

TECHNICAL EFFICIENCY OF COMBINE HARVESTER IN MINDUGADING VILLAGE



Dwi Kusuma Wati¹⁾, Hamidah Hendrarini^{1*)}, Risqi Firdaus Setiawan¹⁾

¹Universitas Pembangunan Nasional "Veteran" Jawa Timur

*Corresponding author: hamidah_h@upnjatim.ac.id

To cite this article:

Wati, D. K., Hendrarini, H., & Setiawan, R. F. (2024). Technical Efficiency of Combine Harvester in Mindugading Village. *Jurnal Ilmiah Membangun Desa Dan Pertanian*, 9(4), 312–321. <https://doi.org/10.37149/jimdp.v9i4.1326>

Received: June 30, 2024; **Accepted:** August 01, 2024; **Published:** August 31, 2024

ABSTRACT

Farmers' adjustments in combining harvesters cause rice production to fluctuate yearly. This research intends to analyze factors impacting rice production and the degree of technical proficiency of rice farming using a combine harvester in Mindugading village. The study was accomplished in Mindugading Village, Tarik District, Sidoarjo Regency, East Java, from February to March 2024. A total of 53 farmers were sampled using a simple random sampling technique in this study. The variables utilized in this research are land area, seeds, labor, fertilizer, pesticides, and rental costs. The analytical method utilized in this research applies a parametric approach through models of Stochastic Frontier Analysis. The first stage uses the Ordinary Least Square (OLS) method, and the second uses the Maximum Likelihood Estimation (MLE) method. This analysis was carried out with the assistance of Frontier Stochastic 4.1 software. The research outcomes reveal that rice production is affected by land area, fertilizer, seeds, and rental costs. The value of the combine harvester's technical efficiency is 0.87.

Keywords: combine harvester; production; technical efficiency.

INTRODUCTION

Currently, agricultural mechanization is crucial to the development of the agricultural sector. That matter aims to guard the availability of enough food to increase the economy's social and political stability. Food availability itself is synonymous with the availability of rice, which fulfills the basic food needs of the Indonesian people. The facts show that high consumption levels are not commensurate with its estimated production level, only 30.90 million tons in 2023 (BPS, 2023). The high level of rice consumption makes it essential to pay attention to rice production from pre-harvest to post-harvest activities (Intiaz *et al.*, 2022). Apart from that, the area of agricultural land also needs to be considered when increasing rice production.

Sidoarjo district government has begun distributing post-harvest machinery assistance through combine harvesters to support rice farming activities as a form of efficiency. It is hoped that the distribution of machinery assistance will positively impact the productivity of agricultural work. This results in a reduction in the burden of agricultural labor, resulting in advanced technology that is relatively more capital-intensive (Setiawan, 2022). Combine harvester itself is an example of innovation made to improve work efficiency and effectiveness, especially in harvesting activities (Zainuddin *et al.*, 2016). Combine harvester is designed in such a way as to increase rice yields. This is one way to overcome severe problems in increasing rice production, namely the significant yield loss (shrinkage) during the harvesting process (Haryono *et al.*, 2021).

The policy regarding the distribution of machinery assistance was created to help farmers run rice farming. Still, the policies that the government has regulated have not been entirely directed toward comprehensive agricultural development (Hendrarini & Santoso, 2020). So, ideal circumstances and reality do not coincide with the use of combine harvesters. Ideally, farmers who use combined harvesting machines efficiently will increase rice production. However, the application of the combine harvester has not been able to overcome the decline in rice production, which has



caused farmers to experience decreased yields and insufficient production. This shows that rice production is not optimal because production factors are inefficient.

They are quoting research from (Mahasin *et al.*, 2021) regarding efforts to increase income and efficient use of rice farming inputs, where farmers often imagine using less than optimal inputs, which ultimately affects farmers' income. This also happens to rice farmers in Mindugading Village, Tarik District, Sidoarjo Regency, so researchers want to examine the efficiency of combining harvesting machines to maximize rice production.

The level of rice production is the most crucial thing in assessing the outcomes of a rice farming venture. According to previous research conducted by (Damayanti *et al.*, 2023) and (Firdaus and Sumarni, 2022), they have examined efficiency in terms of income. However, no research has examined the technical side or input management using combined harvesting machines in Mindugading Village. With this description, this research was accomplished to determine how using a Combine Harvester can be said to be efficient or not through empirical data. It is anticipated that the findings of this study will offer solutions for farmers to reduce crop yield losses to increase rice production.

MATERIALS AND METHODS

The study was accomplished in Mindugading Village, Tarik District, Sidoarjo Regency, East Java, over two months, from February to March 2024. The research location was selected with a specific purpose in mind. Simple random sampling was employed in this study, which ensured that all farmers had an equal opportunity to be selected (Sugiyono, 2017). The population under investigation comprised rice farmers in Mindugading village, Tarik District, Sidoarjo Regency, who cultivated paddy fields during the 2024 season. Sampling was conducted by applying the Slovin formula. The sample size of the farmer population in Mindugading village was 111 individuals, with an error rate of 10%, resulting in a sample size of 53 farmers. The following table presents the population of rice farmers in Mindugading village:

Table 1. The population of rice farmers in Mindugading Village

No	Hamlet	Farmer (Person)
1	Mindu	29
2	Gading	82
	Total	111

Source: Secondary Data, 2023

Primary and secondary data were included in the data collection for this research, which were gathered through survey methods and direct observation. The primary material came from respondents via interviews or questionnaires from several rice farmers in Mindugading Village. Meanwhile, the secondary data was obtained from the Sidoarjo Regency Agricultural Service, Tarik District Agricultural Extension Center, and related agencies.

