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Technical efficiency of organic *caisim* farming using Data Envelopment Analysis (DEA)

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Abstract. This study aims to assess the level of technical efficiency in organic *caisim* (mustard green) farming and identify the socio-economic factors influencing it among farmers in the Organic Farming Group of Sumberejo Village, Batu City. Technical efficiency is a crucial indicator for optimizing input use in agricultural production, yet it remains underexplored in the context of organic vegetable farming. The research employs the Data Envelopment Analysis (DEA) method using the Variable Return to Scale (VRS) input-oriented model to evaluate technical efficiency, while Tobit regression is utilized to examine the determinants of efficiency levels. Results indicate that the average technical efficiency score among respondent farmers is 0.737, suggesting suboptimal input utilization and room for improvement in production practices. The Tobit regression results indicate that age has a negative and significant impact on technical efficiency. This suggests that older farmers are less likely to adopt innovative or adaptive farming practices, which can limit their ability to optimize input use. In contrast, farming experience shows a positive and significant effect, reflecting the value of accumulated practical knowledge and improved decision-making in managing resources efficiently. Meanwhile, education level and household size do not exhibit a significant influence on technical efficiency. This finding implies that, in the context of small-scale organic farming, formal education may not be as critical as experiential learning, and a larger household does not necessarily enhance labor productivity without effective role distribution and management. The study is limited to a localized farming group and a specific organic crop, warranting broader investigations for general applicability. Nevertheless, it offers valuable insights into technical efficiency in sustainable farming practices.

Keywords: Data Envelopment Analysis, Technical Efficiency, Organic Farming, *Caisim*, Tobit Regression

INTRODUCTION

Consuming organic food plays a vital role in promoting both individual health and environmental sustainability (Hansmann et al., 2020; Winterstein, 2024). Unlike conventionally grown produce, organic food is cultivated without synthetic pesticides, fertilizers, or harmful chemicals, thereby reducing human exposure to toxic substances. Organic vegetables are also often richer in essential nutrients, including vitamins and antioxidants, which contribute to a stronger immune system. From an environmental perspective, organic farming practices help maintain soil fertility, reduce water pollution, and promote biodiversity. Furthermore, choosing organic food supports ethical practices, including humane animal treatment and the reduction of antibiotic resistance, making it a responsible choice for long-term ecological and public health sustainability.

Organic *caisim* (*Brassica juncea* L.), a leafy vegetable commonly consumed in Indonesia, is a key source of vitamins, minerals, fiber, and protein. Due to its widespread use in traditional Indonesian cuisine—such as salads, Javanese noodles, and chicken noodles—demand for *caisim* remains consistently high. This demand is expected to grow in line with population growth and rising purchasing power. The increasing trend toward organic food consumption, driven by health awareness and a preference for produce free from chemical residues (Irmawati, 2018), presents an opportunity for the expansion of organic vegetable production (Aliansi Organik Indonesia, 2015). In response, agricultural entrepreneurs have the potential to scale their operations to meet market demands and enhance business growth (Muljaningsih, 2011; Priastuti et al., 2014).

To ensure sustainable production, particularly of *caisim*, farmers must increase productivity through efficient farming practices and the adoption of appropriate technologies. Current production primarily meets domestic needs, while export volumes remain limited (Hasrati & Sumastuti, 2011). Efforts to improve productivity must include the application of organic fertilizers, which are essential for maintaining soil health. Organic fertilizers enhance soil structure, porosity, water retention, and nutrient absorption, and can also increase soil pH in acidic conditions (Fahrudin, 2011; Rahman et al., 2020; Purwantini, 2016). However, disparities in technology adoption among farmers often lead to variations in productivity, income, and farm efficiency (Berger, 2001; Cunguara & Darnhofer, 2011).

Inefficiencies in *caisim* farming are frequently linked to improper use of production inputs. According to Silitonga et al. (2017), these inefficiencies are influenced by both limited capital—restricting farmers' ability to purchase quality seeds, fertilizers, and crop protection products—and socio-economic factors such as age, education level, farming experience, and household size. Addressing these challenges is essential for optimizing input use, increasing output, and improving the overall welfare of *caisim* farmers in Indonesia.

