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DETERMINING TECHNICAL AND RESOURCE-USE EFFICIENCY IN RICE PRODUCTION IN EAST JAVA

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Abstract: This study aimed to determine the technical and resource-use efficiency of East Java. The secondary data were used from the Paddy Cultivation Household Survey ST2013 handled by BPS-Statistics Indonesia. The data was cross-sectional and were derived from ST2013 in 2014. The stochastic frontier analysis analyzed the factors that drive rice output and quantified rice production's technical efficiency. In contrast, the marginal value product-marginal factor cost (MVP-MFC) approach was used to quantify resource-use efficiency in rice production. The SFA indicated that these factors positively affect rice output except for seed, fertilizer, labor, and land utilization. However, other factors were considered apart from the land size, such as exaggerated land and labor advantage in production and bad seed and fertilizer utilization. Technical efficiency varies considerably among rice farmers, ranging from 1 percent to 100 percent, with an average of 89 percent. Their technical inefficiency was influenced by their group membership, irrigation, credit, education level, and farmer age - external farm insect pests. The government and the private sector are involved in the programs through farmer groups.

Keywords: agricultural production, allocative efficiency, resource-use efficiency, parametric frontier, ST2013, technical efficiency

Abstrak: *Tujuan dari studi ini adalah untuk memperkirakan efisiensi teknis dan penggunaan input usahatani di Jawa Timur. Data untuk penelitian ini adalah kerad lintang dan berasal dari ST2013 pada tahun 2014. Analisis menggunakan stochastic frontier digunakan untuk menganalisis faktor-faktor yang mempengaruhi output usahatani untuk mengukur efisiensi teknis petani, sedangkan faktor marjinal nilai produk-marginal (MVP-MFC) digunakan untuk mengukur efisiensi penggunaan input dalam usahatani padi. Variabel input seperti benih, pupuk, tenaga kerja, dan luas lahan , hasil SFA menunjukkan bahwa semua faktor tersebut berpengaruh positif terhadap produksi padi. Selain ukuran lahan, ada faktor lain yang perlu dipertimbangkan, seperti luas lahan yang berlebihan dan keuntungan tenaga kerja dalam produksi, serta penggunaan benih dan pupuk yang kurang. Efisiensi teknis sangat bervariasi di antara petani padi, berkisar antara 1 persen hingga 100 persen dengan rata-rata 89 persen. Inefisiensi teknis petani dipengaruhi oleh keanggotaan kelompok, irigasi, kredit, tingkat pendidikan, dan usia petani - hama serangga eksternal pertanian. Studi ini merekomendasikan agar dilakukan upaya untuk meningkatkan efisiensi teknis. Pemerintah dan swasta sama-sama terlibat dalam program melalui kelompok tani.*

Kata kunci: *produksi pertanian, efisiensi alokatif, efisiensi penggunaan input, batas parametrik, ST 2013, usahatani padi, efisiensi teknis*

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INTRODUCTION

Rice is the most famous food crop in Asia, accounting for around 90 percent of the total global output in the region. Even though this product contributes to revenue and food security in Asian countries, this sector employs around 250 million farmers in Asia. Increased demand growth is required to maintain the production advantage (Simatupang and Peter, 2008).

Supplying countries confront difficulties since their approach to production is determined by technology. When farmers face climate change, low technology adoption serves as a warning. Directly due to technological adoption, rice output in Indonesia is very dependent on external circumstances. Agriculture financing plays a critical part in agricultural productivity as a whole. Concerning BPS (2013), approximately 39.96 percent of rice commodity producers fight plant pest species, and around 10.3 percent struggle with climate change.

In proportion to BPS (2019), the total change in production and acreage climbed by 2.25 percent, while land declined by minus 1.09 percent. The growth rate fluctuated considerably, with the lowest recorded in 1997 at a negative 3.35 percent. In 2009, production increased by 6.75 percent. Similarly, land area fluctuated in percentage terms, peaking at 3.8 percent in 2012 and falling to a negative 6.15 percent in 2014.

Mariyono (2018) has affirmed that boosting rice productivity is necessary to ensure food security in Indonesia. BPS (2013) stated that 70 percent of 26.14 million agricultural families in Indonesia are engaged in rice commodity production. Counter to recent literature, rice production is inextricably linked to socioeconomic, demographic, and environmental aspects.