This research employs a parametric approach to technical efficiency analysis, utilizing the Stochastic Frontier Analysis model with the Maximum Likelihood Estimation (MLE) estimation method. This is carried out through a two-stage process. The initial stage employs the Ordinary Least Squares (OLS) methodology to approximate the technological parameters and production inputs (β_1), and the second stage employs estimates of the overall production factor parameters (β_1), the intercept (β_0), and the variance of the two error components vi and ui described through the *Maximum Likelihood Estimation* (MLE) method. This analysis was conducted using Microsoft Excel and Frontier Stochastic 4.1 software. In the context of paddy farming, this function model employs a transformed Cobb-Douglas production function in the linear form of the natural logarithm, as illustrated by the following equation:

$$\ln Y = \ln \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \beta_6 \ln X_6 + vi - ui \quad (1)$$

Information : $\ln Y$: natural log of production output variables, β_0 : intercept, β_1 : estimator parameter coefficients, where $i = 1, 2, 3, \dots, 6$, $\ln X_1$: log of the natural variable land area, $\ln X_2$: log of the seed natural variable, $\ln X_3$: log of the natural variable labor, $\ln X_4$: log of the natural variable fertilizer, $\ln X_5$: log of the natural variable pesticide, $\ln X_6$: natural variable log of rice harvester rental costs (*Combine Harvester*), $vi - ui$: Error term (vi is the noise effect, ui is the technical inefficiency effect)

After that, to find out the production factors are considered technically efficient if the production factors used produce maximum production (Coelli et al., 2005) and can be explained mathematically as follows:

$$ET = \frac{Y_i}{Y_{ii}} = \frac{\exp(X_i\beta - u_i)}{\exp(X_i\beta)} = \exp(-u_i) \tag{2}$$

Information : ET: Technical efficiency level, Y_i : The size of production, Y_{ii} : The amount of production estimated from observations is obtained using the *Cobb-Douglas frontier production function*, $\exp(-u_i)$: The expected value of u_i (mean) towards u_i

According to (Coelli et al., 2005), mark efficiency technical between zero and one. Suppose the more approach marks one, the more efficient farming is in a technical way, and on the contrary, Mark index efficiency technical can categorize as a) ≥ 0.70 is quite efficient, b) efficiency value = 1 is fully efficient, c) < 0.70 is not yet efficient.

RESULTS AND DISCUSSION

Respondent Characteristics

Respondent characteristics are employed to ascertain the variety of respondents according to land area, age, educational attainment, and farming experience. This is expected to offer a relatively clear understanding of the respondents' situation and its connection to the issue and study purposes. This study uses research objects in the form of rice farmers spread across Mindugading village. The sample consisted of 53 farmers, specifically farmers who used a combine harvester machine during the rice harvest process. The following are some characteristics of the respondent farmers:

Table 2. Characteristics of respondents

Characteristics	Total (Person)	Percentage (%)
Wide Land (Ha)		
0.19-0.49	29	55
0.50-0.80	21	40
0.81-0.94	3	5
Age		
30-45	3	5
46-59	20	53
≥ 60	20	42
Education		
No School	7	13
Elementary School	26	49
Junior High School	5	9
Senior High School	14	27
S1	1	2
Experience Farming (Years)		
1-10	13	25
11-20	15	28
21-30	13	25
31-40	12	22

Source: Processed Primary Data (2024)

According to Table 2, the commonly used size of agricultural land is hectares. However, rural farmers often still use traditional measurements such as bricks, spans, stakes, shoulders, and so on (Imran, 2022). In Mindugading village, brick measuring tools are used at each rice field unit. Therefore, when research is underway, researchers need to understand the land area farmers use to transform the traditional land size into hectares. The average land area inherited by farmers in the study location is 0,45 Ha. The land area farmers own for rice farming varies widely, ranging from 0,19 Ha to 0,94 Ha. The data in Table 2 reveals that the land area group in the interval 0,19-0,49 Ha has the highest percentage, namely 55% or 29 farmers. The group of planted land areas in the 0,50-0,80 Ha interval numbered 21 farmers or 40%, then the least amount of land owned by farmers in the 0,81-0,94 Ha interval consisted of 3 farmers or 5%. Most farmers in Mindugading Village own small rice fields with an average land area of 0,45 Ha. According to (Suratiah, 2015), agricultural land use that can be categorized as narrow land is land area of less than 0,50 Ha. The area of the farming business

is affected by the area of agricultural land and will influence increasing farming efficiency (Hendrarini *et al.*, 2023). Also, land area influences farmers to use technology to farm more efficiently (Maulana *et al.*, 2021).

