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Technical Efficiency of Irrigated and Rain-fed Rice Farms in North Sumatra, Indonesia

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Abstract

The present paper compares the efficiency of irrigated and rain-fed farming in North Sumatra using a household farm survey for the 2022 growing season. The authors use the Data Envelopment Analysis (DEA) model, mean difference test, and Tobit regression. Empirical results reveal that irrigated farming is more efficient than rain-fed based on CRS and SE assumptions. However, access to irrigation was found to harm rice farming efficiency. Unequal distribution of water, scarcity of water during the growth period, and excess water during the harvest cause a decrease in the efficiency of irrigated farming. The age of the head of household, education, and access to credit was also found to harm technical efficiency. In contrast, the experience variable in participating in farmer groups because it has a positive impact on the efficiency of rice farming. The results provide valuable insights for transforming water management and strengthening the need for investment in irrigation infrastructure as a poverty alleviation mechanism and means to achieve rice farming sustainability in North Sumatra.

Keywords: Irrigation, Rice, DEA, Technical Efficiency, North Sumatra

Introduction

Although Indonesia's economy has diversified away from agricultural dependency since the government focused on downstream industry programs in 2010, rice production remains the primary economic sector. Rice farming is given higher priority than other agricultural activities because rice is a staple food and provides food security for rural farmers. In total, 58% of rice farmers own small plots of less than half a hectare, 47.5% of agricultural households cultivate rice, and 39.7% of the main livelihood for agricultural households comes from rice farming (BPS-Statistics, 2018). Java produces approximately 50% of rice, while the islands of Sumatra and Sulawesi contribute 20% and 12%, respectively (FAS & USDA, 2020). North Sumatra Province contributes 3.73% to national rice production (BPS, 2021).

Approximately 85% of Indonesia's rice production comes from irrigated paddy fields (FAS & USDA, 2020). Countries such as Thailand, the Philippines, and Brazil use irrigated land to increase national rice production (Sumaryanto et al., 2023). Apart from contributing to increasing farm production, irrigation also contributes to the welfare of farmer households. The study by Dillon, (2008) and Kuwornu & Owusu (2012) explains that access to irrigation contributes positively to household expenditure. (Dillon, 2008) study also found access to irrigation to increase savings and maintain household food security. Another study found that an increase in the area of irrigated land contributed to reducing rural poverty (Septiadi et al., 2016).

Although access to irrigation contributes to rice production and household welfare, not all farmers have access to irrigation. 40% of rice fields in Indonesia are not irrigated (FAS & USDA, 2020). Specifically in Sumatra, only 11% of paddy fields have irrigation infrastructure, while the rest rely on rainwater for rice farming (Wahyunto & Widiastuti, 2017). Furthermore, 50% of the irrigation networks were damaged causing rice fields to experience water scarcity (Purwantini & Suhaeti, 2017). Extreme climate change, such as drought, also results in water scarcity (Khanal & Regmi, 2018). Water scarcity due to no access to irrigation, damaged irrigation networks, and climate change has decreased rice production and economic losses (Dar et al., 2020; Gedara et al., 2012).

Increasing rice productivity is essential because it maintains political and economic stability in Indonesia. Increasing efficiency, increasing land area, and developing technology are ways to increase productivity (Antriyandarti, 2015) Small-scale farmers need more capital to increase their land. Efficient utilization of existing technology to its full potential is more important than developing technology in the short term. Kalirajan et al., (1996) explained that it is not wise to introduce new technology if the existing technology is not used optimally.

An agricultural production process is technically efficient if and only if the maximum quantity of output can be achieved for a given number of inputs and technologies (Haryanto et al., 2015). Most previous studies that measure efficiency always refer to the concept of efficiency stated by Farrell, (1957). Farrell (1957) stated that efficiency could be measured in relative terms as a deviation from the producers' best practices compared to producer groups. The concept of efficiency expressed by Farrell relates to benchmarking techniques. The benchmarking techniques aim to analyze how the more successful growers achieve their high-performance levels, determine what and where improvements are needed, and use this information to enhance farm performance (Alem et al., 2018). In general, efficiency assessments provide two essential pieces of information: information about the efficient allocation of resources and actions to reduce inefficient inputs (Anang et al., 2020). Farm inefficiency can be defined as the degree to which a grower uses more resources to produce a given output level than the resources used by best-practice growers (Alem et al., 2018). Therefore, growers must reduce inputs to make their farms efficient.

