,47], namely:

$$\mathrm{TE}_{it} = \exp(-u_{it}). \tag{7}$$

It was assumed that u_i was identically independent distribution (iid) and nonnegative error term normally distributed independently truncated at 0, with a certain average value and constant variance.

The change direction of TE (η) could be derived from the following relations:

$$u_{it} = \eta_{it}u_i = \{\exp[-\eta_{(t-T)}]\}u_i, \tag{8}$$

$$\eta_{it} = \exp[-\eta_{(t-T)}], \tag{9}$$

$$\ln \eta_{it} = -\eta_{(t-T)}, \tag{10}$$

meanwhile $\eta_{it} = \frac{u_{it}}{u_i}$, thus:

$$\eta_{(t-T)} = -\ln \frac{u_{it}}{u_i}, \tag{11}$$

where η_{it} represents time-varying TE conditions. The estimates give positive, negative, or equal to zero statistically. η values indicate TE changes.

$$\eta = \begin{cases} \text{statistically}\eta > 0 \\ \quad \Rightarrow \text{representing increased technical efficiency} \\ \text{statistically}\eta < 0 \\ \quad \Rightarrow \text{representing decreased technical efficiency} \\ \text{statistically}\eta = 0 \\ \quad \Rightarrow \text{representing no technical efficiency change} \end{cases} \tag{12}$$

2.3.2 Estimating TE

Estimating the factors affecting inefficiency was carried out using the Tobit model as follows:

$$u_{it} = b_0 + \sum_{m=1}^{5} b_m z_{mit} + \sum_{w=1}^{3} d_w \mathrm{Dum}_{wit} + \varepsilon_{it}, \tag{13}$$

where u_{it} is the rice farming technical inefficiency of ith farmer's household in tth year, z_{it} is the ith farmer's household age in tth year (year), z_{2t} is the ith farmer's household formal educational level in tth year (year), z_{3t} is the total household members working on the farm (person), z_{4it} is the total land holding size per year, included outside land holding for rice farming (hectare), z_{5t} is the rice farming income share to farmer's household income (%), Dum_1 represents the variable dummy of land-holding status (0 = owned, 1 = others), Dum_2 represents the variable dummy of the farmer's main job (0 = on the farm, 1 = others), and Dum_3 represents the dummy variable of the region (0 = Java Island, 1 = off-Java Island).

2.4 Data

The primary data analyzed were panel data collected from the farmer's household survey. The survey was carried out in 2010, 2016, and 2021 in seven villages and three rainfall regimes with their respective agroecosystems of favorable irrigated rice fields distributed in seven districts of five provinces in Indonesia (Table 1).

The total sample farmers in 2010 were 187 households. Due to attrition, the samples in 2016 and 2021 were each of 137 and 128 households. Thus, the primary data analyzed were unbalanced panel data. It showed that the cross-sectional unit had unequal time-series observations. STATA application was employed for data processing and analysis in this article. STATA is able to regress unbalanced panel data to balanced panel data [48].

3 Results and discussion

As shown in Table 2, rice seed varieties adopted by the sample farmer in the study location were as follows. Most rice farmers, i.e., 444 out of 451 farm household samples, adopted the high-yielding varieties (HYVs). However, most of the sample farmers (73%) grew uncertified rice seeds, namely, they grew the seeds that they produced. The certified rice seed adoption rate was around 27%, mainly found in Java Island, i.e., Sindangsari, Tugu, Mojorejo, and Padomasan villages. Among the most popular HYVs were *Inpari32*, *Mekongga*, and *Ciherang*. The farmers sowed seeds several days before land tillage. Seed transplantation was carried out in about 2–3 weeks after sowing. HYVs were harvested at 95–100 days, on average, after planting.

The rice yield trend was not linear. The yield in 2010 was lower than that in 2016 (t = −3.3365), and the yield in

Table 1: Number of respondents by study location in 2010, 2016, and 2021

Island and province	District*	Subdistrict	Village	Respondents		
				2010	2016	2021
Java island						
West Java	Karawang (RR_3)	Kutawaluya	Sindangsari	27	19	19
	Indramayu (RR_3)	Lelea	Tugu	28	21	20
Central Java	Sragen (RR_3)	Karang Malang	Mojorejo	25	17	15
East Java	Jember (RR_4)	Jombang	Padomasan	32	22	21
Off-Java island						
North Sumatera	Serdang Bedagai (RR_2)	Perbaungan	Lidah Tanah	19	13	13
South Sulawesi	Sidrap (RR_3)	Watang Pulu	Carawali	29	23	20
	Luwu (RR_2)	Lamasi	Salujambu	27	22	19
	Total			187	137	127

*RR – rainfall regime.

2016 was higher than that in 2021 (t = 3.6307). Inter-seasonal yield was found to be highest in the first growing season (rainy season) and lowest in the third growing season (second dry season). Inputs applied for the same growing seasons were relatively more intensive. Descriptive outputs and inputs applied per hectare and per growing season are depicted in the Appendix.

3.1 Stochastic frontier estimates

The stochastic frontier production function estimate results are shown in Table 3. Referring to a Cobb–Douglass model, the coefficients of each estimated parameter indicated its respective elasticity [49].