Age is a factor that can impact farmers' absorption and decision-making when implementing new technology and innovation in their farming business. According to (Delaseh *et al.*, 2020), the age range of productive farmers is between 15 and 54 years old. The ability of farmers to farm at a productive age will be better than that of older farmers because age influences the ability to run a farm. The age range of respondent farmers in Mindugading village was divided into three age groups. In this age group, most rice farmer respondents were aged 46-59 years, with a 53% percentage totaling 30 farmers. With this age, it can be said that the age group is still productive. At age >60, there are 20 farmers, with a percentage of 42%. Then, the age range of 30-45 years is only three farmers, with a 6% percentage. Farmers aged 46-59 years have the physical capacity to maintain vibrant, creative, and fast farming activities and accept technological innovations, one of which is using a combine harvester machine to harvest rice plants (Susanti *et al.*, 2019). Apart from that, the productive age condition of the farmer is expected to provide a more significant contribution of labor to the rice farming business being undertaken, and the farmer's age can also influence decision-making in running the farming business (Alwi *et al.*, 2024). Meanwhile, farmers aged >60 years have benefits in terms of expertise, awareness, ethical conduct, and dedication to quality. However, the drawback of farmers aged >60 years is that their ability to work has decreased (Moonik *et al.*, 2020).

The level of education is an indicator of the socio-economic condition of society and an essential factor in efforts to enhance the caliber of human resources. The higher the farmer's education, the more it can influence the way of thinking or acceptance of an agricultural innovation (Moonik *et al.*, 2020). The highest level of education is elementary school, totaling 26 farmers with a 49% percentage. At the senior high school education level, there are 14 farmers or 27%. They are followed by junior high school education level with seven farmers, or 9%, and only one farmer with a bachelor's degree, or 2%. However, there are farmers in Mindugading Village who do not have formal education, and this is due to economic factors, where there are seven farmers who do not go to school, or 13%. So, farmers who do not have formal education usually only get non-formal education through local agricultural extension services. (Setiyowati *et al.*, 2022) Revealed that the greater an individual's level of education, the more open they will be to receiving knowledge, information, and innovation. Education is used as a measure of each farmer's knowledge and understanding.

Farming inevitably leads to transformations in how farmers manage their agricultural enterprises. By using their farming knowledge, it is anticipated that they could identify more effective alternative solutions for their agricultural enterprise. Extensive experience may provide valuable insights, as farmers can learn from past failures. The relationship between farming experience and the amount of production has a positive relationship, where the longer a farmer's farming experience, it could be said that the farmer is used to dealing with situations or things that will happen in farming activities (Dewi *et al.*, 2017). Mindugading village farmers' experience in farming is almost evenly distributed, ranging from 1-10 years, totaling 13 farmers or 25%. 11-20 years, totaling 15 farmers or 28%. 21-30 years, totaling 13 farmers or 25%, and the most extended farming experience is 31-40 years, amounting to 12 farmers or 22%. Most rice farmers in Mindugading village have been involved in agriculture since they were teenagers. When they were teenagers, the respondent farmers had already joined their parents in farming. So, the respondent farmers continued what they had previously done with their parents. With long experience of around 5-10 years or more, you can be said to be exceptionally experienced in farming. In contrast, farmers who have less than five years of experience are categorized as still inexperienced or in the process of learning about farming (Hardin, 2019).

Factors Affecting Rice Production

Before analyzing the *Cobb Douglas Stochastic Frontier production function*, the testing requirements must be met so that there are no violations of the assumptions in the *cross-section data model*, namely perfect heteroscedasticity and multicollinearity. If multicollinearity occurs in the stochastic frontier model, certain variables must be eliminated, whereas heteroscedasticity will cause substantial bias, leading to misleading coefficient significance (Kumbhakar & Lovell, 2000). The outcomes of the classical assumption test reveal that heteroscedasticity does not occur because the data is distributed randomly and does not form a pattern. The normality test has a significance value (*Asym Sig 2-tailed*) of $0.193 > 0.05$, so the data is normally distributed. Furthermore, perfect multicollinearity does not occur ($VIF < 10$).

Two stages were used to carry out the Cobb-Douglas Stochastic Frontier production function parameters. The first stage estimates technological parameters and production inputs (β_1) using the

Ordinary Least Square (OLS) technique. OLS estimation only estimates the average revenue level, which will later be used as a deterministic initial value for the estimation (Coelli et al., 2005). The second stage estimates all production factor parameters ((1), intercept ((o), and using the Maximum Likelihood (MLE) method. The outcomes of the analysis of the estimation of the Stochastic Frontier Cobb-Douglas model of the rice production function model utilizing the OLS technique are seen in the following table:

Table 3. Production function results of the OLS method

Variable	Coefficient	t-ratio
Constant ($\text{Ln}\beta_0$)	21,817	***9,386
Vast land ($\text{Ln}\beta_1$)	1,480	*1,696
Seed ($\text{Ln}\beta_2$)	0.227	**2,191
Power work ($\text{Ln}\beta_3$)	-0.071	ns-0.770
Fertilizer ($\text{Ln}\beta_4$)	0.296	***4,059
Pesticides ($\text{Ln}\beta_5$)	-0.336	ns-3.981
Cost rent combine harvester ($\text{Ln}\beta_6$)	1,053	***6,368
Sigma-squared (σ^2)	0.011	
Gamma (γ)		0.942
df		46

Source: Processed Primary Data (2024)