Efforts to increase agricultural production through technological innovation are valuable but must be supported by key factors such as farmers' characteristics, access to capital, and farm scale. Without adequate extension services and consistent support, farmers often revert to using simpler, less efficient technologies. Improving technical efficiency by optimizing existing resources is essential to enhance productivity, reduce production costs, and ultimately increase farmers' income (Indraningsih, 2018). Enhancing output through technical efficiency is increasingly viewed as a viable alternative, particularly in the context of organic farming, where cost minimization and resource optimization are critical (Kusnadi et al., 2011). Technical efficiency in organic *caisim* farming includes the efficient use of high-quality seeds, organic fertilizers, labor, and other inputs to reduce costs and improve profitability.

Previous research from China and Indonesia indicates that organic *caisim* cultivation can achieve yields comparable to conventional methods while offering significantly higher nutrient content, including vitamins and antioxidants. Studies in Malaysia and Germany highlight the role of organic methods in improving soil fertility through natural composting, enhancing the availability of essential nutrients such as nitrogen and phosphorus (Winterstein et al., 2024). In Thailand, organic pest control methods—including neem oil and biological agents—have proven effective in managing pests while maintaining ecological balance (Thongkham et al., 2024). Research in the Philippines demonstrates that organic *caisim* farming reduces water and soil contamination by eliminating chemical inputs, thereby supporting environmental sustainability. Economic studies from India show that although organic farming may incur higher initial labor costs, it remains financially viable due to premium prices and reduced dependency on external inputs. Consumer preference data from Australia further suggest strong urban market demand for organically grown *caisim*, driven by perceived health benefits and superior taste. In Vietnam, Le Loan et al. (2024) found that organic *caisim* farming systems are more resilient to climate variability due to the use of diverse cropping systems and organic soil amendments.

In Sumberejo Village, organic *caisim* farmers apply a variety of inputs based on their individual assessments. However, when input use does not align with land capacity or recommended practices, farming becomes inefficient. Therefore, it is necessary to improve the application of production inputs to enhance efficiency and productivity within the Organic Farming Group in Sumberejo Village. In this context, the present study aims to measure the technical efficiency level of organic *caisim* farming and to identify the socio-economic factors that influence efficiency among farmers the Organic Farming Group in Sumberejo Village, Batu City, East Java Province, Indonesia.

METHODS

This study was conducted in Sumberejo Village, Batu District, Batu City, East Java, Indonesia. The population in this study comprises all farmers cultivating organic *caisim* who are members of the Batu City Organic Farming Group. The total population consists of 30 farmers. A census method was employed, in which all members of the population are used as the sample, as defined by Ridwan and Sunarto (2012). Accordingly, the sample size in this study corresponds to the entire population, totaling 30 respondents. The study applies a quantitative analysis approach, utilizing mathematical, statistical, and econometric tools to examine technical efficiency and the factors influencing it. The level of technical efficiency among organic *caisim* farmers was measured using Data Envelopment Analysis

(DEA), which evaluates the performance of individual farms treated as Decision Making Units (DMUs). DEA calculates an efficiency score for each DMU, which is used to identify inefficient units and guide input-output adjustments to improve performance. The efficiency score, expressed as a ratio of weighted total output to input, is compared against benchmark DMUs—those achieving a technical efficiency score of 1. These benchmark DMUs serve as references for improving others.

The efficiency improvements are determined using shadow prices (Y multipliers), which indicate the proportional adjustments needed for inefficient DMUs to reach the efficient frontier. This study employs an input-oriented Variable Return to Scale (VRS) model, which assumes that the relationship between input and output is not constant—that is, an increase in inputs does not necessarily lead to a proportional increase in outputs. The input-oriented DEA-VRS model seeks to minimize input usage while maintaining current output levels.