Rice stockpiles must be constructed from the production side with two considerations: increasing rice demand and changing climate conditions, with technology adoption being the most practical approach (Afrin et al. 2017). The combined objective in this situation is to employ cutting-edge technology to address future agriculture issues. Increased output through efficient technology utilization requires a robust financial structure to support it.

Rice is the primary food crop in Indonesia and substantially contributes to food security and the agricultural economy. The contribution of rice to rural development is contingent upon three factors: more significant agricultural input usage, technological advancements, and technical efficiency (Hilalullaily et al. 2021). Implicitly, production performance can be determined by ensuring productivity. Productivity in production centers varies dramatically over time, mainly owing to crop failure and production area.

Farrell (1957) said that farm efficiency is defined as the effective use of available resources for profit maximization within the constraints of available technology, fixed factor, and factor. Furthermore, it refers to a successful farm producing the maximum output possible from a given set of inputs when both the inputs and output are accurately measured.

Economic efficiency can be divided into two components: technical and allocative efficiency, which, when combined, form economic efficiency (Meeusen and van den Broeck, 1977). Its goal is to maximize profit while minimizing expenses. If a firm maximizes profit by equating the marginal value of each variable input's product (MVP) to its price, it is said to be allocative or price efficient.

A resource allocation is Pareto efficient if no one individual (or activity) can be benefited without affecting a whole other individual (or activity) (Junankar, 1989). The Pareto principle can be used to evaluate alternative resource allocation strategies. In addition, productivity in agriculture is primarily measured in terms of the efficiency with which factor inputs are utilized (Farrell, 1957).

Input utilization, socioeconomic factors, management methods, meteorological circumstances, credit, institutional restraints, and the extent of technology adoption contribute to several of the primary reasons for the yield difference. Concerning Adedoyin et al. (2016), the low yield of this commodity partly owes to the low physical potential of commodities and inefficient input allocation.

Numerous studies on the efficiency of the Indonesian rice sector have been conducted, although with disparate objectives. Numerous research focused on finance Santoso et al. (2020), while others examined efficiency (Hilalullaily et al. 2021; Mariyono, 2018).

Increased agricultural productivity will contribute to rural food output per capita and rice self-sufficiency. This study determined the technical efficiency and input allocation described previously. Technical efficiency considers a variety of external farmer-supplied variables allocation of inputs based on input utilization efficiency.

The objective of this research is to determine the efficiency of rice growing. There are two specific purposes. First, determine the level of technical efficiency, which determines the number and sources of technical inefficiency. Second, determine allocative efficiency, which allocates agricultural inputs.

Our work contributes to the body of knowledge in the literature. We were initially pledging support for future policy actions to promote rice production development. Second, no prior research has been conducted at the research location. Thirdly, most empirical investigations have ignored elements outside the control of farmers. In terms of methodology, we estimate technical efficiency using a stochastic frontier approach and allocative efficiency using a marginal value product approach.

METHODS

The data used in this research is a cross-section. The data used in this study is secondary data resulting from ST2013 in the 2014 Rice Crops Business Household Research conducted by BPS. The sample in this study produced products in the growing season period from June to September 2013. The number of samples analyzed was 6,988 respondents—these respondents layout across all regencies and cities in East Java.

We eliminated the observation data, although there was a missing value in production. The census data are mostly discrete, but they adequately answered the research questions. To simplify the analysis, we implemented the STATA 16 software to process data here until the output happens.

The research purpose is to determine production and efficiency levels. The Cobb-Douglas production function, as proposed by (Coelli et al. 2005). The Cobb–Douglas functional form, on the other hand, is the most frequently used model because it best fits agricultural output data. The following Equation is determined:

$$\ln Y = \alpha_0 + \alpha_1 \ln X_1 + \alpha_2 \ln X_2 + \alpha_3 \ln X_3 + \alpha_4 \ln X_4 + \alpha_5 \ln X_5 + (v\text{-}u) \quad (1)$$

$$\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5 > 0$$

The error term is defined as Vi-Ui, where Vi is a random variable associated with external factors (climate, pest, or disease), and Ui is a non-negative random variable associated with internal factors. The following formula is used to determine the level of technical efficiency:

$$TE_i = \frac{E(Y^*|U_i,X_1,X_2,X_3,X_4,X_5)}{E(Y^*|U_i=0,X_1,X_2,X_3,X_4,X_5)} \quad (2)$$
$$= E[\exp(-u_i|\varepsilon_i)],\ i=1,\ldots,n$$