In general, most rice yield function estimates were significantly different, i.e., 9 out of 10 variables in the model. The signs of the coefficients met the general economic theory. Those variables were application rates of seeds, fertilizer nutrients of N, P, K, and pesticides, as well as the dummies of seed quality, *cropping season,* rainfall regime, and islands. Detailed descriptions of the nine variables are provided in the following sections.

3.1.1 Application of quality seed

The findings showed that the more seed volume the farmers applied, the yield was lowered significantly. It was in accordance with the results in the Nigeria case [50]. Conversely, the quality rice seed adoption improved the rice yield significantly. Technical irrigated lowland was quite suitable for quality seed application such that it positively affected the rice yield. On the other hand, low-quality seed application at a higher rate decreased the rice yield.

Based on estimation, high-quality seed application significantly increased the rice yield by 10.8% compared

Table 2: Sample farmers' distribution by high-yielding rice varieties adopted in each study village: 2010, 2016, and 2021

No.	Island/village	Uncertified seed		Certified seed		Total	Rice HYVs
		N	%	N	%		
1	Java island						
1.1	Tugu	20	29.9	47	70.1	67	Inpari32, Mekongga
1.2	Sindangsari	28	43.1	37	56.9	65	Inpari32
1.3	Padomasan	62	86.1	10	13.9	72	Inpari32, Mekongga
1.4	Mojorejo	42	73.7	15	26.3	57	Mekongga, Inpari32
2	Off-Java island						
2.1	Carawali	70	97.2	2	2.8	72	Inpari32, Mekongga
2.2	Lidah Tanah	40	88.9	5	11.1	45	Inpari32
2.3	Salujambu	64	97.0	2	3.0	66	Ciherang, Inpari32
	Total	326	73.4	118	26.6	444	Inpari32, Mekongga, Ciherang

Table 3: Stochastic frontier production function estimate

Dependent variable: Yield	Coefficient	Robust Std. Err.	$P > \|z\|$
Frontier			
x_1 = seed (kg/ha)	−0.017	0.016	0.286
x_2 = nitrogen (kg/ha)	0.093	0.047	0.046
x_3 = phosphorus (kg/ha)	0.051	0.007	0.000
x_4 = potash (kg/ha)	0.064	0.008	0.000
x_5 = labor (man-days eq./ha)	0.006	0.028	0.832
x_6 = other input (IDR standardized by average village output price)	0.014	0.023	0.560
Dummy variables			
(a) Quality of seed	0.106	0.013	0.000
(b) Cropping season:			
II (first dry season)	−0.034	0.033	0.310
III (second dry season)	−0.101	0.005	0.000
(c) Rainfall regime (RR)			
RR_3	0.009	0.011	0.411
RR_4	−0.036	0.004	0.000
(d) Island	−0.050	0.001	0.000
_cons	7.839	0.161	0.000
/lnsigma2	3.225	0.075	0.000
/ilgtgamma	6.002	0.056	0.000
/mu	−187.899	10.191	0.000
/eta	−0.338	0.023	0.000
sigma2	25.143	1.893	
Gamma	0.998	0.000	
sigma_u2	25.081	1.889	
sigma_v2	0.062	0.005	

Time-varying decay model (truncated-normal), group variable: unbal_farmer, time variable: year and season, Log pseudolikelihood = −133.2150, number of obs. = 1,012, number of groups = 507, Prob > chi^2 = 0.0000, Wald $chi^2(2) = 1.07 \times 10^9$ (SE adjusted for two clusters in Island).

to the application of low-quality seed at a 99% significant level, *ceteris paribus*. This finding was in accordance with the research results of Theingi and Thanda [51] and Houngue and Nonvide [52] indicating that the quality seed adoption elasticity on the rice yield was 0.191 while its elasticity of low-quality seed, i.e., local seed, was only 0.072. The study of Jimi et al. [53] revealed that high TE was achieved by modern hybrid rice varieties compared to the traditional variety. Other studies showed that corn farming TE in Ghana was affected among others by improved variety adoption enhancement [52,53]. The findings pointed out that the quality seed supply and education for farmers to adopt quality rice seeds are strategic policies to be implemented.

3.1.2 Application of N, P, and K nutrients

The application of three main fertilizer nutrients had coefficients of 0.103, 0.067, and 0.074 with their respective significant levels of 99%. If the farmers increased the N nutrient application usually originating from urea, ZA, and the NPK fertilizer by 1%, the rice yield would significantly increase by 0.103% (*ceteris paribus*). It was also true for the application of P and K nutrients. This finding revealed that the technically irrigated lowland was still responsive to inorganic applications, especially those containing N nutrients. The result of this study was consistent with that of Kusnadi et al. [54] that analyzed rice production factors in some rice-producing centers in Indonesia. Thus, fertilizer supply, especially those containing N nutrients on time and appropriate volume in accordance with the rice crop growth demand is the right strategy for rice yield improvement.

Khan et al. [55] found that the application of inorganic fertilizers, namely urea and diammonium phosphate, in Pakistan significantly improved rice yield. In Myanmar, inorganic fertilizers also significantly affected smallholding rice farms [51]. Furthermore, Hendrani et al. [56] used SFA and the generalized linear model and found that rice farming applied the balanced combination of organic and inorganic fertilizers in West Java Province, Indonesia, resulting in 9% higher TE than the conventional method.