Theoretically, two methods commonly used to estimate the frontier function are Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) (Nguyen et al., 2020). The SFA model is a parametric method that accommodates noise in the data and defines functional forms and models to measure the sources of inefficiency (Kumbhakar et al., 2009). However, this estimation procedure has been criticized can produce biased conclusions because the SFA model ignores the assumption independently and identically distributes the error term in the second stage of estimation (Coelli et al., 2005). DEA models that use non-parametric methods are widely applied because they are more flexible than parametric methods. The DEA model's main advantages are avoiding the technology's parametric specifications and avoiding distributional assumptions for inefficiency terms (Nguyen et al., 2020). The ability of a farm manager to convert inputs into outputs through a particular technology is often affected by the environment in which production takes place (Alem et al., 2018). Management skills, access to irrigation, risk attitudes, constraints on institutions, and innovation include environmental factors. Environmental factors cannot be estimated simultaneously with the frontier production function in the DEA model (Haryanto et al., 2015). Therefore, most efficiency studies use Tobit regression to provide information about the impact of environmental factors on agricultural efficiency (Anang et al., 2020).

Literature Review

Many previous studies have compared the technical efficiency of irrigated and rainfed rice and measured the effect of irrigation on technical efficiency. Previous studies, using both the SFA and DEA models, found that irrigated rice farming is more efficient than rainfed rice farming (Anang et al., 2017; Haryanto et al., 2016; Mkanthama et al., 2018; Pede et al., 2018; Watto & Mugera, 2014). In contrast, another study found that rainfed rice farming is more efficient than irrigated rice farming (Al-Hassan, 2008; Thibbotuwawa et al., 2013). Previous studies show that there is still debate about the benefits of irrigation on the efficiency of rice farming. In addition, no study has examined the comparison of technical efficiency in irrigated and rain-fed land in North Sumatra. Therefore, our study aims to measure the technical efficiency of rice farming, compare the technical efficiency of rice farming on irrigated and rainfed land, and measure the effect of irrigation on the technical efficiency of rice farming in Deli Serdang Regency, North Sumatra Province.

Materials and Methods

Study area and data collection

Deli Serdang Regency is the largest rice producing area in North Sumatra Province, which is located at 2°57' to 3°16' North Latitude and 98°33' to 99°27' East Longitude. This area has three water sources: the Lau Simeme Dam, the Sei Serdang Dam, and the Ular River basin. The three water sources are hydropower generation, drinking water, and irrigated agriculture. However, during this study, the Sei Serdang dam was damaged, and the Lau Simeme dam was not yet focused on irrigated agriculture. Therefore, farmers still utilize traditional irrigation systems sourced from the Ular River basin.

This study chose Tanjung Morawa District as the research location because most rice farming utilizes an irrigation system. As a comparison, we chose Hamparan Perak District as the research location because most farmers use rainfed. Field surveys were conducted using structured questionnaires and interview schedules to obtain input and rice production for this study. A simple random sampling technique was used to select 500 farmers who actively participated in irrigation and rainfed schemes. However, only 400 farmers could answer and complete the questionnaires correctly in both farming systems, of which 220 samples were for irrigated farming and 180 were for rainfed farming. Quantities of rice, fertilizer, labor, machinery, seeds, pesticides, land, and socioeconomic attributes were collected between February and April 2023 for the 2022 growing season.

Efficiency measurement

DEA was chosen over other methods because it handles multiple inputs and multiple outputs; does not require prior weighting (as in index numbers); emphasizes individual observations rather than statistical estimates (as in regression analysis); and is a dynamic analytic decision-making tool that does not only provide a "snapshot" of the current efficiency of a DMU compared to a group but also shows possibilities for increasing relative efficiency; use a benchmarking approach to measure the efficiency of a DMU relative to other DMUs in their group; can assist in identifying best practice or efficient DMUs and inefficient DMUs within the group; and DEA results allow policymakers to develop policies that can help relatively inefficient DMUs improve their performance (Agarwal et al., 2010). Based on the assumptions, the DEA model consists of two types: CCR-DEA is a DEA model with the assumption of CRS (constant return to scale), while BCC-DEA is a DEA model with the assumption of VRS (variable return to scale. Based on the orientation, the DEA model consists of input-oriented and output-oriented DEA models. The input-oriented DEA model focuses on reducing the input for a given output level. In contrast, the output-oriented DEA model focuses on maximizing the proportional increase in output with a given set of inputs (Coelli et al., 2005). This study uses an input-oriented DEA model because this model can apply the principle of scarcity through the input targets used and deal with the problem of increasing input prices. The conventional DEA model for estimating technical efficiency can be written as follows (Coelli et al., 2005):

$$\boldsymbol{Min_{\theta,\lambda}\theta_k}$$

Subject to: (1)

$$\boldsymbol{-y + Y\lambda \geq 1}$$
$$\boldsymbol{\theta_{xk} - X\lambda \geq 0}$$
$$\boldsymbol{\sum_{j=1}^{n} \lambda_j = 1}$$
$$\boldsymbol{\lambda \geq 0}$$