This study builds a log-linear CD functional form through hypothesis testing, which allows for the intricate specifications of more adaptive production technology in agricultural policy analysis. Technical inefficiency affects the characteristics of farmers, farm-specific traits, and institutional issues. Coelli et al. (2005) established that the technical inefficiency component ui is a linear function of a collection of agricultural parameters which accurately captures the effects of technical inefficiency. The following is a definition of the technical inefficiency effect model:

$$-u = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6 + \delta_7 Z_7 + \delta_8 Z_8 + w \ (3)$$

$$\delta_1,\delta_2,\delta_3,\delta_4,\delta_5,\delta_6,\delta_7,\delta_8 < 0$$

Where i is the coefficient for estimating the elements affecting social traits. In unbiased agricultural technology, a heteroscedastic error structure is required, efficiency can be predicted from the greatest feasible stochastic limit, assuming random variables have a half-normal distribution $w_i \sim N^+ (\mu, \sigma^2)$.

This research, which began with Wang (2002), has influenced other contemporary investigations (Kumbhakar et al. 2014). This is due to the error structure in Equation (2). Equation 4 illustrates the assumption of an idiosyncratic error variance or a stochastic error component that is inefficiency:

$$v = \omega_0 + \omega_1 r_1 + \omega_1 r_1 + \omega \ (4) \qquad \omega_1,\omega_2 < 0$$

ω_1 the coefficient is used to estimate the factors beyond the control of farmers who contribute to their inefficiency. The variance is concerning as a function of the definition of covariates. The estimated coefficient is denoted by ω, and the variable assuming.

This stage was based on the work of (Houngue and Nonvide 2020). Allocative efficiency happens when farms price their inputs Compliant with their marginal productivity. The Cobb-Douglas frontier production function is estimated from Equation 1 using the MLE technique derivatives of APP and MPP. Description of variables in the stochastic frontier translog production model in Table 1. When the production function is linearized and differentiated with respect to the input (Xi), the following MPP occurs:

$$APP_i = \frac{Y_i}{X_i} \quad (5)$$

$$MPP_i = \frac{d \ln Y_i}{d \ln X_i} = \frac{\partial Y_i}{\partial X_i} \text{ x } = \beta_i \left(\frac{Y_i}{X_i}\right)$$
$$= \beta_i \text{ x } APP_i \quad (6)$$

will receive the MVP award;

$$MVP_i = \beta_i \left(\frac{Y_i}{X_i}\right) \text{ x } P_y = MPP_i \text{ x } P_{yi} \quad (7)$$

Y denotes the farm output, the respective input is denoted by Xi, and the coefficients are estimated. By multiplying marginal physical productivity by the output price, the marginal product value (VMP) is calculated (Py). This strategy is often referred to as resource-use-efficiency (RUE) or input-use-efficiency development. This technique enables researchers such as (Houngue and Nonvide 2020). RUE research begins with assumptions regarding producer objectives. Profit maximization is the conventional premise, which serves as the ideal framework for various forms of production efficiency. RUE is connected to the farm ability of the farm to select inputs efficiently:

$$AE_i = \frac{MVP_i}{P_{xi}} \;/\; RUE_i = \frac{MVP_i}{MFC_i} \quad (8)$$

Three possible estimation results can be used to guide decision-making. To begin, if the RUE value is equal to 1, it signifies that the input has been processed efficiently. Second, if the resulting RUE value exceeds 1, It demonstrates that the input is underutilized and thus increases the level of input use. Third, if the estimated value of RUE is less than 1, it reveals s that inputs are being overused, and reducing their use will contribute to increased productivity.