Note: *** = significant at α 1% (2.687); ** = significant at α 5% (2.013); * = significant at α 10% (1.679); ns = not significant

Table 3 reveals that the variance ratio of the gamma parameter or R^2 is significant at the 1% absolute level with a coefficient of 0,942, which indicates that the rice production results can be elucidated by the variables of land area, seed, labor, pesticide, fertilizer and combine harvester rental costs. Meanwhile, other factors not incorporated in the research model explain the remaining 5.8%. In the production function, the Cobb-Douglas model can determine the condition of returns to scale and whether they are growing, steady, or declining. Based on the results of adding the coefficient values for each independent variable, the return to scale value for rice farming in Mindugading Village is 2,649 or greater than 1. This value indicates that the production functions are in a condition of increasing return to scale, where the percentage of production output quantity is more significant than the addition of input factors. More than one production elasticity is achieved when the marginal production curve is above the average. This is a business scale that shows increasing results. Every additional 1% of input will cause an increase in more significant output than 1%. Therefore, in areas of increasing returns to scale, the profits of rice farming actors can consistently be increased by adding inputs in a fixed proportion.

The Maximum Likelihood Estimated (MLE) parameters are used after OLS. MLE is a measure of the relationship between the maximum level of production (output) and the level of utilization of the available factors of production (inputs). According to (Soekartawi, 2003), the Cobb-Douglas function follows the rule of diminishing returns so that the coefficient value in the model is expected to be positive, which can then provide recommendations for making efforts so that each additional input can produce greater additional output. The results of the analysis of the estimation of the Stochastic Frontier Cobb-Douglas rice production function model using the MLE technique are seen in the following Table 4.

The estimation results using the Maximum Likelihood Estimation (MLE) approach with Frontier 4.1c software show an equation that can be used to show how variable inputs are used, such as land area (X1), seeds (X2), labor (X3), fertilizer (X4), pesticides. (X5), and combined harvester rental costs (X6) can influence rice production ((X6) can influence rice production (Y) based on the table produced from the Douglas Cobb function analysis. From the estimation results above it can be seen the influence of the independent variable on the dependent variable in the equation as follows :

$$\text{Ln}Y = 21,917+1,437\text{Ln}X_1+0,129\text{Ln}X_2-0,051\text{Ln}X_3+0,211\text{Ln}X_4-0,378\text{Ln}X_5+1,067\text{Ln}X_6 \quad (3)$$

Land area (X1) has a positive coefficient value of 1.437 with a t-count value of 5.098. This means the t-count value exceeds the t-table at the 1% level or 2.678. Thus, the land area production factor significantly affects rice production, according to (Syahputra and Rifin, 2023), which reveals that rice production is significantly influenced by land area. Farmers who use large paddy fields will get more production than farmers who use small paddy fields. This indicates that land area is essential in increasing rice farming production. Seed (X2) has a positive coefficient value of 0.129 with a t-count

value of 1.713. This means that the t-count value is greater than the t-table at the 10% level or 1.679, so the seed production factor significantly affects rice production. The use of seeds has a significant effect, as also found in research (Delaseh et al., 2020), where the effect of seeds on rice production is due to the use of superior variety seeds. High-quality seeds affect rice yield growth because they increase rice plants' productivity.

Table 4. Production function results of the MLE method

Variable	Coefficient	t-ratio
Constant ($\text{Ln}\beta_0$)	21,917	**2,203
Vast land ($\text{Ln}\beta_1$)	1,437	***5,098
Seed ($\text{Ln}\beta_2$)	0.129	*1,713
Power work ($\text{Ln}\beta_3$)	-0.051	^{ns} -0.856
Fertilizer ($\text{Ln}\beta_4$)	0.211	***5,249
Pesticides ($\text{Ln}\beta_5$)	-0.378	^{ns} -0.535
Cost rent <i>combine harvester</i> ($\text{Ln}\beta_6$)	1,067	*1,944
Sigma-squared (σ)	0.017	*1,671
Gamma (γ)	0.942	*1,695
<i>Log-likelihood function</i>		49,394
<i>LR test of the one-sided error</i>		3,659

Source: Processed Primary Data (2024)

Note: *** = significant at α 1% (2.687); ** = significant at α 5% (2.013); * = significant at α 10% (1.679); ns = not significant

Labour (X3) has a negative coefficient value of - 0.051 with a t-count value of -0.856. This means that the t-count value is smaller than the t-table. Thus, the production factor of labor does not significantly affect rice production. This is due to poor labor management during the farming process. Following previous research (Wulan et al., 2022), the labor variable does not affect paddy rice production. This causes labor to be unproductive and unable to contribute generously to production. Fertilizer (X4) has a positive coefficient value of 0.211 with a t-count value of 5.249. This means the t-count value is greater than the t-table at the 1% level or 2.687. The fertilizer production factor has a significant effect on rice production. The use of fertilizer also has a significant effect on research (Gracia & Martauli, 2021), where the effect of fertilizer is quite significant on output. Fertilizers are very effective in accelerating plant development because they are components easily soluble in water and easily absorbed by plants.