3.1.3 Other inputs

These inputs significantly (95%) affected the rice yield by 0.026. This implied that an increase of these inputs by 1% would increase the rice yield by 0.03% (*ceteris paribus*). In this context, most of the other inputs were pesticides besides herbicides, irrigation fees, and taxes. All of these inputs were valued in thousand rupiahs or IDR000.

The farmers usually applied pesticides after pests and/or disease attacks, and not anticipatively. Thus, the pesticide dosage applied by farmers depended on the pest attack intensity. The irrigated lowland farmers had good technical knowledge of dealing with the crop's pests and diseases even though the pesticide effect was lower compared to those of other inputs. This finding was in accordance with other research findings that revealed pesticide volumes applied by the farmers did not improve the rice yield significantly [55–58]. However, this finding was different from those found in previous studies [7,23,50,59–61], which showed a significant positive impact of the applied pesticide on the rice yield.

3.1.4 Cropping season

Most farmers (67%) grew rice twice a year in the wet and first dry seasons. Some farmers (37%) grew this crop three times a year, namely the wet, first, and second dry seasons. Rice yields in the wet and first dry seasons were not significantly different. However, the rice yield in the second dry season was lower than those in the two previous seasons. This finding was in line with the study on irrigated rice in the Philippines where the rice yield in the wet season was higher than that in the dry season [10].

3.1.5 Rainfall regime

Referring to Walsh and Lawler [62], the rainfall regime was classified into seven categories, i.e., (i) very equitable, (ii) equitable but with a definite wetter season, (iii) rather seasonal with a short drier season, (iv) seasonal, (v) markedly seasonal with a long drier season, (vi) mostly rain in 3 months or less, and (vii) extreme, almost all rain in 1–2 months.

The estimated results showed that the expected rice yield in the rainfall regime (iii) is not significantly different from the regime (ii). On the other hand, the rice yield in the rainfall regime (iv) is different from that of the regime (ii). This confirmed the field phenomenon that the rainfall effect, mainly in the second dry season, was significant in the favorable irrigated areas.

3.1.6 Region

The Java Island area is only 6.75% of total Indonesia, but the rice harvested area on this island is 52.46% of this country. According to BPS, the rice yield in Java Island was on average, 6% higher than the national yield [63]. The lack of irrigation access, less intensive fertilizer application, and lower application of qualified seed impacted the rice yield outside Java to be relatively lower. This implies that improving the rice yield in off-Java could be carried out by improving irrigation access and more intensified fertilizer application. On the other hand, in the favorable irrigated area, the estimated results showed that the yield discrepancy between Java and off-Java was only 3.2%.

3.1.7 Gamma coefficient

Another important coefficient to be discussed in Table 3 is the gamma coefficient, which indicates the proportion of sigma u^2 with sigma v^2 (sigma u^2 + sigma v^2). Given the gamma coefficient of 0.997, it indicated that almost all rice yield variations were due to TE factors. This finding implied that rice farming technical skill enhancement and farmers' managerial capacity improvement are the dominant factors to boost the rice yield in favorable irrigated areas of Indonesia. It was one of the very intensive agricultural extension impacts implemented in these areas. Other studies also indicated that agricultural extension enabled farmers to improve their technical skills in applying improved technology [7,62].

3.2 TE rating and its dynamics

Table 4 depicts the mean and coefficient variation of the actual yield, frontier yield, and TE rating in 2010, 2016, and 2021. Based on this finding and referring to the TE standard of 70% [39], it was concluded that the TE of rice farming in favorable irrigated areas in Indonesia, in general, was efficient (more than 87%).

During the periods of 2010–2011 and 2016–2021, there were little significant changes in the TE significantly, as depicted in Table 3, namely *eta* = −0.217 with a robust standard error of 0.008. A decrease in rice farming TE in lowland areas was also observed in other Asian countries even with larger magnitudes. For example, in Thailand, rice farming TE decreased by 17.76% between 1987/1988 and 2007/2008 [27]. It was also found that rice farming TE in Bangladesh decreased by 10.84% from 1987 to 2000 and by 18.92% between 2000 and 2004 [28].

The TE change over time is not always along with the output level change per area unit (productivity). Figure 2 shows that even though rice farming TE decreased between 2010 and 2016, its yield increased by 6% (MT-2) and 10.44% (MT-3). The decreased TE is a decreased yield of the input bundle increase. In other words, applied production inputs tended to expand between 2010 and 2016 in which the output increased ratio to increased input or diminishing marginal productivity of the input bundle. The increased input applied revealed a higher intensification level indicated by per hectare input use improvement, especially the fertilizer. More intensified practice dealt with other factors such as agriculture infrastructure, lowered soil fertility, and climate factors. This implies the productivity leveling off. Thus, educating farmers on production inputs such as utilizing more organic fertilizers followed by decreasing inorganic fertilizers could be an effort to improve the rice yield.