Where $\boldsymbol{\theta_i}$ is the value of technical efficiency (TE) ranging from 0 to 1, a TE value equal to 1 implies that a sugarcane farmer is technically efficient. In contrast, a TE value below 1 $(\boldsymbol{0 < OTE < 1})$ means that a sugarcane farmer is technically inefficient. The vector $\boldsymbol{\lambda}$ is a weight vector (constant) Nx1 that defines the linear combination of the counterparts of the k-th DMU (each of N farmers). Y represents the vector of the output quantities, and X represents the vector of the observed inputs. y is the output vector of the i-th DMU compared to the output vector of the theoretically efficient DMU $(\boldsymbol{Y\lambda})$. $\boldsymbol{X\lambda}$ is the minimum input of the theoretically efficient DMU, given the output level produced by the i-th DMU (each of N farmers). Xi is the input level of the k-th DMU (Coelli et al., 2005).

Equation (1) represents the constant return-to-scale (CRS), also known as overall technical efficiency (OTE_{CRS}), suggesting that farmers operate on an optimal scale. The

OTE_{CRS} consists of two components: the pure technical efficiency (PTE), which represents the management practices under the assumption of variable return-to-scale (VRS), hence denoted as PTE_{VRS}, and the residual called the scale efficiency (SE). For efficiency under variable returns to scale (VRS), the additional convexity constraint $\sum \boldsymbol{\lambda} = \mathbf{1}$ gives rise to the VRS frontier. This constraint ensures that the ratio of inefficient farms in the region to the provisions of farm size must be equal. SE is used to determine the scale of farm operations, which is the ratio of OTE to PTE (Coelli et al., 2005). DEA for this study was performed using Max DEA 8, open-source software.

When rice farming is inefficient, DEA allows setting input and output targets to improve performance. Thus, any inefficient rice farm can become efficient as a whole by adjusting its operations to a related target point determined by the performance of the efficient rice farm which determines its reference limit. According to the model, the targets of inefficient rice farming are as follows:

For output:

$$\overline{\boldsymbol{y_{rk}}} = \boldsymbol{y_{rk}} + \boldsymbol{S_{rk}^{+*}} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} \boldsymbol{\lambda_{jk}^{*} y_{rj}}$$

For Inputs (2)

$$\overline{\boldsymbol{x_{ik}}} = \boldsymbol{\theta_k^{*} x_{ik}} - \boldsymbol{S_{ik}^{-*}} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} \boldsymbol{\lambda_{jk}^{*} x_{ij}}$$

Where $\overline{\boldsymbol{y_{rk}}}(\boldsymbol{r = 1})$ and $\overline{\boldsymbol{x_{ik}}}(\boldsymbol{i = 1 \ldots 6})$ are the respective target outputs and inputs for the k-th rice farm; $\boldsymbol{y_{rk}}$ and $\boldsymbol{x_{ik}}$ are actual output and input of the k-th rice farm respectively; $\boldsymbol{\theta_k^{*}}$ is the optimal efficiency score of the k-th rice farm; $\boldsymbol{S_{ik}^{-*}}$ is the optimal slack input from the k-th rice farm for $\boldsymbol{i = 1 \ldots 6}$; and $\boldsymbol{S_{rk}^{+*}}$ is the optimal output slack of the k-th rice farm for $\boldsymbol{r = 1}$

The next step is to compare the efficiency scores of irrigated and rainfed agriculture. The f test is used to investigate whether the data is normally distributed or not. The mean difference test is used to see the significant level of the two efficiency scores.

Regression analysis

Socioeconomic variables that are hypothesized to affect the technical efficiency of rice farming include the age of the head of the household, household size, sex, education, frequency of attending counseling (extension contacts), experience in farmer groups, access to credit, and farming experience are examined. The effect of socio-economic variables on efficiency cannot be tested in the DEA model. According to (Coelli et al., 2005), Tobit regression can be used to determine sources of inefficiency in agriculture. For more details with the following specifications:

$$TE_i = \beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \cdots + \beta_9 Z_9 + \varepsilon_i$$

For efficiency score (3)

$$\begin{aligned} TE_i &= L_{1i}; if\ TE_i^* \leq L_{1i} \\ &= TE_i^*; if\ L_{1i} < TE_i^* \leq L_{2i} \\ &= L_{2i}; if\ TE_i^* \leq L_{2i} \end{aligned}$$