$$
\begin{gathered}
\mathrm{Min}\theta, \lambda\ \theta j \dots\dots\dots\dots\dots\dots\dots (1) \\
\text{s.t.} -qj + (q_1 \lambda_1 + q_2 \lambda_2 + q_3 \lambda_3 + q_4 \lambda_4 + q_5 \lambda_5 + \dots + q_{30} \lambda_{30}) \geq 0 \\
\theta x_{1j} - (x_{11} \lambda_1 + x_{12} \lambda_2 + x_{13} \lambda_3 + x_{14} \lambda_4 + x_{15} \lambda_5 + \dots + x_{130} \lambda_{30}) \geq 0 \\
\theta xij - (x_{i1} \lambda_1 + x_{i2} \lambda_2 + x_{i3} \lambda_3 + x_{i4} \lambda_4 + x_{i5} \lambda_5 + \dots + x_{i30} \lambda_{30}) \geq 0 \\
I1' \lambda j = 1 \\
\lambda j \geq 0
\end{gathered}
$$

The Formula 1 presented above is a mathematical representation of the Data Envelopment Analysis (DEA) model using an input-oriented Variable Returns to Scale (VRS) approach to measure technical efficiency of organic farmers. In this model, the objective is to minimize θ, which represents the technical efficiency score of a specific decision-making unit (DMU), in this case, an individual farmer *j*. The model seeks to determine how much the farmer can proportionally reduce their input usage while still producing at least the same level of output, assuming best practices within the group. Moreover, the first constraint ensures that the output of farmer *j* (denoted as *qj*) is not greater than the weighted sum of outputs from other farmers in the reference set, adjusted by the weights (λ) assigned to each comparison unit. The next three constraints involve the inputs (*xij*)—land, organic fertilizer, seed, and labor—and ensure that each input used by farmer *j*, after being scaled down by θ, is not less than the weighted sum of the corresponding input used by other farmers. This ensures a fair efficiency comparison. The constraint $I1'\lambda j = 1$ guarantees convexity and allows the model to account for variable returns to scale by ensuring that the comparison is made within a convex combination of peer units. Finally, $\lambda j \geq 0$ ensures that the weights are non-negative, meaning only actual observed combinations of peer farmers are used in constructing the efficiency frontier. This model evaluates how much input usage can be proportionally reduced (θjθj) while still producing at least the same output level, by comparing each farmer (DMU) to a benchmark of best-performing peers. A value of θj=1θj=1 indicates that the farmer is operating efficiently, while values less than 1 indicate input inefficiency.

Furthermore, the second formula represents a Tobit regression model used to identify the factors that influence the technical efficiency (θ) of organic *caisim* farmers. This equation models θ as a function of several explanatory variables (Z1 to Z4), which include demographic and socioeconomic characteristics of the farmers. In the equation, β_0 is the intercept term, while β_1 to β_4 are the regression coefficients indicating the strength and direction of the relationship between each independent variable and the technical efficiency score. Specifically, Z_1 represents the farmer's age, Z_2 is the education level (in years of schooling), Z_3 denotes the number of family members, and Z_4 captures the experience in organic *caisim* farming (in years). The error term e accounts for unobserved factors or random disturbances that may influence efficiency but are not captured by the model. Each regression coefficient (β_1 to β_4) in the Tobit model reflects the expected change in technical efficiency (θ) associated with a one-unit increase in the corresponding independent variable, assuming other variables remain constant. For instance, the coefficient β_1, which represents the farmer's age, indicates whether age has a positive or negative impact on efficiency. A positive β_1 suggests that older farmers tend to be more efficient, possibly due to accumulated experience, whereas a negative value may imply that aging reduces adaptability or physical capacity. The coefficient β_2, related to the farmer's education level, implies that higher levels of education enhance technical efficiency, likely because education improves the farmer's ability to understand and adopt better farming practices. Meanwhile, β_3 captures the effect of organic *caisim* farming experience; a positive value indicates that longer experience contributes to greater efficiency, reflecting the benefits of practical learning over time. Lastly, β_4, which corresponds to the number of family members, can be interpreted in two ways: a positive coefficient suggests that more family members provide additional labor and thus improve efficiency, while a negative coefficient may indicate that a larger household leads to resource constraints or increased consumption demands that detract from farming efficiency.

$$\theta = \beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + \beta_4 Z_4 + e \qquad (2)$$

Additionally, Tobit regression results must be evaluated through both overall and partial testing. The overall test is conducted using the Prob > chi2 statistic, which determines whether the independent variables collectively have a significant effect on the dependent variable. This test is used to assess the joint influence of all the independent variables included in the model. If the p-value from this test is less than 0.05, it indicates that the independent variables, as a group, significantly affect the dependent variable at the 5% significance level.