The distribution of farmers by the TE group is shown in Table 5. If the TE of 0.7 was used as the lower limit of

Table 4: Rice farming TE in 2010, 2016, and 2021

	Mean	Coef. Var
Year: 2010 (*n* = 419)		
Actual yield (ton/ha)	5.669	0.250
Predicted (frontier) yield (ton/ha)	6.123	0.090
TE	0.881	0.075
Year: 2016 (*n* = 302)		
Actual yield (ton/ha)	6.057	0.267
Predicted (frontier) yield (ton/ha)	6.437	0.082
TE	0.878	0.083
Year: 2021 (*n* = 291)		
Actual yield (ton/ha)	5.583	0.279
Predicted (frontier) yield (ton/ha)	6.354	0.090
TE	0.871	0.103

high TE, the rice farmers classified with high TE in 2010, 2016, and 2021 were 90, 88, and 87%, respectively

3.3 Factors affecting technical inefficiency

There were five out of eight variables affecting rice farming technical inefficiency significantly for the observed period (Table 6). The five variables that were significant at the 95% level were the household head age, the total family labor working on farms, the total land holding size, the agricultural income share, and the main jobs of household heads. The variables that were not significant were the educational level, land ownership status, and regional dummy of household heads. The following are descriptions of both significant and insignificant variables.

Table 5: Distribution of TE levels by groups in 2010, 2016, and 2021 (%)

TE group	2010	2016	2021
TE ≤ 0.50	0.72	0.99	2.41
0.51 < TE ≤ 0.60	1.67	1.66	2.75
0.61 < TE ≤ 0.70	7.40	9.27	7.56
0.71 < TE ≤ 0.80	40.10	39.40	39.86
TE > 0.80	50.12	48.68	47.42

3.3.1 Household heads' age

The household head age parameter was positive, indicating that the older the household head the higher the technical inefficiency. Rice farming carried out by younger farmers would be more efficient as they were stronger physically and more capable. Older farmers are usually more conservative in adopting new technology. The other studies were in accordance with this study [23,27,50,60,63–65].

3.3.2 Total household members working on the farm

This variable was significantly positive at a 95% level on rice farming technical inefficiency. The more household members working on the farm, the more inefficient rice farming was. This finding was in accordance with other studies stating that more total household members working on the farm indicated more inefficient farming compared to those with fewer household members [39,52,66]. It was possible to take place if the household members involved in rice farming were less skilled. Rice farming would be more

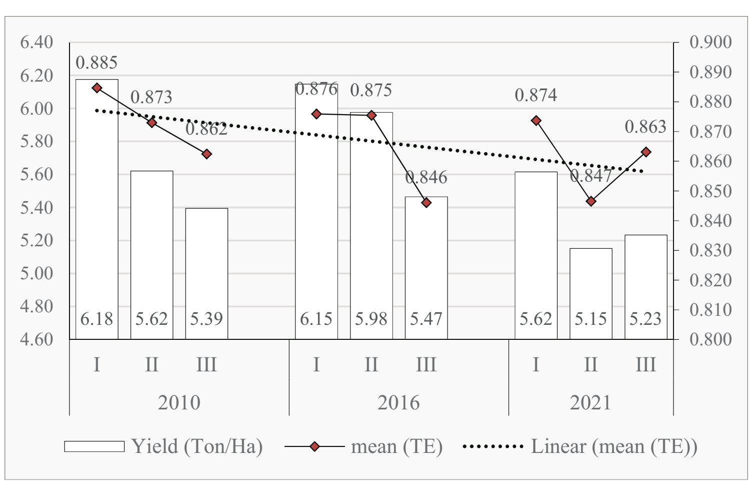

Figure 2: Mean of yield and TE by season and year.

efficient if hired labor was employed rather than family labor. Hired labor played more role in increasing efficiency as most of the production process depends on them. Previous studies found that more farmer household members increased TE due to increased labor and substituted hired labor [10,27,28,67,68].

Total households working on farms tended to increase by more than twofold during the three periods of the panel, i.e., on average from 1.43 persons per household in 2016 to 3.89 persons per household in 2021. The drastic increase in farmer's household members working on farms was one of the impacts of the COVID-19 pandemic. Some household members who previously worked in urban areas went back to their villages due to labor layoff and worked on farms with fewer skills.

3.3.3 Total land holding size

The total land holding size was the outcome of the area size with cropping intensity. In 1 year, the average land areas for rice farming in Java Island and off-Java were 0.93 and 1.19 ha, respectively. The average total land holding areas in Java Island and off-Java were 1.22 and 1.12 ha, respectively.

The total land holding significantly and positively affected the rice farming technical inefficiency. This indicated that the more a farmer's total land-holding area, the more technically inefficient the rice farming would be. The total land holding size in this study consisted of lowland, perennial-tree planted land, dryland, and home yard. Thus, the findings of the study were different from the other studies. Some studies found that the farmers with more land-holding sizes were more technically efficient [27,28,69,70].

3.3.4 Share of farm income

The farmer family's income shares from farming negatively affected the technical inefficiency of rice farming at a 95% level for the 2010, 2016, and 2021 cropping seasons. This revealed that the higher the farming income ratio, the rice farming would be more technically efficient. Other studies also revealed that the higher farming income ratio revealed the farmer household's participation in managing rice farming to be more efficient [10,27].

The average sample household's income farming share in 3 years was 69.8% but it tended to decrease, i.e., 76% in 2010, 74% in 2016, and 54% in 2021. This decreased ratio of farmers' household income was in line with those of household heads' main jobs of farming that tended to decline, namely 95, 89, and 91% in 2010, 2016, and 2021, respectively. The increased ratio of household heads with farming main jobs in 2021 was affected by the COVID-19 pandemic ratio.