Where TE_i is the dependent variable being reviewed; TE_i^* is the technical efficiency of farmers in rice production; β_i is a vector of parameters to be estimated; Z_i is an explanatory variable vector that represents socioeconomic characteristics; Z_1 is the age of the head of the household (years); Z_2 is the size of the household (number); Z_3 is the sex of the head of the household (0 if female and one if male); Z_4 is the duration of formal education (years); Z_5 is an extension contact (frequency in the last year); Z_6 is experience in farms group (years); Z_7 is access to credit (0 if not and one if yes); Z_8 is farming experience (years); Z_9 represents access to irrigation (0 if no and one if yes); ε_i is error term; L_{1i} and L_{2i} are the lower and upper limit. This model will be estimated by the maximum likelihood method with Stata 16.

Result and Discussion

Descriptive statistics of the variables used in the study

Table 1 presents the socio-demographic characteristics and input and output variables of a sample of rice farmers disaggregated by access to irrigation, with probabilities showing the test results for the mean difference between irrigated and rainfed agriculture. The results show that rice produced from irrigated agriculture is 75 % significantly higher than rainfed agriculture. The average labor force and pesticides used in irrigated and rainfed agriculture were not statistically significant. The fertilizer used in irrigated agriculture is significantly two times higher than in rainfed agriculture. The difference is statistically significant at the 1% significance level found in the machine variable, in which rice farming on irrigated land uses more agricultural machinery than farming on rainfed land. In contrast, rainfed rice farmers cultivate an area of 0.83 ha, 28 % larger than irrigated rice farming. Rainfed rice farming also uses more seeds by 65% than irrigated rice farming, a statistically significant difference at the 1% significance level.

Table1. Descriptive statistics of the variables used in the study

Variable	Irrigated farms (N=220)		Rain-fed farms (N=180)		Prob (T)
	Mean	SD	Mean	SD	
Rice yield (kg/ha)	6953.729	662.496	3973.609	586.296	0.0000
Labor (man days/ha)	32.819	17.192	34.324	14.739	0.3465
Fertilizer (kg/ha)	501.876	175.399	158.480	55.996	0.0000
Land (ha)	0.646	0.504	0.830	0.868	0.0123
Machine (man days/ha)	15.721	4.163	1.999	1.144	0.0000
Seed (kg/ha)	45.123	10.599	74.295	10.584	0.0000
Pesticide (liter/ha)	1.715	1.370	1.860	2.127	0.4307
Age (years)	49.313	9.519	47.761	10.798	0.1275
Household size (number)	4.6	1.536	4.255	1.398	0.0207
Sex (1:male; 0:female)	0.831	0.374	0.872	0.334	0.2613
Education (years)	10.486	2.418	7.361	3.819	0.0000
Extension contact (number)	1.681	1.158	1.3	0.902	0.0002
Experience in farms group (years)	7.818	7.407	10.566	9.340	0.0015
Access credit (1:yes; 0:no)	0.177	0.382	0.266	0.443	0.0337

Farm experience (years)	18.968	11.739	20.711	11.401	0.1353

In reviewing socio-demographic characteristics, we found irrigated rice farmers had higher family members, education, and frequency of contact with extension agents than rainfed rice farmers, in which the differences were statistically significant at the 1% and 5% levels. Furthermore, we found that rainfed rice farmers had more prolonged experience joining farmer groups and greater access to credit than irrigated rice farmers. The differences were statistically significant at the 1% and 5% levels. Lastly, there were no statistically significant differences in age, sex, and farming experience for the two rice farming systems.

Results of rice farming technical efficiency

The estimated efficiency of the sample rice farms under the assumptions of CRS, VRS, and SE is presented in Table 1. Under CRS, TE ranged between 0.44 and 1, with a mean score of 0.818. Based on the mean CRS score, rice farmers must reduce inputs by 18.2 % to make their rice farming efficient. Under the VRS, TE ranged between 0.62 and 1, with a mean score of 0.911. Based on the mean VRS score, the sample of rice farmers must reduce inputs by 8.89% so that their rice farming is efficient. Under SE, TE ranged between 0.54 and 1, with a mean score of 0.899. Based on the mean SE score, the sample of rice farmers must reduce inputs by 10.1% so that their rice farming is efficient.