In addition to the overall test, a partial test is performed using the t-test to evaluate the individual effect of each independent variable (Z) on the dependent variable (θ). This is done by comparing the p-value (prob > t) of each independent variable with the significance level. If the p-value is less than 0.05, it means that the independent variable has a statistically significant individual effect on the dependent variable. Both tests are essential in understanding the overall and specific contributions of variables within the Tobit regression model.

The hypotheses used in the partial test of the Tobit regression are: the null hypothesis (H_0) assumes that the coefficients of all independent variables (β_1 to βn) are equal to zero, meaning the variables do not significantly affect the dependent variable. If the p-value (prob > t) is greater than the 5% significance level, H_0 is accepted. The alternative hypothesis (H_1) assumes that at least one coefficient is not equal to zero, indicating a significant effect. If the p-value is less than 0.05, H_0 is rejected, and the variable is considered to have a significant influence.

RESULT AND DISCUSSION

3.1 Technical Efficiency of Organic *Caisim* Farming

The scale of the farming business really determines the efficiency and profits of the farming business. The small scale of farming causes inefficient use of inputs so that farmers often experience losses. Most farmers' farming scale in Indonesia is small. The results of the distribution analysis of the organic *caisim* farming efficiency scale using DEA are presented in Table 1.

Table 1. Distribution of organic *caisim* production scale

Production Scale	Number of Farmers (Person)	Percentage (%)
Constant Returns to Scale (CRS)	4	13.333
Decreasing Return to Scale (DRS)	3	10.000
Increasing Returns to Scale (IRS)	23	76.667
Total	30	100

Source: Author's computation, 2024

Table 1 shows that the value of the IRS scale organic *caisim* farmer respondents was the highest, namely 23 farmers. From the IRS value that dominates and has a percentage of 76.67%, it can be concluded that the majority of organic *caisim* respondents in the Organic Farming Group in Sumberejo Village are not at the optimal scale. According to Asmara et al. (2016), On the IRS scale, each additional input will increase the amount of output greater than the addition of a given input. Farmers who are on the DRS scale each addition of one input will produce an output that is smaller than the addition of the given input. The value of farmer efficiency in the CRS scale, i.e. every addition of one unit of input will increase the output of the input constantly.

Analysis of the technical efficiency level of organic *caisim* farming in Sumberejo Village was carried out using DEAP Version 2.1 Software with a VRS (Variable Return to Scale) model. If the efficiency value shows a score of 100%, it indicates perfect efficiency and if it is entered at 0%, it enters the lowest efficiency level. Based on calculations using DEA will produce three conditions, namely (Maharani, 2014):

1. A green range of 1 or 100% is a safe project and is on the track you want to achieve.
2. The amber range is 0.900 - 0.999 or 90%-99.9%, i.e. the project may be at risk if the problem is not addressed, so it needs attention.
3. Red range of 0 - 0.899 or 0% - 89.99% is a risky project because it is far from the track to be achieved, so that in this range management action is needed.

Table 2. Distribution diagram of the Technical Efficiency of Organic *Caisim* Farming

No	Efficiency Level	Efficiency Category	Number of Farmers (Person)	Percentage (%)
1	0 – 0.899	Red	19	64
2	0.900-0.999	Amber	1	3
3	1	Green	10	33
	Total		30	100
	Average		0.737	
	Maximum		1	
	Minimum		0.309	

Source: Author's computation, 2024

The distribution of the technical efficiency of organic *caisim* farming in Sumberejo Village using DEAP Software Version 2.1 is presented in Table 2. Table 2 shows the level of technical efficiency of organic *caisim* farming from the majority of respondent farmers in the reed range, which is 10 people or 64% of the total respondents. This explains that the majority of organic *caisim* farmers are not efficient. A significant proportion (64%) of farmers in this study are not achieving optimal output levels. This may be due to several potential factors, including lack of proper training or knowledge regarding organic farming practices, inadequate use of inputs or mismanagement of resources, and Limited access to advanced technologies or support systems.