3.3.5 Main jobs of the household heads

This dummy significantly and positively affected technical inefficiency. This revealed that the household heads with non-farming main jobs decreased the rice farming TE. Another study also showed that increasing non-farming job opportunities by 10% would increase farming technical inefficiency by 0.3% [28]. This result was in

Table 6: Parameter estimate of factors affecting inefficiency (u_{it})

		Coefficient	Std. Err.	$P > \|z\|$
z_{1t}	Age of the household head	0.0011	0.0004	0.0030
z_{1t}	Education of the household head	−0.0012	0.0010	0.2060
z_{1t}	Number of household members working on the farm	0.0081	0.0017	0.0000
z_{1t}	Total land holding size	0.0114	0.0029	0.0000
z_{1t}	Share of the farm income	−0.0219	0.0090	0.0140
Dummy variables:				
Dum_1	Main job of the household head (0 = agriculture, 1 = non)	0.0228	0.0105	0.0300
Dum_1	Tenurial status (0 = owned, 1 = non-owned)	0.0100	0.0078	0.1980
Dum_1	Region (0 = Java, 1 = off-Java)	0.0049	0.0099	0.6210
	_cons	0.0490	0.0230	0.0330
	/sigma_u	0.0581	0.0037	0.0000
	/sigma_e	0.0405	0.0018	0.0000
	Rho	0.6732	0.0361	

Log-likelihood = 643.83667.

accordance with the study of Balcombe et al. [71] that non-farming main jobs would distract the farmers' focus on farming activities.

4 Conclusions

This research found the TE estimate of rice farming using the panel data in the favorable areas of irrigated lowlands. During the last decade, the rice farming TE in the favorable irrigated areas in Indonesia decreased significantly even though its magnitude was relatively small. This direction change was not linear, i.e., during the first 5 years it tended to increase and tended to decrease during the next five years. In general, the rice farming TE in the region, which was more advanced economically, namely in rural areas of Java Island, was higher.

The main foothold of rice yield improvement is quality rice seed adoption, namely certified seed of improved variety. The yield response to chemical fertilizer was significantly positive but its magnitude was small.

Higher TE was achieved by the relatively younger farmers and those with more income share from agriculture. The farmers who employed more family labor tended to be more inefficient technically. On the other hand, farmers' formal educational background did not significantly affect TE.

Based on the research results, there are some policy recommendations. First, enhancing the adoption of certified rice seeds of improved variety. In the middle and long term, it is urgent to conduct a research and development program for improving rice varieties adaptive to climate change stress. Second, a conducive incentive policy on encouraging young farmers to rely on rice farming as their main job. It is suggested that the research be continued on larger areas including those of non-favorable irrigated areas.

Acknowledgments: The authors would like to thank the Director of the Indonesian Center for Agricultural Socio-Economic and Policy Studies (ICASEPS), Ministry of Agriculture, for supporting and financing this research. We also thank the enumerators who have helped to collect data during the research.

Funding information: The study was financed with sources of Indonesian Center for Agricultural Socio-Economic and Policy Studies (ICASEPS) and Indonesian Ministry of Agriculture.

Conflict of interest: The authors state no conflict of interest.

Data availability statement: The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

References

[1] Nikmatul K, Ratya A, Nuhfil H, Wahib MA, Wahib MA. The analysis demand for animal source food in Indonesia: Using quadratic almost ideal demand system. Bus Theory Pract. 2020;21:427–39. doi: 10.3846/btp.2020.10563.
[2] Jumiati E, Sulistyo A, MacHmuddin N, Jafar R. Technical efficiency of upland and downland rice farming in border area using MLE frontier production. IOP Conf Ser Earth Env Sci. 2021;748:1–7. doi: 10.1088/1755-1315/748/1/012021.
[3] Sardjono W, Christian L, Juwitasary H, Putra EP. Rice development availability model using system dynamics method. Int J Recent Technol Eng. 2019;8:2741–6. doi: 10.35940/ijrte.C3871.098319.
[4] BPS. Penghitungan dan analisis kemiskinan makro Indonesia Tahun 2021. Jakarta, Indonesia; 2021.
[5] Salam M, Sari AN, Bakri R, Arsyad M, Saadah, Jamil MH, et al. Determinant factors affecting farmers' income of rice farming in Indonesia. IOP Conference Series: Earth and Environmental Science. Vol. 343. 2019; p. 012115. doi: 10.1088/1755-1315/343/1/012115.
[6] Sa'diyah AA, Anindita R, Hanani N, Muhaimin AW. Strategic pattern of households' food consumption in Indonesia. Russ J Agric Socio-econ Sci. 2019;87:79–83. doi: 10.18551/rjoas.2019-03.10.
[7] Purba KF, Yazid M, Hasmeda M, Adriani D, Tafarini MF. Technical efficiency and factors affecting rice production in tidal lowlands of south sumatra province Indonesia. Potravin Slovak J Food Sci. 2020;14:101–11. doi: 10.5219/1287.
[8] Wahyunto W, Widiastuti F. Lahan sawah sebagai pendukung ketahanan pangan serta strategi pencapaian kemandirian pangan. J Sumberd Lahan Ed Khusus. 2014;8:17–30.
[9] Suwanmontri P, Kamoshita A, Fukai S. Recent changes in rice production in rainfed lowland and irrigated ecosystems in Thailand. Plant Prod Sci. 2021;24:15–28. doi: 10.1080/1343943X.2020.1787182.
[10] Yao RT, Shively GE. Technical change and productive efficiency: Irrigated rice in the Philippines. Asian Econ J. 2007;21:155–68. doi: 10.1111/j.1467-8381.2007.00252.x.
[11] Sampaio Morais GA, Silva FF, de Freitas CO, Braga MJ. Irrigation, technical efficiency, and farm size: The case of brazil. Sustain. 2021;13:1–21. doi: 10.3390/su13031132.
[12] Sumaryanto S, Maghraby W, Siregar M. Determinan efisiensi teknis usahatani padi di lahan sawah irigasi. J Agro Ekon. 2016;21:72. doi: 10.21082/jae.v21n1.2003.72-96.
[13] Saeri M, Hanani N, Setyawan B, Koestiono D. Technical efficiency of rice farming during rainy and dry seasons in Ngawi district of East Java Province, Indonesia. Russ J Agric Socio-econ Sci. 2019;91:270–7. doi: 10.18551/rjoas.2019-07.31.