The findings are comparable to other studies. Based on a study on the efficiency of rice farming in Indonesia, the efficiency score we found was lower than the rice farming efficiency score presented by Junaedi et al. (2016) and Sumaryanto et al. (2023), while our results were still higher than Haryanto et al. (2016) and Heriqbaldi et al. (2015) findings. Based on a study on the efficiency of rice farming in North Sumatra, the efficiency score we found is the same as the Heriqbaldi et al. (2015) findings. The results indicate an enormous scope to enhance the TE of the respondents through improvement in input allocation at the farm level.

Table 1. Rice farming technical efficiency score

Efficiency	Mean	Std. Dev	Minimum	Maximum
TE CRS	0.81801	0.12152	0.44263	1
TE VRS	0.91122	0.09849	0.62346	1
SE	0.89975	0.1035	0.54298	1

Table 2 compares efficiency scores based on irrigated and rainfed farming. Under the CRS assumptions, our study found the efficiency score of irrigated farming to be significantly higher than the efficiency score of rainfed agriculture. In contrast, under the VRS assumptions, the efficiency score of rainfed agriculture is significantly higher than the efficiency score of irrigated farming. The CRS TE score is lower than the VRS TE score because the DEA model assumes that the CRS focus on agrarian production is at an optimal scale (Coelli et al., 2005). In other words, small-scale producers are unfairly compared to the most productive producers on the CRS assumption (Dalei & Joshi, 2020).

Furthermore, the DEA model assumes CRS focuses on overall efficiency, while the DEA model assumes VRS focuses on the managerial expertise of producers (Perrigot & Barros, 2008). Better managerial skills in rainfed farms may cause the TE VRS score to be higher than its competitors. However, we found that the SE scores of irrigated farming were significantly higher than those of rainfed agriculture. SE denotes producers operating on the most productive scale (score = 1) or represents a highly efficient performance measure regarding the maximization of average productivity (Nandy et al., 2019). Therefore, we conclude that irrigated rice farming is more efficient than rainfed lowland rice farming based on TE CRS and SE scores. Many previous studies stated that irrigated farming is more efficient than rain-fed farming (Anang et al., 2017; Haryanto et al., 2016; Mkanthama et al., 2018; Pede et al., 2018; Watto & Mugera, 2014). However, Al-Hassan, (2008), Makombe et al. (2017), and Thibbotuwawa et al. (2013) found rain fed agriculture to be more efficient than irrigated agriculture, possibly due to poor water management and the lack of volume of water distributed for crop production that causes inefficient irrigated agriculture (Makombe et al., 2017). Biswas et al. (2021) stated that irrigation infrastructure needs to be improved, and the high cost of accessing irrigation water causes irrigated rice farming to be inefficient in allocating inputs.

Table 2. Efficiency scores based on irrigated and rainfed farms

Efficiency	Irrigated farms (N=220)		Rain-fed farms (N=180)		Mean difference
	Mean	Std. error	Mean	Std. error	
TE CRS	0.82836	0.00761	0.80535	0.00972	1.8627*
TE VRS	0.87363	0.00743	0.95717	0.004	-9.8927***
SE	0.94916	0.00397	0.83937	0.00848	11.7182***

***,* denotes significant levels at 1% and 10%, respectively.

Return to scale and reduction of inputs

Rice farming is at optimal or not optimal scale presented in Table 3. CRS (constant return to scale) shows the optimal scale, while IRS (increasing return to scale) and DRS (decreasing return to scale) represent sub-optimal operating scales. Most rice farmers, whether using irrigation or rainfed farming, are at a sub-optimal operating scale. In other words, only 15% of farming is at optimal scale.

The IRS situation is dominant for both farming systems, which is 69.09 % for irrigated farming and 84.44 % for rain-fed farming. The IRS situation shows that its operating scale is below optimal (Sufian & Kamarudin, 2014). Rice farms in an IRS situation are advised to scale up their operations to save costs and improve efficiency. The scale of operations can be increased when producers can consolidate their business sectors (Sufian & Kamarudin, 2014). Anang et al. (2017) stated that cooperation in farmer groups could make it easier for them to obtain credit, allocate production inputs efficiently, and increase production efficiency. Therefore, rice farms in an IRS situation need to work together in farmer groups to increase their scale of operation and efficiency.