Table 1. Description of variables in the stochastic frontier translog production model

Variable	Description	Measurement	Expected sign
Y	Quantity of output	kilogram (kg)	+
X1	Quantity of land	Acreage (ha)	+
X2	Quantity of seed	kilogram (kg)	+
X3	Quantity of labor	working-people-day (HOK)	+
X4	Quantity of fertilizer	kilogram (kg)	+
X5	Quantity of pesticide	Liters (L)	+
Z1	Years in education	Number of years	-
Z2	Age of respondents	Number of years	-
Z3	Sex of respondents	Dummy (male=1 and female =0)	-
Z4	Farmers Organisastion	Dummy (member = 1and not member = 0	-
Z5	Access to credit	Dummy (Yes = 1 and No = 0)	-
Z6	Access to insurance	Dummy (Yes = 1 and No = 0)	-
Z7	Irrigation land	Dummy (Yes = 1 and No = 0)	-
Z8	Subsidized fertilizer	Dummy (Yes = 1 and No = 0)	-
W1	Attacked by pests	Dummy (Yes = 1 and No = 0)	-
W2	Climate Changed	Dummy (Yes = 1 and No = 0)	-

RESULTS

Descriptive statistics of variables

The size of the research area changes Suitable for the responder. The smallest cultivable land area was 0.01 hectares. The largest paddy field cultivated by agriculture was six hectares. On average, 52.41 kilograms of seeds were consumed each year. The average working day (HOK) duration was 27.18. The average fertilizer application was 252 kg in the research region, independent of the type of fertilizer utilized. Pesticides were applied on an average of 89 liters every season in the research area.

In agreement with the study, Rice production requires an average farm size of 2.37 acres. These imply that most farmers in the study area were smallholders with less than a hectare of farmland. They might result from the prevailing land tenure system in the study area. Large agricultural sizes encouraged agricultural performance and efficiency producers to increase their technical and allocative capacities. The average seed total number used in rice production in the study area was 82.6 kilograms, comparable to the Lasmini et al. (2016) and (Hilalullaily et al. 2021). Rice production was directly proportional to the amount and quality of seed used. Increased output was achieved by using high-quality and optimal quantities of planting material in production.

The statistical distribution of rice demographic and farm-specific characteristics in the research region is shown in Table 2. As directed in the table, rice farmers, on average, were 45 years old. The implicit assumption was why younger farmers were more willing to adopt new innovative ideas to increase production efficiency than older farmers (Adedoyin et al. 2016).

Moreover, the study discovered that approximately 88 percent of farmers were male, while only 12 percent were female. Around 8 percent of farmers had access to bank loans for rice production. Access to financial credit improved the purchase of farmers of the necessary inputs to boost productivity (Hilalullaily et al. 2021).

Determining the parameters in the SPF function

The highest likelihood estimates for the stochastic production frontier parameters are shown in Table 3. Following Coelli et al. (2005), individual variables had been corrected for their normalized mean and could be read as partial elasticities. The monotonicity criteria were satisfied because the sum of the first-order coefficients of the model was one. This table represents the elasticity of rice production inputs in East Java. Most of the coefficients were computed to the expected sign. Except for pesticides, all input factors qualified for increased rice output, and seed elasticity was the greatest of all input factors. All input variables for coefficients agreed with a confidence level of 1 percent.

Table 2. Variables in the stochastic frontier production model using descriptive statistics

Variables	Minimum	Maximum	Average	Standard deviation
Quantity of output	81	31.500	1.759,22	1871,38
Quantity of land	0,01	6	0,33	0,32
Quantity of seed	0,6	480	16,54	16,43
Quantity of labor	0,6	841	27,18	25,72
Quantity of fertilizer	1	8.300	252.51	315.70
Quantity of pesticide	0	4.500	89,39	242,32
Years in education	1	8	2,12	1,14
Age of respondents	19	99	52,30	11,45
Sex of respondents	0	1	0,88	0,32
Farmers Organisastion	0	1	0,29	0,45
Access to credit	0	1	0,08	0,28
Access to credit	0	1	0,00	0,05
Irrigation land	0	1	0,59	0,49
Subsidized fertilizer	0	1	0,94	0,23
Attacked by pests	0	1	0,72	0,45
Climate Changed	0	1	0,16	0,36

The elasticity of inputs to rice production in East Java is seen in Table 3. Almost all parameters computed acquired the expected sign. Except for pesticides, most input parameters increased rice output, and seed elasticity was always the greatest of all variable inputs.

Production elasticity

Elasticity corresponded to the expected sign of economic theory; the seed had the most elasticity. The elasticity of this factor was 0.42, which suggested that an increase of 1 percent increased production by 0.40 percent. In agriculture, seeds were a symbol of technology (Wu, 2020). The idea implied that a more outstanding seed grade or a better seed grade would improve yields even if there is overpopulation, resulting in competition for limited nutrients and poorer products per a study conducted by (Lasmini et al. 2016).