[14] Gunawan H, Majid MSA, Masbar R. Technical efficiency of rice farming in Aceh Province, Indonesia. IOP Conf Ser Earth Env Sci. 2022;951:1–9. doi: 10.1088/1755-1315/951/1/012075.
[15] Mulyadi M, Sukiyono K, Sriyoto S. Analysis of efficiency of technical and factors affecting in aromatic rice farming in the seluma regency. J Agri Socio-econ Bus. 2021;3:1–12. doi: 10.31186/jaseb.3.1.1-12.
[16] Hakim R, Haryanto T, Sari DW. Technical efficiency among agricultural households and determinants of food security in East Java, Indonesia. Sci Rep. 2021;11:1–9. doi: 10.1038/s41598-021-83670-7.
[17] Battese GE, Coelli TJ. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. J Econ. 1988;38:387–99. doi: 10.1016/0304-4076(88)90053-X.
[18] Ahmad M, Bravo-Ureta BE. Technical efficiency measures for dairy farms using panel data: A comparison of alternative model specifications. J Product Anal. 1996;7:399–415. doi: 10.1007/BF00162049.
[19] Schmidt P, Sickles RC. Production Frontiers and Panel Data. J Bus Econ Stat. 1984;2:367. doi: 10.2307/1391278.
[20] Kumbhakar SC. Production frontiers, panel data, and time-varying technical inefficiency. J Econ. 1990;46:201–11.
[21] Battese GE, Coelli TJ. Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. J Product Anal. 1992;3:153–69. doi: 10.1007/BF00158774.
[22] Rahmawati N, Rozaki Z. Sustainable value of rice farm based on economic efficiency in Yogyakarta, Indonesia. Open Agric. 2021;6:563–72. doi: 10.1515/opag-2021-0039.
[23] Ellis F. Peasant economics: Farm households and agrarian development. 2nd edn. United Kingdom: Cambridge Universiy Press; 1988.
[24] Heriqbaldi U, Purwono R, Haryanto T, Primanthi MR. An analysis of technical efficiency of rice production in Indonesia. Asian Soc Sci. 2015;11:91–102. doi: 10.5539/ass.v11n3p91.
[25] Kea S, Li H, Pich L. Technical efficiency and its determinants of rice production in Cambodia. Economies. 2016;4:1–17. doi: 10.3390/economies4040022.
[26] Kalirajan KP, Shand RT. Frontier production functions and technical efficiency measures. J Econ Surv. 1999;13:149–72. doi: 10.1111/1467-6419.00080.
[27] Srisompun O, Isvilanonda S. Efficiency change in Thailand rice production: Evidence from panel data analysis. J Dev Agric Econ. 2012;4:101–8. doi: 10.5897/jdae11.122.
[28] Alam MJ, Van Huylenbroeck G, Buysse J, Begum IA, Rahman S. Technical efficiency changes at the farm-level: A panel data analysis of rice farms in Bangladesh. Afr J Bus Manag. 2011;5:5559–66.
[29] Pradhan AK. Measuring technical efficiency in rice productivity using data envelopment analysis: A study of Odisha. Int J Rural Manag. 2018;14:1–21. doi: 10.1177/0973005217750061.
[30] Nodin MN, Mustafa Z, Hussain SI. Assessing rice production efficiency of the granary and non-granary areas in Malaysia using data envelopment analysis approach. J Phys Conf Ser. 2021;1988:11. doi: 10.1088/1742-6596/1988/1/012110.
[31] Mariyono J. Impacts Seed Technology Improvement on Economic Aspects of Chilli Production in Central Java - Indonesia. J Ekon Pembang Kaji Masal Ekon Dan Pembang. 2016;17:1. doi: 10.23917/jep.v17i1.1453.
[32] Charnes A, Cooper WRE. Measurement the efficiency of decision making units. Eur J Oper Resour. 1978;2:429–44.
[33] Sumaryanto S, Wahida W, Siregar M. Estimasi Tingkat Efisiensi Usahatani Padi dengan Fungsi Produksi Frontir Stokastik. J Agro Ekon. 2001;19:65. doi: 10.21082/jae.v19n1.2001.65-84.
[34] Saptana S. Konsep Efisiensi Usahatani Pangan Dan Implikasinya Bagi Peningkatan Produktivitas; 2012. p. 109–28.
[35] Silva E, Mendes AB, Santos J. Efficiency measures in the agricultural Sector: The beginning. New York: Springer; 2013.
[36] Silva E, Arzubi ABJ. An application of data envelopment analysis (DEA) in Azores dairy farms, Portugal. N MEDIT III. 2004;3:39–43.
[37] Coelli T, Perelman S. A comparison of parametric and non-parametric distance functions: With application to European railways. Eur J Oper Res. 1999;117:326–39.
[38] Coelli TJ. Recent developments in frontier modelling and efficiency measurement. Aust J Agric Econ. 1995;39:219–45. doi: 10.1111/j.1467-8489.1995.tb00552.x.
[39] Coelli TJ, Rao DS, O'Donnell CJ, Battese GE. An introduction to efficiency and productivity analysis. New York: Springer; 2005.
[40] Reinhard S, Knox Lovell CA, Thijssen GJ. Environmental efficiency with multiple environmentally detrimental variables; estimated with SFA and DEA. Eur J Oper Res. 2000;121:287–303. doi: 10.1016/S0377-2217(99)00218-0.
[41] Pitt MM, Lee LF. The measurement and sources of technical inefficiency in the Indonesian weaving industry. J Dev Econ. 1981;9:43–64. doi: 10.1016/0304-3878(81)90004-3.
[42] Abadie A, Athey S, Imbens GW, Wooldridge J, Athey S, Wooldridge J. When should you adjust standard errors for clustering? NBER Work Pap. 2017;24003.
[43] Bertrand M, Duflo E, Mullainathan S. How much should we trust differences-in-differences estimates? Q J Econ. 2004;119:249–75.
[44] Cameron AC, Miller DL. Robust inference with clustered data. Working Papers 318, University of California, Davis, Department of Economics. 2010.
[45] Wooldridge JM. Econometric analysis of cross section and panel data. London: The MIT Press Cambridge; 2010.
[46] De Datta SK. Principles and practices of rice production. Canada: John Wiley & Sons, Inc.; 1981.
[47] Aigner D, Lovell CK, Schmidt P. Formulation and estimation of stochastic frontier production funtion model. J Econ. 1977;6:21–37.
[48] Belotti F, Daidone S, Ilardi G, Atella V. Stochastic frontier analysis using Stata. Rome: Elsevier; 2012. doi: 10.2139/ssrn.2145803.
[49] Debertin DL. Agricultural production economics. USA: Macmillan; 2012.
[50] Balogun OL. Farmers entrepreneurial competencies and technical efficiency of rice farms. Rev Agric Appl Econ. 2021;24:12–9. doi: 10.15414/raae.2021.24.02.12-19.
[51] Theingi M, Thanda K. Analysis of technical efficiency of irrigated rice production system in Myanmar. Conference on International Agricultural Research for development-Stuttgart-Hohenheim, October 11–13; 2005.
[52] Houngue V, Nonvide GMA. Estimation and determinants of efficiency among rice farmers in Benin. Cogent Food Agric. 2020;6:1–21. doi: 10.1080/23311932.2020.1819004.
[53] Jimi NA, Nikolov PV, Malek MA, Kumbhakar S. The effects of access to credit on productivity: separating technological