Table 3. Distribution of efficiency scores and returns to scale

Indicator	Irrigated farms (%)			Rain-fed farms (%)		
	TE CRS	TE VRS	SE	TE CRS	TE VRS	SE
0.4-0.49	0	0	0	0.56	0	0
0.5-0.59	0.91	0	0	6.67	0	2.22
0.6-0.69	13.64	9.09	0.45	11.11	0	9.44
0.7-0.79	27.27	18.64	3.19	33.89	0	22.22

0.8-0.89	31.82	26.81	17.72	19.44	17.22	33.90
0.9-0.99	11.36	21.82	63.64	13.33	41.11	17.22
1	15	23.64	15	15	41.67	15
CRS			15			15
DRS			15.91			0.56
IRS			69.09			84.44

Irrigated rice farming operating on DRS is 15.91%, while 0.56% for rainfed rice farming. The DRS situation shows that their operating scale is above the optimal scale. Rice farming in a DRS situation is advised to reduce the scale of operations to save costs and increase efficiency (Sufian & Kamarudin, 2014). Reducing the scale of operations can be done by reducing the area of rice farming land so that they are efficient. (Schultz, 1964) states that small-scale farmers are more efficient than large-scale farmers because small-scale farmers are more efficient in allocating resources. In other words, poor farmers who use family labor intensively on small plots have an impact on increasing land productivity. Another way to reduce the scale of operations is to replace rice crops with cash crops. Cash crops are plants produced and sold immediately after harvest, while food crops are agricultural commodities primarily for household consumption. Rice is a food crop because most farmers save some rice for household consumption while the rest is sold. Farmers' decision to change food crops to cash crops has the potential to increase technical efficiency and reduce poverty (Ubabukoh et al., 2023). Therefore, reducing the land area by utilizing intensive family labor and replacing some rice crops with cash crops can potentially increase the productivity and efficiency of irrigated and rainfed rice farming.

Table 4. Reduction of inputs by farming system

Variable	Irrigated farms (N=220)		Rain-fed farms (N=180)		Mean difference
	Mean (%)	Std. error	Mean (%)	Std. error	
Input reduction based on CRS assumption					
Labor	20.48471	1.01597	22.65059	1.02741	1.4857
Fertilizer	19.72045	0.85653	38.62109	2.892	-6.2664***
Land	11.74785	0.95159	13.48646	1.1559	-1.1722
Machine	20.59435	0.88142	19.65411	0.98097	0.7134
Seed	18.53703	0.81679	24.99057	1.21855	-4.3992***
Pesticide	25.98257	1.35978	26.41691	1.65223	-0.2049
Input reduction based on VRS assumption					
Labor	15.27635	0.96036	4.66876	0.41128	10.1535***
Fertilizer	16.09904	0.92951	7.77435	0.80476	6.7708***
Land	13.52701	0.8153	4.36464	0.40618	10.0588***
Machine	14.23111	0.82954	4.52015	0.42476	10.4198***
Seed	13.52503	0.77846	5.07393	0.4651	9.3194***
Pesticide	19.81423	1.37216	12.56113	1.50899	3.5543***

*** denotes significant levels at 1%

The estimation of efficiency results shows that all inefficient farmers are advised to reduce the use of inputs to make their farming efficient. Table 4 presents the percentage reductions for each input and the mean differences in the two farming systems, both irrigated and rainfed. Under the CRS assumption on irrigated farming, the reduction of land, seeds, fertilizers, labor, machinery, and pesticides is 11.74%, 18.53%, 19.72%, 20.48%, and 25.98%, respectively. Under the CRS assumption in rainfed farming, the reduction of land, machinery, labor, seeds, pesticides, and fertilizers is 13.48%, 19.65%, 22.65%, 24.99%, and 26.41%, respectively. Based on the mean difference, the reduction of seed and fertilizer in rain-fed farming was significantly higher than the reduction of the two inputs in irrigated farming. At the same time, for the rest, there was no difference in the reduction of inputs in the two farming systems.

The recommendation to reduce input is also seen in the VRS assumption. Under the VRS assumption on irrigated agriculture, the reduction in seeds, land, machinery, labor, fertilizers, and pesticides is 13.525%, 13.527%, 14.23%, 15.27%, 16.09 and 19.81%, respectively. Under the VRS assumption on rainfed agriculture, the reduction of land, machinery, labor, seeds, fertilizers, and pesticides is 4.36%, 4.52%, 4.66%, 5.07%, 7.77%, and 12.56%, respectively. Based on the mean difference, all input reductions in rainfed agriculture were significantly lower than those in irrigated agriculture. The relatively small reduction in inputs for rainfed agriculture is likely due to the relatively high-efficiency score on the assumed VRS.