The peer analysis used in this study intends to provide information on how much input use is used by fully efficient respondent farmers in order to become a reference (peer) for farmers who are not yet efficient. There were 10 farmers who were used as peer farmers in this study with an efficiency value of 1. Table 3 illustrates the comparison of the use of inefficient farmer inputs with peer farmers in the Organic Farming Group in Sumberejo Village.

Table 3. Comparison of the use of inefficient farmers' inputs with peer farmers

Description (Unit)	DMU Inefficient		DMU Efficient	
	DMU 1 Tamat Aji Supoko	DMU 26 Marsaji	DMU 2 Suyit	DMU 3 Rogib
Production (Kg)	2.000	1.800	3.200	80
Land area (Ha)	0.150	0.100	0.200	0.010
Seed (Kg)	0.100	0.125	0.100	0.010
Organic fertilizer (Kg)	500	600	500	50
Labor (Day of Labor)	23.625	24.125	29	4.563

Source: Author's computation, 2024

Table 3 means that DMU 1 can refer to DMU 2, 3 and 26. If DMU 1 wants to achieve full efficiency on a land area of 0.15 ha, it can use 0.125 ha of seeds, 600 kg of organic fertilizer and 24.125 day per labor by imitating DMU. 26. Farmer 1 can adjust the use of inputs according to table 10 if they want to imitate the use of inputs from DMU 1 and 2 farmers. DMU 1 that is not yet efficient can see the projected value that should be obtained to obtain maximum efficiency. DMU 1 can improve its farming efficiency by following the radial movement and Slack values in order to achieve the projected value.

Table 4 shows the projected value for DMU 1 in order to improve the value of farming efficiency. Table 4 can be used as a reference that DMU 1 farmers according to the analysis using DEA are recommended on a land of 0.126 ha using 360, 893 kg of organic fertilizer, 0.68 kg of seeds, and a total of 19.883 labor.

Table 4. Comparison of Original value, Radial movement, Slack movement, and Projected value DMU 1

Average value	Land Area (Ha)	Organic Fertilizer (Kg)	Seed (Kg)	Labor (Day of Labor)
Original Value	0.150	500	0.100	23.625
Radial Movement	-0.024	-79.197	-0.016	-3.742
Slack Movement	0.000	-79.910	-0.016	0.000
Projected Value	0.126	340.893	0.068	19.883

Source: Author's computation, 2024

The analysis shows that most organic *caisim* farmers in Sumberejo Village function under Increasing Returns to Scale (IRS), indicating that they have not attained maximum efficiency and can enhance production by proportionally increasing their input usage. This indicates an opportunity for expansion and increasing production. Utilizing the DEA model with Variable Returns to Scale (VRS) assists in pinpointing particular inefficiencies at the farm level. For instance, DMU 1 can enhance its performance by modifying input utilization to align with more efficient reference units such as DMU 2, 3, and 26. The projected data offer a distinct framework for farmers to enhance the distribution of inputs-land, seeds, fertilizers, and labor to achieve maximum efficiency. These findings highlight the significance of benchmarking and focused input management to improve overall technical efficiency in organic *caisim* cultivation.

3.2 Analysis of Factors Affecting Technical Efficiency Using Tobit Regression

The results of the calculation of efficiency using DEA basically have not considered the factors that influence it. Therefore, to measure the factors that affect the efficiency of DMU (farmers responding to organic *caisim*) a second stage analysis is used. The second analysis of this study uses the Tobit model. The tobit model is used because the dependent variable is an efficiency value between 0 and 1 (Rusdiyana, 2013). The second stage is performed. Tobit regression is used to measure what factors affect the efficiency level of the DMU. Factors used in this study include age (years), education level (years), experience in organic *caisim* farming (years), and number of family members (persons). Tobit regression results for the factors that affect the technical efficiency of organic *caisim* farming are presented in Table 5.