changes from changes in technical efficiency. J Product Anal. 2019;52:37–55. doi: 10.1007/s11123-019-00555-8.
[54] Kusnadi N, Tinaprilla N, Susilowati SH, Purwoto A. Analisis efisiensi usahatani padi di beberapa sentra produksi padi di Indonesia. J Agro Ekon. 2016;29:25. doi: 10.21082/jae.v29n1.2011.25-48.
[55] Khan S, Shah SA, Ali S, Ali A, Almas LK, Shaheen S. Technical efficiency and economic analysis of rice crop in Khyber Pakhtunkhwa: A stochastic frontier approach. Agric. 2022;12:1–15. doi: 10.3390/agriculture12040503.
[56] Hendrani Y, Nugraheni S, Karliya N. Technical efficiency of paddy farming in West Java: a combination of synthetic and organic fertilisers versus conventional farming. J Agric Rural Dev Trop Subtrop. 2022;123:51–62. doi: 10.17170/kobra-202201195572.
[57] Wibowo LS. Analisis efisiensi alokatif faktor-faktor produksi dan pendapatan usahatani padi (Oryza sativa L.) (Studi Kasus di Desa Sambirejo, Kecamatan Saradan, Kabupaten Madiun). Malang, Indonesia: Brawijaya University; 2012.
[58] Sulistyorini S, Sunaryanto LT. Dampak Efisiensi Usahatani Padi Terhadap Peningkatan Produktvitas. Jambura Agribus J. 2020;1:43–51. doi: 10.37046/jaj.v1i2.2680.
[59] Sareza M. Pengaruh Sistem Tanam, Biaya Pemupukan dan Biaya Pestisida Terhadap Pendapatan Usahatani Padi Sawah di Kecamatan Birem Bayeun Kab. Aceh Timur. J Penelit Agrisamudra. 2019;6:30–8.
[60] Susanti M, Ramli R, Amaluddin LO. Pengaruh Penggunaan Pupuk Dan Pestisida Terhadap Produksi Padi Sawah Di Desa Cialam Jaya Kecamatan Konda Kabupaten Konawe Selatan. J Penelit Pendidik Geogr. 2019;4:185. doi: 10.36709/jppg.v4i4.9274.
[61] Acharya P, Regmi PP, Gauchan D, KC DB, KC GB. Comparative study on technical efficiency of mechanized and traditional rice farm in Nepal. J Agric Nat Resour. 2020;3:82–91. doi: 10.3126/janr.v3i2.32484.
[62] Walsh RP, Lawler DM. Rainfall seasonality: description, spatial patterns and change through time. Weather. 1981;23:201–8.
[63] BPS. Luas Daerah dan Jumlah Pulau Menurut Provinsi, 2021. Badan Pus Stat 2022:1. https://www.bps.go.id/indikator/indikator/view_data_pub/0000/api_pub/UFpWMmJZOVZlZTJnc1pXaHhDV1hPQT09/da_01/1.
[64] Samarpitha A, Vasudev N, Suhasini K. Technical, economic and allocative efficiencies of rice farms in Nalgonda district of Telangana state. Econ Aff. 2016;61:365. doi: 10.5958/0976-4666.2016.00047.4.
[65] Winata VV, Rondhi M, Mori Y, Kondo T. Technical efficiency of paddy's farming in various types of paddy's seeds in Indonesia. JSEP (J Soc Agric Econ). 2020;13:286. doi: 10.19184/jsep.v13i3.20281.
[66] Khai HV, Yabe M. Technical efficiency analysis of rice production in Vietnam. J ISSAAS. 2011;17:135–46.
[67] Mariko K, Macalou M, Xiangmei L, Matafwali E, Alavo J-PE, Eltom EA, et al. Stochastic meta frontier analysis of smallholder rice farmers' technical efficiency. J Agric Sci. 2019;11:31. doi: 10.5539/jas.v11n8p31.
[68] Obianefo CA, Nwigwe CA, Meludu TN, Anyasie IC. Technical efficiency of rice farmers in Anambra State value chain development programme. J Dev Agric Econ. 2020;12:67–74. doi: 10.5897/jdae2020.1150.
[69] Tasila Konja D, Mabe FN, Alhassan H. Technical and resource-use-efficiency among smallholder rice farmers in Northern Ghana. Cogent Food Agric. 2019;5:1–15. doi: 10.1080/23311932.2019.1651473.
[70] Chandio AA, Jiang Y, Gessesse AT, Dunya R. The nexus of agricultural credit, farm size and technical efficiency in Sindh, Pakistan: A stochastic production frontier approach. J Saudi Soc Agric Sci. 2019;18:348–54. doi: 10.1016/j.jssas.2017.11.001.
[71] Balcombe K, Fraser I, Latruffe L, Rahman M, Smith L. An application of the DEA double bootstrap to examine sources of efficiency in Bangladesh rice farming. Appl Econ. 2008;40:1919–25. doi: 10.1080/00036840600905282.