Estimating the determinants of technical efficiency

Our study investigates the determinants of rice farming efficiency based on three models: the regression model for all samples, irrigated farming, and rain-fed farming. The dependent variables in our study consisted of three types: TE CRS, TE VRS, and SE scores. However, the regression model we use is only efficiency based on the VRS assumption because this is the only regression model that passes for model fit. The log-likelihood statistics that determine the fit of the model show that the Tobit regression model using the dependent variable TE VRS can be applied with a significant chi-square (p-value) at the 1% and 5% levels. Furthermore, Table 5 presents each regression model's coefficients and marginal effects. We use the marginal effect because the parameter coefficients in the Tobit regression model cannot be directly interpreted; in other words, the value of the marginal effect can represent the magnitude of change between the dependent and independent variables. See Williams (2012) for more details about the benefits of marginal effects in non-linear regression models. Arouna & Dabbert (2010) uses the marginal effect to represent the magnitude of change between the independent variables and efficiency.

Table 5. Determinants of rice farming efficiency

Variable	Irrigated farms (N=220)		Rain-fed farms (N=180)		All samples (N=400)	
	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect
Age	0.00026	0.0151737	-0.00107**	-0.0539288	-0.00003	-0.0019262
Household size	0.00538	0.0028309	0.0035	0.0156015	0.00314	0.0153614
Sex	0.03334	0.0315929	-0.01812	-0.0165522	0.01308	0.0121998
Education	-0.00534	-0.064183	-0.00269**	-0.0207979	-0.00104	-0.0104841
Extension contact	0.00195	0.003738	-0.01119	-0.015321	-0.00236	-0.0039494
Experience in farms group	0.00271**	0.0238437	-0.00011	-0.0012624	0.00082	0.0080749
Access credit	-0.04600**	-0.0096468	-0.01291	-0.003629	-0.0228**	-0.0055059
Farm experience	-0.00123	-0.0268005	.0006321	0.0136623	-0.00025	-0.0054304
Irrigation					-0.07996***	-0.0501322
Likelihood ratio chi square	15.93		18.63		86.83	

p value chi square	0.0435**		0.0170**		0.0000***	
VIF	1.56		1.97		1.55	

***,** denotes significant levels at 1% and 5 %

Two variables significantly affect the technical efficiency of rice farming based on each regression model during the observation period. The variables of experience following farmer groups and access to credit affect the technical efficiency of irrigated agriculture with a significant level of 95%. In contrast, the other six variables have no significant effect. The variables of age and education affect the technical efficiency of rain-fed agriculture with a significant level of 95%, while the other six variables have no significant effect. The variables of access to credit and irrigation affect the technical efficiency of rice farming with a significant level of 95% and 99%, while the other six variables have no significant effect.

Based on the regression model for all sample farmers, we found that the irrigation variable harms the technical efficiency of rice farming. The average marginal effect for the irrigation variable is estimated at -0.05. This value implies that for farmers whose irrigation access increases by 1%, the efficiency of rice farming decreases by 0.05%. This finding contradicts irrigated farming being more efficient than rainfed farming. Field observations can explain the condition of access to irrigation. The only source of irrigation water is from the Ular River basin because the infrastructure of the other two dams is inadequate in distributing water. The volume of water in the river is very dependent on rainfall, which is when rainfall is high, then the water is distributed to agricultural land in large volumes. In contrast, low rainfall has the opposite effect. Other studies show that a shortage of irrigation water occurs during land preparation and the growth period, excess water during the rice harvest, and the amount of waste in the irrigation canals often faced by irrigated rice growers (Amalia, 2020; Nababan, 2013). Farmers also responded to the uneven water distribution during rice cultivation when we interviewed them. Our observations and previous studies explain why access to irrigation negatively affects the efficiency of rice farming. Other studies show that the problem of relatively long distances to irrigation canals, high irrigation costs, and access to irrigation systems harms rice farming efficiency (Biswas et al., 2021; Kinkingninhoun-Mêdagbé et al., 2010). Rainfed growers use shallow water, water from rivers, and ponds to overcome water scarcity (Biswas et al., 2021). In contrast, another study found that access to irrigation contributes positively to the technical efficiency of rice farming in Indonesia (Hakim et al., 2021; Haryanto et al., 2015, 2016).

Based on the regression model for all sample farmers and the regression model for irrigated farming, we found that access to credit significantly negatively affects the technical efficiency of rice farming. Our findings mean that non-borrowers are more efficient than borrowers. We found that only 17.7% are willing to access credit on irrigated agriculture and 26.6% are willing to access credit on rainfed agriculture. Based on interviews with respondents, they stated that the interest on credit was too high and the requirements for applying for credit were too complicated, causing them to be unwilling to access credit. Furthermore, insufficient credit funds to purchase inputs impact input shortages, maximum output is not achieved, and reduced efficiency is the main reason the credit variable is negatively related to efficiency. According to Tenaye (2020), 66% of farmers use credit funds for consumption which causes credit to harm the technical efficiency of smallholder farmers in Ethiopia. Long et al. (2020)

also demonstrated a negative relationship between technical efficiency and credit constraints, while Anang et al. (2016) and Ojo & Baiyegunhi (2020) illustrated a positive relationship between credit and the technical efficiency of rice farming in Africa.