Table 5. Analysis of factors affecting technical efficiency

Variables	Coeff.	Std. Error	P > |t|
Age (Z_1)	-5.976	2.607	0.030
Education Level (Z_2)	3.224	10.860	0.769
Number of Family Members (Z_3)	-1.636	22.214	0.942
Farming Experience (Z_4)	15.592	2.391	0.000
Constant	680.490	197.342	0.002
Prob. > Chi^2 Significant at 95% level	0.000		

Source: Author's computation, 2024

Table 5 shows from the results of the Prob>chi2 test that has been carried out, the independent variables (age, education level, organic *caisim* farming experience and number of family members) affect the dependent variable (technical efficiency) as a whole. The regression equation obtained based on table 5 is presented as follows:

$$\theta = -5.976274Z_1\ 3.223733Z_2 + -1.635566Z_3 + 15.59221Z_4$$

Table 5 shows the Prob>chi2 value of 0.000 which is smaller than the 0.05 error rate. This shows that simultaneously all the independent variables analyzed affect the technical efficiency of organic *caisim* farming. Furthermore, a partial test using a t-test was conducted to determine whether there was a significant effect of the independent variable on the technical efficiency of the input VRS orientation partially. The technical efficiency of this test is seen from the comparison of the value of P>|t| with a specified error rate of 0.05. If the value of P>|t| smaller than the error rate, then the variable has a significant effect on the technical efficiency of organic *caisim* farming. The partial test results in table 5 are described as follows:

a. Farmer's age (Z_1)

According to the results of the partial test on the age variable, the value of P>|t| of 0.030 is smaller than the error rate of 5% or 0.05, then H_1 is accepted where $H_1 \neq 0$, meaning the age variable has a significant effect on the technical efficiency of organic *caisim* farming at a significance level of 95%. The coefficient of the age variable shows a negative sign, namely -5.9763, so every additional age of 1 year will reduce the level of efficiency by -5.9763. This is in accordance with the statement (Isyanto, 2011) The older the farmer, the lower the efficiency level. This is because the older the farmer, the lower the physical and mental strength of the farmer in carrying out farming, so that the higher the level of technical inefficiency of farming or the lower the level of technical efficiency of farming carried out.

Furthermore, the decline in efficiency as one ages might also stem from a diminished ability to adapt to new technologies, decreased rates of embracing innovative agricultural practices, and an inclination to depend on conventional methods. These elements might restrict older farmers' ability to adapt to evolving agricultural methods, market needs, and environmental circumstances. Consequently, the findings indicate the significance of focused interventions, including ongoing education, training initiatives, and access to labor-saving technologies, to assist aging farmers in sustaining or enhancing their technical efficiency. Policymakers and agricultural extension services ought to develop age-targeted strategies to promote sustainable productivity in organic farming sectors.

b. Farmer's education level (Z_2)

The results of the partial test on the education level variable show that the value of P>|t| of 0.769 greater than the error rate of 0.05 at a significance level of 95%, then H_0 is accepted where $H_0 = 0$. This shows that the education level variable has no significant effect on the technical efficiency of organic *caisim*. This is in accordance with research by (Kusumaningrum, 2019) that the education level variable has no significant effect on the level of efficiency. The majority of respondent farmers' education levels in Sumberejo Village are elementary school graduates or have received 6 years of education. The knowledge and skills of respondent farmers related to cultivation practices are not based on considerations of education level but through socialization programs, training, counseling, and intensive assistance provided by business partners. Therefore, with the activities of farmers in these activities is expected to further increase the level of technical efficiency of farmers.

c. Number of Family Members (Z_3)

The results of the partial test on the number of family members variable show that the value of P>|t| of 0.942 is greater than the error rate of 0.05 at a significance level of 95%, then H_0 is accepted where $H_0 = 0$. This shows that the education level variable has no significant effect on the technical efficiency of organic *caisim*. This is in accordance with research by (Kusumaningrum, 2019) the variable number of family members does not affect the level of efficiency. The size of the number of family members does not affect the achievement of farmers' technical efficiency. This is because farmers work alone without being assisted by other family members. Thus, farmers determine their own use of inputs in farming and are not influenced by other family members.