Appendix

Descriptive statistics of yields and per hectare inputs used in rice farming by cropping season and year.

	Year 2010			Year 2016			Year 2021		
	Obs	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Cropping season I									
Y	187	5996.79	1488.00	137	6210.1-5	1735.94	126	5851.28	1747.01
*x*1	187	45.00	17.34	137	44.16	18.51	126	43.79	17.90
*x*2	187	138.19	34.36	137	145.35	33.93	126	140.59	43.70
*x*3	187	46.70	13.21	137	55.70	14.71	126	50.77	13.82
*x*4	187	40.74	19.88	137	44.67	18.34	126	46.68	21.11
*x*5	187	226.01	192.07	137	270.90	244.85	126	228.54	237.24
*x*6	187	176.85	104.14	137	241.17	105.77	126	231.66	102.02
Cropping season II									
Y	175	5459.16	1176.34	130	6038.-39	1489.82	112	5315.67	1449.84
*x*1	175	45.62	17.41	130	44.68	18.90	112	45.26	18.15
*x*2	175	138.51	34.11	130	142.25	31.78	112	144.85	44.05
*x*3	175	45.91	12.98	130	55.84	14.53	112	51.00	13.05
*x*4	175	38.99	19.29	130	44.78	17.96	112	45.25	19.72
*x*5	175	229.23	201.37	130	258.78	230.08	112	223.93	235.08
*x*6	175	175.41	107.09	130	219.79	96.34	112	221.48	96.62
Cropping season III									
Y	57	5239.16	1647.82	35	5522.4-0	1515.89	53	5510.69	1171.80
*x*1	57	44.72	16.22	35	40.90	12.23	53	41.88	12.03
*x*2	57	144.84	37.19	35	158.62	27.25	53	153.38	36.38
*x*3	57	49.60	14.17	35	64.05	13.84	53	55.18	13.49
*x*4	57	40.76	16.05	35	54.04	13.70	53	52.34	19.61
*x*5	57	261.50	220.74	35	287.17	258.91	53	300.21	281.35
*x*6	57	140.47	108.98	35	274.15	95.76	53	217.88	93.52