Pesticides (X5) have a negative coefficient value of -0.378 with a t-count value of -0.535. This means that the t-count value is smaller than the t-table. Thus, the pesticide production factor has no significant effect on rice production. The overuse of pesticides will affect the development of rice grain content, where the chemical content of pesticides is easily absorbed by rice (Hartina et al., 2018). This supports the results of (Moonik et al., 2020) that there is an opposite effect between pesticides and the amount of paddy rice production. In other words, if there is an increase in pesticides, there is a decrease in rice production. The rental cost of the combine harvester (X6) has a positive coefficient value of 1.067 with a t-count value of 1.944. This means that the t-count value is greater than the t-table at the 10% level or 1.679, so the production factor of combine harvester rental costs significantly affects rice production. The use of combine harvester also significantly increased rice production in a study conducted by (Permana et al., 2020) and also increased the technical efficiency of rice farming.

The sigma square (σ) value is a variance that shows whether or not there is an influence from technical efficiency. Table 4 reveals that the sigma-squared value (σ) is 0.017, more significant than zero with a significance level of 10%, so 98.3% of the model is influenced by technical inefficiency. Meanwhile, according to the literature, it is stated that if the value of $\sigma = 0$, then there is no influence from technical inefficiency (Coelli et al., 2005). The estimated gamma parameter (γ) is the ratio of the technical efficiency variance (u_i) to the total variance (ϵ_i). The estimation results of the stochastic frontier production function model with frontier 4.1c reveal that this model has a significant γ value at $\alpha = 10\%$, meaning rice production is inefficient. The gamma coefficient of 0,952 explains that the differences in outcomes among sample farmers are due to the gap between their actual production and the maximum possible production, primarily caused by technical inefficiency (U), which is 95,2%. Only a slight 5.8% is caused by noise (v), which is another factor (random) or error outside the model (Noer et al., 2018).

The test carried out in this study used the outcomes of the Likelihood Ratio Test (LR) estimation using the MLE method, which was 3,659. The results of the LR Test value are then

compared with the critical value $X_{R}^{\frac{2}{2}}$ (Kodde & Palm, 1986) with several restrictions of 1 with an error rate of 5%, which is 2,706. After comparison, it was found that the LR Test value was more significant than the critical value $X_{R}^{\frac{2}{2}}$. This shows that it is not 100% efficient in the research area. The outcomes of this study are also consistent with the findings (Rizkiyah *et al.*, 2014) that in the research area, it is also not 100% efficient because the Likelihood Ratio Test value is higher than the critical value $X_{R}^{\frac{2}{2}}$.

Analysis Efficiency Technical

Technical efficiency has to do with how farmers' management of inputs results in maximum output or production. This analysis aims to identify the highest, lowest, and average levels of technical efficiency in rice production achieved by the farmers in rice cultivation in the Mindugading village. The table reveals the frequency distribution of the technical efficiency of rice production of the respondent farmers in the research area:

Table 5. Frequency distribution of rice farming technical efficiency

No	Efficiency Level	Amount Farmer (Person)	Percentage (%)
1	< 0.70	1	2
2	0.70 – 0.79	10	19
3	0.80 – 0.89	20	38
4	0.90 – 0.99	22	41
Amount		53	100

Source: Processed Primary Data (2024)

The data in Table 5 reveals that the interval 0.90-0.99 is the number of farmers with the highest technical efficiency, amounting to 41% or 22% of the total number of rice farmers surveyed. At the technical efficiency interval level of 0,80-0,89, there are 20 farmers or 38%. Meanwhile, in the technical efficiency interval of 0.70-0.79, there were ten farmers or 19%, and the lowest technical efficiency value >0,70 was one farmer or 2%. This data means farmers still have a 70% opportunity (0,6999) to increase rice production overall. These different efficiency levels among farmers indicate differences in the usage of inputs for each farmer.

Table 6. Statistical distribution of rice farming technical efficiency

No	Statistics	Efficiency Level
1	Minimum	0.69
2	Maximum	0.98
3	Average	0.87

Source: Processed Primary Data (2024)

The distribution of technical efficiency levels represents the variability in efficiency. Overall potential input can be achieved if all aspects operate at complete technical efficiency levels (Ngeno, 2012). The data presented in Table 6 reveals that the lowest technical efficiency level for rice production is 0,69 or 69%, meaning that at this efficiency level, farmers still have a 31% potential to boost their production. This low level of technical efficiency occurs due to an inappropriate combination of inputs in running a farming business (Kune *et al.*, 2016). Meanwhile, the highest efficiency level is 0,98. This indicates that farmers have reached 98% of potential rice production obtained by combining inputs. Then, the average technical efficiency is 0,87, meaning that the average farmer can achieve 87% of potential production from combining input use and still has the opportunity to increase production by 13% to achieve efficiency or reach potential production levels.