The results additionally indicate that neither the level of education nor the number of family members significantly impacts the technical efficiency of organic *caisim* farming in the region studied. This result might indicate the context-dependent characteristics of agricultural methods in Sumberejo Village, where formal education and family labor inputs are not the main factors influencing productivity. Rather, practical knowledge is obtained through informal methods like training, counseling, and teamwork with business associates, which can effectively replace formal education in improving agricultural skills. Moreover, the absence of impact from family size suggests a mainly individual strategy in farm management, where labor input choices are determined autonomously by the farmer. These findings emphasize the significance of prioritizing capacity-building efforts and access to extension services instead of depending only on demographic elements to enhance technical efficiency.

d. Farming experience (Z_4)

According to the results of the partial test of the variable length of farming (Z4) According to the results of the partial test on the age variable, the value of P>|t| of 0.000 is smaller than the error rate of 5% or 0.05, then H1 is accepted where $H_1 \neq 0$, means the variable length of farming has a significant effect on the technical efficiency of organic *caisim* farming at a significance level of 95%. The variable coefficient of farming duration shows a positive sign, namely 15.5922, so every additional 1 year of farming time will reduce the efficiency level of 15.5922. This is in accordance with the statement (Karmini, 2018) The experience of more and more farmers makes farmers more skilled and easier to overcome problems in farming. Experience in farming can affect the behavior of farmers in managing their farming. Usually, farmers who do farming with a longer period of time tend to be more careful in making decisions in doing farming.

The notable and beneficial link between farming experience and technical efficiency indicates that as farmers accumulate more years of experience, their skill in managing farming tasks enhances. The positive coefficient suggests that seasoned farmers are more effective, probably because of their knowledge of farming methods, problem-solving abilities, and improved decision-making in resource utilization. This reinforces the notion that agricultural experience is crucial for improving decision-making and adjusting to farming difficulties. Thus, encouraging knowledge exchange among farmers and guidance from seasoned growers may be effective methods to enhance efficiency in organic *caisim* cultivation.

CONCLUSION

Measurement of technical efficiency by using the DEA approach with Variable Return to scale (VRS) input model, it is found that the average level of technical efficiency of respondent farmers in the Organic Farming Group in Sumberejo Village, is with an efficiency value of 0.737. Based on these results, the average farmer has not reached the green range category. The majority of farmers in Sumberejo Village are in the red range level of 0 - 0.899 or 0% - 89.99%, which is a risky project because it is far from the track to be achieved, so that in this range there needs to be management action, namely with the number of respondents as many as 19 or 64 % of the total number of respondents. In measuring the efficiency scale, the majority of farmers are on the Increasing Return to Scale (IRS) scale, so farmers can still make it possible to increase their farming while farmers who are on the Decreasing Return to Scale (DRS) scale must reduce the use of their inputs.

The results of the tobit regression analysis showed that the variable age (years) had a significant and negative effect on the technical efficiency of organic *caisim* farming, while the length of farming had a significant and positive effect on the technical efficiency of organic *caisim* farming. Meanwhile, the variables of education level (years), and the number of family members (persons) do not affect the technical efficiency of organic *caisim* farming.

Suggestions for Improvement of cuisim farming such as follow; Farmer Education and Training: Providing targeted training programs to improve knowledge about efficient organic farming techniques can significantly enhance productivity. Resource Optimization: Assessing input use and identifying areas for better allocation of labor, fertilizers, or irrigation systems could help improve efficiency. Access to Technology and Support: Introducing appropriate technologies and ensuring access to affordable organic inputs may bridge gaps in efficiency. Policy Support: Policymakers could implement subsidies or incentives for organic farmers to adopt best practices. Peer Learning: Encouraging efficient farmers to share their practices with others could be an effective low-cost solution.

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