Coefficient of fertilizer of 0.25. The positive sign denoted that the yield varied At one with fertilizer utilized. The fertilizer input elasticity of variable ranks was third in terms of the contribution to the output. These findings emphasize the crucial importance of fertilizers. On the other hand, several other research did not believe that fertilizers did not affect crop yields, but in Malaysia, rice production has the same result as in developing countries (Subedi et al. 2020).

Labor and land had coefficients of 0.16 and 0.12, respectively. The excellent sign involves that the yield fluctuates. Incompatible fertilizer used. The land had the lowest elasticity of the positive coefficient, indicating that land had a negligible effect on output. This conclusion was consistent with (Adedoyin et al. 2016).

Rice output was inversely proportional to the number of pesticides applied, contradicting previous studies (Afrin et al. 2017). Pesticide input factors were negatively connected to rice output and were statistically significant at 1 percent for farmers who used pesticides for chemical and organic pest control—the explanation for the wasteful application of pesticides in rice production. The usage of pesticides ensured a detrimental influence if the pesticide products were not applied, As said by the manufacturer's guidelines. The majority of rice growers were illiterate. Another sign was that the pesticides employed were ineffective at managing pests.

Summary statistics distribution of technical efficiency of rice farmers

Rice producers in the research area had an average technical efficiency score of 0.89. This explained that rice farmers in the research area attained an output of 89 percent 11 percent of the product obtained by rice farmers was dropped, associated with production inefficiency. As a result, rice farmers in the research area extended frontier yields with an average of 11 technical efficiencies. This distribution of technical efficiency among rice farmers corroborated the findings of (Lasmini et al. 2016).

The data revealed that 59 percent of respondents lived close to the technical efficiency border, while 0.01 percent lived far from it. This study appeared that even the most efficient responses did not utilize resources wisely and required development to achieve frontier technical efficiency (Kea et al. 2016). If the typical farmer in the sample achieves the highest degree of technological efficiency, he or she could save 11 percent [1-(89/100)x100]. The findings specified an opportunity to increase production through input optimization.

Table 3. Determinants of the stochastic production frontier model using maximum likelihood

Variables	Expected sign	Coefficient	Robust S.E.
Land	+	0.121***	0.012
Seed	+	0.472***	0.015
Labor	+	0.165***	0.014
Fertilizer	+	0.251***	0.011
Pesticide	+	-0.009***	0.003
Constant	+/-	4.219***	0.044
Prob > chi2			0.000
Wald chi2(4)			7,205.33
Log-likelihood MLE			-4,617.23

***significant at 1 percent level of significance

Determinants of technical efficiency in rice production

This gamma (γ) estimate of 0.29 was statistically significant at 1 percent. The one-sided random inefficiency component significantly outweighs standard errors and other random disturbances, implying that around 28 percent of measured output variance was due to deviation from the maximum output. The model demonstrated that technical inefficiency in production was related to factors that influenced farmers (farmer characteristics) and external factors affecting farmers (who were not within the control). External factors account for approximately 62 percent of technical inefficiency. Table 4 recapped the findings of the variables impacting technical inefficiency. As shown in Table 4, all technical inefficiency factors satisfied economic criteria. Five of the eight factors were statistically significant at 1 percent. Agricultural insurance, gender, and subsidized fertilizer were all factors that did not affect inefficiency.

The most likely variables to reduce inefficiency were farmer groups and irrigation variables. Farmers who participated in farmer groups and farmed on irrigated land were more technically efficient. Since farmer groups serve as a vehicle for enacting policy, farmers were a critical component of rice farming in East Java (Siaw et al. 2020).