Based on an average technical efficiency value of 0.87, rice farming in Mindugading Village combines input use efficiently. This decision-making is adjusted to the literature from (Coelli *et al.*, 2005) that the technical efficiency assessment criteria $\geq 0,70$ are categorized as quite efficient. In other words, the technical efficiency of rice farming in Mindugading Village is considered medium. Graphically, the distribution of technical efficiency levels for each farmer respondent can be seen in the picture below :

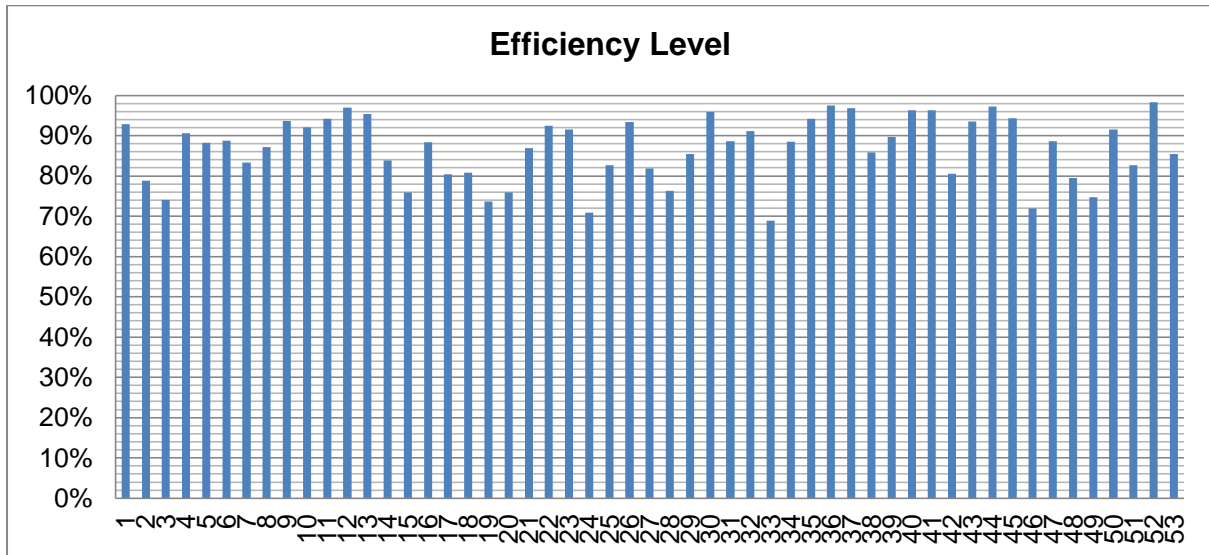


Figure 1 Distribution of technical efficiency levels for each farmer

Increasing rice production is still possible by increasing the number of production factors until they reach the optimum point that can be used. The technical efficiency value category in this research is also almost the same as research (Burhansyah, 2016) and (Permana *et al.*, 2020), showing that rainfed rice farming is classified as technically efficient, with an average efficiency value of 0.81 from the potential production acquired from the combination of sacrificed production inputs. (Barus *et al.*, 2021) In their research, they stated that a high technical efficiency value indicates that existing technology can be utilized well by farmers so that optimal production can be achieved optimally. In contrast, a low technical efficiency value suggests that existing technology cannot be used optimally to obtain maximum results.

Not much research has been completed on technical efficiency in the use of combine harvesters, but each researcher has characteristics that distinguish it from other studies. This study's novelty shows that combining harvester machines is more efficient than in previous studies. This research is essential for farmers because it can provide knowledge about the usage of production factors in running rice farms to be more efficient and can enhance rice production. In addition, using a combine harvester can be one of the solutions to save production costs. While carrying out this research, some limitations may affect the study's outcomes, such as the number of farmer respondents, which only totaled 53 farmers. This is certainly not enough to fully explain the current situation at the research location. In addition, this study only used a few variables tested to ascertain the factors influencing rice production and the level of technical efficiency. So, it is necessary to add other variables so that similar research can be more developed. Furthermore, there are limitations in the research process, where some farmer respondents are less able to understand the questions on the questionnaire, so they need further explanation when filling out the questionnaire.

CONCLUSIONS AND RECOMMENDATIONS

Factors impacting rice production include land area, fertilizers, seeds, and combine harvester rental costs. While the average value of technical efficiency is 0.87, rice farming is said to be quite efficient or on a medium scale. This shows that increasing rice production to the entire efficient category can be done by increasing the number of production factors to approach the optimum point that can be used.

REFERENCES

- Alwi, L. O., Abdullah, B., Budiyo, B., Gafaruddin, A., & Juniardin, J. (2024). Pengaruh Umur Petani, Luas Lahan Garapan, Serangan Hama atau Penyakit serta Produktivitas Kakao terhadap Keputusan Petani Mengganti Tanaman Kakao Menjadi Nilam di Desa Puduria Jaya Kabupaten Konawe Selatan. *Jurnal Ilmiah Membangun Desa Dan Pertanian*, 9(1), 54–60. <https://doi.org/10.37149/jimdp.v9i1.379>