We found a negative association with the following variables: age and rainfed farming efficiency. The average marginal effect for the estimated age variable is -0.001. This value indicates that the farmer's age increases by one year, causing a decrease in technical efficiency of 0.001%. Physical solid abilities are needed in the agricultural business (Seok et al., 2018). Decreased aerobic and musculoskeletal capacity in workers aged between 40 and 60 years causes a decrease in physical work capacity of an average of 20% (Kenny et al., 2008). The average age of the head of the household is 47 years, indicating a decrease in physical work capacity, which impacts the productivity and efficiency of rainfed rice farming. In addition to declining physical abilities, old farmers dare not take risks in innovation or adopt new farming techniques (Ojo & Baiyegunhi, 2020). This finding aligns with the study of Seok et al. (2018) and Ojo & Baiyegunhi (2020). In contrast, another study found a positive relationship between age and farming technical efficiency (Anang et al., 2016; Tenaye, 2020). However, both studies agree that the older age of growers makes them less willing to adopt new technologies and avoid risks.

The final variables we found a negative association with were education and rainfed farming efficiency. The average marginal effect for the estimated age variable is -0.00269. This value indicates that the formal education of farmers, which increases by one year, causes a decrease in technical efficiency of 0.00269%. The average formal education of farmers is elementary school graduates. Workers who had only graduated from elementary school could not find work in the city, so they returned to the village to work in the agricultural sector. They will learn and dare to take risks to increase production and income from agriculture because this activity is the source of their livelihood—this reason why low education has the potential to increase technical efficiency. Anang et al. (2017) 's findings align with our study, in which educated farmers are more likely to be involved in non-agricultural employment opportunities, which can reduce the time they allocate for activities on the farm, resulting in low agricultural productivity. Tenaye (2020) found that education positively impacted agricultural efficiency, while Long et al. (2020) stated that education was unable to explain agricultural efficiency.

Only the variable experience of participating in farmer groups positively impacts agricultural technical efficiency. The average marginal effect for the estimated variables is 0.00271. This value means that the experience of participating in farmer groups increases by one year, so the technical efficiency of irrigated farming increases by 0.00271%. The logical reason is that their knowledge to apply new agricultural technologies increases when there is an exchange of information within farmer groups, and it is likely to have an impact on increasing agricultural productivity. Anang et al. (2017) and Ojo & Baiyegunhi (2020) also found that membership in farmer groups positively affected the efficiency of rice farming in Ghana and Nigeria. Another study found that membership in farmer groups harmed farming efficiency due to farmer groups' low interest in adopting new agricultural technologies (Anang et al., 2020).

Conclusion

Our study found TE CRS, TE VRS, and SE scores for all samples to be 0.818, 0.911, and 0.899, respectively. The results indicate an enormous scope to increase the TE of the respondents through improvement in input allocation at the farm level. Furthermore, we found irrigated agriculture to be more efficient than rainfed agriculture. These results indicate that irrigated agriculture is more efficient in allocating inputs than its competitors.

Interestingly, we found that access to irrigation is negatively related to the efficiency of rice farming. Water scarcity in irrigated agriculture is likely due to the uneven distribution of water and the incompatibility of the water volume needed during rice growth and harvest. Unlike the case with rainfed agriculture, they have the expertise to overcome water scarcity by utilizing shallow water and making water-holding ponds. The negative relationship to the efficiency of rice farming is found in the variables of the age of the head of the household, education, and access to credit. However, what we found, in contrast, was a positive relationship between experience in joining farmer groups and farming efficiency.

Based on the findings in this study, we provide several recommendations to policymakers so that they pay attention to increasing rice production in North Sumatra Province. The first recommendation is that policymakers allocate a budget to build and repair irrigation infrastructure and clean up waste in irrigation canals. The following recommendation is that policymakers must actively invite farmer group cooperation in terms of water management and maintenance of irrigation canals. The final recommendation is that policymakers need to invite formal financial institutions so that they reduce credit interest and ease the requirements for applying for credit. Policymakers must pay attention to these recommendations so that rice farming is sustainable and reduces rural poverty.

Declaration of conflicting interest

The authors declare that there is no conflict of interest in this work.

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