Table 4. Frequency distribution of technical efficiency index

Range	Frequency	Percentage (%)
< 0.1	1	0.01
0.1 ≤ x < 0.2	1	0.01
0.2 ≤ x < 0.3	1	0.01
0.3 ≤ x < 0.4	7	0.10
0.4 ≤ x < 0.5	12	0.17
0.5 ≤ x < 0.6	60	0.86
0.6 ≤ x < 0.7	223	3.19
0.7 ≤ x < 0.8	740	10.59
0.8 ≤ x < 0.9	1,764	25.24
> 0.9	4,179	59.80
Observation		6,988
Minimum ET		0
Maximum ET		1
Std Dev. ET		0.09
Average ET		0.89

As was the case with farmer organizations and irrigated land, more education and credit facilitate efficiency. The educational qualification had a significant negative correlation with technical inefficiency. The more educated farmers were, the more efficient their farming would be. Because educated farmers were familiar with how production acquires new information, particularly about markets and new technology, they thought they would achieve greater production efficiency.

Capital loans affected technical efficiency to a degree. It demonstrated that technical efficiency and agricultural loans have a good relationship. These findings confirm why agricultural financing could improve rice farming efficiency, provided that it increases short-term output. This study documented the findings of (Martey et al. 2019; Santoso et al. 2020; Siaw et al. 2020). As per Martey et al. (2019), capital loans and farmer organizations promoted both sides. This condition revealed that increasing their access to sources of financing other than their families and farmer associations would increase their efficiency level.

Counter to Table 5, the variables that contributed to inefficiency came from sources outside farmers' control, such as pests and climate change. These two factors were inextricably linked to the decrease in their technical efficiency. At the 1 percent confidence level, pest attacks had the highest and most significant coefficient. Farms afflicted with pests were no more efficient than farmers who were not afflicted. This was significant because farmers who faced difficulties produced small farms. Due to insects sucking and damaging the processes of plants, the insect performs services by disseminating the host (War et al. 2016).

Determinant of Resource use efficiency

The RUE of land, seed, labor, fertilizer, and pesticide was shown in Table 6. The RUE of rice farmers was calculated in this study as the ratio of the MVP of each input utilized to its corresponding factor price. The MVP was distributed as a yardstick for evaluating how resources were spent. Under strict competitiveness, inputs were efficiently allocated without a divergence between their MVP and unit price. It was worth noting that the non-negative input MVP suggests that rice cultivation continues to utilize this input within an economically viable range despite its suboptimal use. The findings indicate that many needs exceed the optimal input utilization gap. This finding was consistent with Subedi et al. (2020), who discovered that the MVP/MFC ratio was more than one for seed, land, and fertilizer.

Notably, the MVP of land area, seed, labor, and fertilizer were not damaging, indicating why rice production continued to use these resources within an economically efficient range despite their suboptimal performance. The deviation was used to describe the MVP modification necessary for effective concept utilization. A percentage increased the marginal value product for optimal input utilization in Table 6. Adjusting input usage necessitated increasing or decreasing inputs based on whether the information had been overused (Hidayah and Susanto, 2013).

MVP correction for optimal input utilization or percent correction dispersed distribution. The degree of adjustment required to achieve the best outcomes would serve as a reference for rice cultivation in the area, government agricultural agencies, and the involvement of the private sector. They might effectively apply these findings to promote modern agriculture and support sustainable agricultural development. Table 6 highlights the importance of effective input allocation. The land area was nearly fully utilized in the application. The land area had an efficiency ratio of 0.99, indicating that it has been overutilized. Nonetheless, this input variable was the most efficient. Increased land use meant that farmers in the research area would approach input efficiency. At least 71 percent of farmers must lower their land area to achieve 70 percent efficiency. This research demonstrated that farmers could invest additional costs to rent production efficiently.

Table 5. Determinants of technical inefficiency in rice production

Variables	Expected sign	Coefficient	Robust S.E.
Internal farmer			
Years in education	-	-0.647***	0.095
Age of respondents	-	-0.038***	0.007
Sex of respondents	-	-0.178***	0.144
Farmers Organisastion	-	-1.501***	0.270
Access to credit	-	-0.606***	0.215
Access to insurance	-	-4.153***	6.160
Irrigation land	-	-1.505***	0.270
Subsidized fertilizer	-	-0.293***	0.213
Constant	+/-	1.761***	0.470
External farmer			
Attacked by pests	-	-1.886***	0.042
Climate Changed	-	-0.016***	0.082
σ^2_u			0.228
σ^2_u			0.563
Gamma $\gamma = \sigma^2_u / \sigma^2$			0.289