- Barus, E. F., Priyarsono, D. S., & Hartoyo, S. (2021). Analisa Efisiensi Teknis, Alokatif dan Ekonomi Produksi Kubis di Kabupaten Karo. *Jurnal Agrica*, 14(2), 116–130. <https://doi.org/10.31289/agrica.v14i2.4458>
- BPS. (2023). *Luas Panen dan Produksi Padi di Provinsi Jawa Timur 2022-2023 (Angka Sementara)*. <https://jatim.bps.go.id/pressrelease/2023/03/01/1384/pada-2022--luas-panen-padi-mencapai-sekitar-1-69-juta-hektare-dengan-produksi-sebesar-9-53-juta-ton-gkg--jika-dikonversikan-menjadi-beras--maka-produksi-beras-pada-2022-mencapai-5-50-juta-ton-.html>
- Burhansyah, R. (2016). Efisiensi Teknis Usahatani Padi Tadah Hujan Di Kawasan Perbatasan Kabupaten Sambas Dengan Pendekatan Stochastic Frontier Fungsi Produksi (Kasus Di Desa Sebusus, Kecamatan Paloh). *Informatika Pertanian*, 25(2), 163–170. <http://ejurnal.litbang.pertanian.go.id/index.php/IP/article/view/8566/7392>
- Coelli, T. J., Prasada Rao, D. S., O'Donnell, C. J., & Battese, G. E. (2005). An Introduction To Efficiency And Productivity Analysis. In *An Introduction to Efficiency and Productivity Analysis*. <https://doi.org/10.1007/b136381>
- Damayanti, D., Irmayani, & Darmawan. (2023). Analisis Efisiensi Usahatani Padi Sawah dengan Sistem Alsintan Combine Harvester Pada Proses Pemanenan di Desa Padangloang Kecamatan Dua Pitue Kabupaten Sidenreng Rappang. *Saintifik (Multi-Science Journal)*, 21(3), 115–124.
- Delaseh, S. S., Yurisinthae, E., & Kusriani, N. (2020). Pengaruh Faktor Produksi terhadap Produksi Usahatani Padi Sawah Tadah Hujan di Desa Menjalin. *JIA (Jurnal Ilmiah Agribisnis) : Jurnal Agribisnis Dan Ilmu Sosial Ekonomi Pertanian*, 5(5), 192. <https://doi.org/10.37149/jia.v5i5.14127>
- Dewi, N. L. P. R., Utama, M. S., & Yuliarini, N. N. (2017). Faktor-faktor Yang Mempengaruhi Produktivitas Usahatani dan Keberhasilan Program Simantri di Kabupaten Klungkung. *Ekonomi Dan Bisnis*, 2(6), 701–728.
- Firdaus, & Sumarni. (2022). Efficiency Analysis of Using Combine Harvester In Rice Paddy (Oryza sativa L) Harvesting Activities. *Journal of Agriculture and Veterinary Science (IOSR-JAVS)*, 15(9), 37–41. <https://doi.org/10.9790/2380-1509013741>
- Gracia, S., & Martauli, E. D. (2021). Analisis Pendapatan dan Faktor-Faktor Yang Mempengaruhi Produksi Usahatani Padi Sawah di Kabupaten Deli Serdang. *Jurnal Ilmiah Manajemen*, 18(2), 120–135.
- Hardin, H. (2019). Identitas Petani Yang Mempengaruhi Pendapatan Bagi Usahatani Padi Sawah Di Kota Baubau. *Media Agribisnis*, 3(2), 121–144. <https://doi.org/10.35326/agribisnis.v3i2.493>
- Hartina, H., Tuwo, M., & Indrasyih, Y. (2018). Pengaruh Faktor Produksi terhadap Produksi Usahatani Padi sawah di Desa Sanggi-Sanggi Kecamatan Palangga kabupaten Konawe Selatan. *Jurnal Agribisnis dan Ilmu Sosial Ekonomi Pertanian*, 3(1), 1-6. *Jurnal Agribisnis Dan Ilmu Sosial Ekonomi Pertanian*, 3(1), 1–6.
- Haryono, D., Hudoyo, A., & Mayasari, I. (2021). The Sustainable Agricultural Mechanization Of Rice Farming and its Impact On Land Productivity and Profit in Lampung Tengah Regency. *IOP Conference Series: Earth and Environmental Science*, 739(1), 1–7. <https://doi.org/10.1088/1755-1315/739/1/012056>
- Hendrarini, H., Kusumastuti, E. R., Amir, I. T., & Sunarsono, R. J. (2023). Analyzing the Influential Factors of Farmer Exchange Rate Simultaneously and Partially in Candi District, Sidoarjo, Indonesia. *Ymer*, 22(01), 527–551.
- Hendrarini, H., & Santoso, W. (2020). Agribusiness Sedap Malam Flower's (Polianthes Tuberosa L.) In Pasuruan Regency : A Study Of Perceived Strengthening. *Tanjungpura International Journal on Dynamics Economics, Social Sciences and Agribusiness*, 1(2), 13–24. <https://doi.org/10.26418/tijdessa.v1i1.41450>
- Imran, S. (2022). *Ekonomi Produksi Pertanian* (M. Mirnawati (ed.); 1st ed.). Ideas Publishing. www.ideaspublishing.co.id
- Intiaz, L. F., Subhan Prasetyo, A., & Prayoga, K. (2022). Tingkat Adopsi Inovasi Teknologi Combine Harvester di Kelompok Tani Balong 01 Desa Tanjungbaru. *Forum Agribisnis*, 12(2), 113–125. <https://doi.org/10.29244/fagb.12.2.113-125>
- Kodde, D. A., & Palm, F. C. (1986). Wald Criteria for Jointly Testing Equality and Inequality. *Econometrica*, 54(5), 1243–1248.
- Kumbhakar, S. C., & Lovell, C. A. K. (2000). Stochastic Frontier Analysis. In *International Series in Operations Research and Management Science* (1st ed.). Press Syndicate Of The University Of Cambridge. https://doi.org/10.1007/978-1-4419-7961-2_7

- Kune, S. J., Muhaimin, A. W., & Setiawan, B. (2016). Analisis Efisiensi Teknis dan Alokatif Usahatani Jagung (Studi Kasus di Desa Bitefa Kecamatan Miomafo Timur Kabupaten Timor Tengah Utara). *Jurnal Agribisnis Lahan Kering*, 1(1), 3–6.
- Mahasin, A. N., Arifin, Z., & Susilowati, D. (2021). Efisiensi Penggunaan Mesin Pemanen Padi (Combine harvester) Dengan Pemanenan Secara Tradisional di Desa Wadang Kecamatan Ngasem Kabupaten Bojonegoro. *Jurnal Sosial Ekonomi Pertanian Dan Agribisnis*, 9(5), 1–7.
- Maulana, R., Yunus, L., & Fyka, S. A. (2021). Factors Affecting Land Conversion From Rice Plants to Lime Plants in Watabenua Village Landono District. *Jurnal Ilmiah Membangun Desa Dan Pertanian*, 6(3), 95. <https://doi.org/10.37149/jimdp.v6i3.19149>
- Moonik, F. E., Kaunang, R., & Lolowang, T. F. (2020). Analisis Faktor-Faktor Yang Mempengaruhi Produksi Usahatani Padi Sawah Di Desa Tumani Kecamatan Maesaan. *Agri-Sosioekonomi*, 16(1), 69. <https://doi.org/10.35791/agrsosek.16.1.2020.27073>
- Ngeno. (2012). Measuring Technical Efficiency Among Maize Farmers In Kenya's Bread Basket. *Agricultural Journal*, 7(2), 106–110.
- Noer, S. R., Zakaria, W. A., & Murniati, K. (2018). Analisis Efisiensi Produksi Usahatani Padi Ladang di Kecamatan Sidomulyo Kabupaten Lampung Selatan. *Jurnal Ilmu-Ilmu Agribisnis*, 6(1), 17–24.
- Permana, D., Fariyanti, A., & Yusalina. (2020). Efisiensi Teknis Dan Faktor Penentu Inefisiensi Usahatani Padi Dengan Dan Tanpa Menggunakan Combine Harvester Di Kabupaten Indramayu. *Jurnal Pengkajian Dan Pengembangan Teknologi Pertanian*, 23(1), 53–71.
- Rizkiyah, N., Syafrial, & Hanani, N. (2014). Faktor-Faktor Yang Mempengaruhi Efisiensi Teknis Usahatani Kentang (*Solanum Tuberosum* L) Dengan Pendekatan Stochastic Production Frontier (Kasus Desa Sumber Brantas Kecamatan Bumiajai Kota Batu). *Jurnal Habitat*, XXV(1), 5–8.
- Setiawan, R. F. (2022). Kemiskinan Dan Kesejahteraan Dalam Kaitannya Pada Pembangunan Pertanian. *Berkala Ilmiah AGRIDEVINA*, 11(1), 57–68. <https://doi.org/10.33005/adv.v11i1.3095>
- Setiyowati, T., Fatchiya, A., & Amanah, S. (2022). Pengaruh Karakteristik Petani terhadap Pengetahuan Inovasi Budidaya Cengkeh di Kabupaten Halmahera Timur. *Jurnal Penyuluhan*, 18(02), 208–218. <https://doi.org/10.25015/18202239038>
- Soekartawi. (2003). *Teori Ekonomi Produksi dengan Pokok Bahasan Analisis Fungsi Cobb-Douglas* (1st ed.). PT Raja Grafindo Persada.
- Sugiyono. (2017). *Metode Penelitian Kuantitatif, Kualitatif Dan R&D*. PT Alfabeta.
- Suratiyah, K. (2015). *Ilmu Usahatani* (S. R. Annisa (ed.); Revisi). Penebar Swadaya. <http://www.penebar-swadaya.net>
- Susanti, D., Listiana, N. H., & Widayat, T. (2019). Pengaruh Umur Petani, Tingkat Pendidikan dan Luas Lahan Terhadap Hasil Produksi Tanaman Sambung. *Jurnal Tumbuhan Obat Indonesia*, 9(2). <https://doi.org/10.22435/toi.v9i2.7848.75-82>
- Syahputra, A. R., & Rifin, A. (2023). Efisiensi Teknis Usahatani Padi Kalimantan Tengah: Pendekatan Stochastic Frontier Analysis. *SEPA: Jurnal Sosial Ekonomi Pertanian Dan Agribisnis*, 20(2), 203–213.
- Wulan, S., Indriani, R., & Bempah, I. (2022). Pengaruh Penggunaan Faktor-Faktor Produksi Terhadap Produksi Usahatani Padi Sawah Di Desa Bulotalangi Kecamatan Bulango Timur. *AGRINESIA: Jurnal Ilmiah Agribisnis*, 6(2), 118–125. <https://doi.org/10.37046/agr.v6i2.15913>
- Zainuddin, Mursalim, & Waris, A. (2016). Analisis Ekonomi Penggunaan Combine Harvester Tipe Crown CCH 2000 Star. *Jurnal AgriTechno*, 9(1), 36–43.