Table 6. Determinants of allocative efficiency measures for rice inputs

Input Variables	APP	MPP	MVP	MFC	Elasticity	RUE
Land	5,481.88	650.82	2,359,199.60	3,867,517.50	0.121	0.99**
Seed	117.89	55.76	201,942.02	9,047.21	0.472	24.04**
Labor	76.61	12.63	45,694.44	94,746.29	0.165	0.50**
Fertilizer	9.64	2.43	8,796.02	1,951.92	0.251	4.44**
Pesticide	777.62	-6.48	-23,757.40	20,640.31	-0.009	-37.51**

**Overutilisation; **Underutilisation

Because of RUE score was 24.04, the seeds were underutilized. As a consequence, an additional allocation of resources is possible. However many at 99 percent of the farmers need to improve their seed consumption, as they had a 94 percent chance of improving their inputs. Opportunities that reduced seed prices could sometimes be exploited by purchasing high-quality sources that produce high yields for farms depending on their anticipated input efficiency. Along with this study, rice farming requires expanding the number of sources employed in production to boost farm productivity. This conclusion consisted by Tasila Konja et al. (2019) and (Subedi et al. 2020).

Fertilizer efficiency of 4.41 advised that less fertilizer was used. This one was close to certain other factors, even though the user was still not perfect. The expenditures associated with fertilizer use would be negligible in comparison to the value of the marginal fertilizer product. As well as Table 7, 99 percent of the farmer who responded to the survey were required to increase their inputs. To compensate for the 70 percent efficiency adjustment that was missed. In line with the value of the second-highest elasticity of those other inputs to production. Adedoyin et al. (2016) and Tasila Konja et al. (2019) both reported underutilization of seeds and fertilizers and excessive labor.

With an efficiency of labor consumption of 0.50, it was clear that shifting labor was already being utilized. Distribution was overused, with 92 percent of responders requiring a reduction of approximately 207 percent. Furthermore, labor costs shift due to mechanization the re-allocation of labor inputs that occurs when farming is mechanized for crop management operations. Increased labor in such labor-intensive agriculture would result in a decline in the yield of all these crops. Tasila Konja et al. (2019) and Subedi et al. (2020) confirm these original study conclusions regarding the extensive utilization of human labor. As a result, there was no feasible method of utilizing more units of these elements (Houngue and Nonvide, 2020).

Pesticides and productivity have an antagonistic relationship that must be observed. This was intriguing since the theory expects a positive correlation. The results in Tables 3 and 6 would be resolved when the results in Table 5 were compared. The primary source of inefficiency was external sources, where many pests attacked. These findings displayed that farmers should utilize with recommended manufacturing pesticides. Because the nature of pests is an impermanent improvement, farmers might consider applying technical and allocative pesticides at approved dosages. Pesticides were crucial, and pest attacks should be considered when trying to be more efficient with technology and resources.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The purpose of this study was to calculate the RUE in East Java. The findings of this study, parameters affecting production inputs, except pesticides, had a favorable effect. In consort with this study, rice farming technical efficiency in East Java was 89 percent, although there was scope for improvement. Membership in a group, irrigation, credit, education level, and farmer age all substantially impact technical efficiency. Inefficiency originates from the outside; the farmer suffers from insect pests.

Table 7. Respondent and input frequency distributions – specific allocative efficiencies of selected inputs decisions

Allocative Efficiency	Land	Seed	Labor	Fertilizer	Pesticide
MPV > MFC	28.43	99.99	7.37	99.38	18.72
MPV < MFC	71.57	0.01	92.63	0.62	81.28
Divergence	-70.66	94.28	-207.52	70.74	266.54

This initial study results suggest that only land measures up to input usage efficiency. Apart from some of the inputs that affect the production, there were numerous ways in which inputs were over-and under-utilized. We identified that variables that significantly affect elasticity but were relatively frequently utilized, such as seeds and fertilizers, significantly affect elasticity. Labor has been overused as a factor. We have to concentrate on pest management, which will decrease technical efficiency.

Recommendations

This study advises that technical efficiency should increase by maximizing input utilization. These inputs were the obligation of all parties involved in promoting technical efficiency improvement. The government and the private sector, via farmer groups, were involved in the programs. There was a requirement for improved training in selecting the optimal combination of inputs. Future research should examine the impact of climate change, fertilizer subsidies, agricultural insurance, and the gender disparity in rice production, as suggested by this study.

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