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RESEARCH ARTICLE
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Determinants of Efficiency of Hill Paddy Farms Among Indigenous Smallholders in Sarawak, Malaysia—A Data Envelopment Analysis Approach

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ABSTRACT

The indigenous people in the state of Sarawak widely cultivate hill paddy in Malaysia. The study examines the levels of technical and scale efficiency, productivity, and the determinants of technical efficiency among indigenous smallholder farms in the Belaga district. A cross-sectional survey was conducted, and data were collected from 148 farmers using the non-probability convenience sampling method. The results revealed that the mean overall technical efficiency, pure technical efficiency, and scale efficiency were 0.856, 0.901, and 0.950, respectively. In terms of productivity, only 45 of the decision-making units were found to operate at an optimal production level. Farmers' education, experience, age, and household size were found to have a negative relationship with technical efficiency, while association membership and distance to farm exhibited a positive relationship. The study supports interventions that target region-specific constraints to enhance efficiency, productivity, and improve food security among rural indigenous communities in Sarawak.

Keywords: Technical efficiency, Hill paddy farming, Indigenous smallholders, Data Envelopment Analysis (DEA), Scale efficiency, Productivity determinants

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INTRODUCTION

Rice, a crop grown in an equatorial climate with an average temperature of 25°C, where a hot, humid climate is optimal for rice cultivation (Nishad et al., 2018). The continent of Asia produces the most amount of rice, with China being the largest producer (USDA, 2023). More than 3.5 billion people all over the globe consume rice as a staple, with hundreds of millions of poor people depending on farming it as their source of income (Muteti, 2024).

In Malaysia, the state of Kedah has produced rice accounting for over 37% of the total production. Because of its high rate of production, Kedah is referred to as Malaysia's rice bowl. The states of Kelantan and Perak, which account for about 12 and 10% of the overall production, are the second and third major producing states (Department of Agriculture Sarawak, 2022). From the overall production, West Malaysia collectively produced approximately 87% of the total output. The most prevalent rice in this region of Malaysia is lowland rice from wet (or irrigated) paddy. East Malaysia, which is located approximately 400 miles from the west, accounts for the remaining 13% of the production. Sarawak accounts for about 9% of rice output, while Sabah accounts for about 4%. In this region of Malaysia, upland rice from hill paddy is most prevalent (Department of Statistics Malaysia, 2022).

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Hill paddy is a rice crop that is grown in highland or lowland that is dry. The crop planted on dryland, completely relies on rain as their water source. Hill paddy can also be known as upland rice, dryland rice or indigenous wild rice. Thirteen% of the world's harvested rice land is made up of hill rice (Saito et al., 2017). Subsistence farmers and farmers from the poorest regions of Asia, Africa, and Central America are those who typically produce hill paddy (Saito et al., 2017). The term "subsistence" is frequently used interchangeably with food insecurity and poverty. The issue with hill paddy is its lower productivity and efficiency than other rice production systems.

In Malaysia, the hill paddy cultivation has not been given importance. Recent report by Khazanah Research Institute (2022) on the paddy and rice industry of Sabah and Sarawak stated that hill paddy has been remain wanting due to the Malaysian paddy regulatory which is bias towards high-yielding wet paddy. The report also quoted that the paddy regulatory has neglected the heirlooms rice in East Malaysia. Hill paddy accounts for roughly 2 to 3% of Malaysia's overall production, despite being one of the most underappreciated agricultural crops. The poor yield of hill paddy production is unquestionably significant since it contributes to food security of the rural indigenous community In Sabah and Sarawak, preserves the diversity for sustainable food system, and help in supporting nation's rice self-sufficiency. Currently, Malaysia produces approximately 54 thousand metric tons (Department of Statistics Malaysia, 2022).

Hanafi et al. (2009) asserted that hill paddy production in Malaysia can rise dramatically with the proper management and resource availability. Increasing the production of hill paddy is not impossible. Taridala et al. (2019), Saito et al. (2018), Budiono and Adinurani (2017), and Filho and Yamada (2002), who conducted intensive studies on hill paddy, have all agreed that productivity can be increased with adequate knowledge, skills, resources, genetic enhancement, and market potential. The DEA technique was first introduced by Farrell in 1957 as the piece-wise-linear convex hull approach. Michael Farrell's efficiency findings were built on Koopman's and Debreu's findings in 1951. Farrell developed two ideas for measuring efficiency: input-oriented and output-oriented. The goal of the input-oriented measures is to maintain output quantities while lowering input quantities. Meanwhile, the output-oriented paradigm establishes how much output should increase without changing the inputs.

Farrell's work was only taken into consideration by a small number of authors for twenty years until Charnes et al. (1978) referred to the piece-wise-linear convex hull approach as data envelopment analysis using the constant returns to scale measurement. Since then, the technique has garnered a lot of attention and has been widely applied as a non-parametric efficiency model. Banker et al. (1984) and Färe et al. (1983) later offered an alternative set, the DEA-VRS, which advanced the discovery.

Fig. 1 shows the output-oriented measures considered using the case where two outputs q_1 *and* q_2 are involved in the production of one input (x) and by assuming the firms are producing at CRS. The curve YY' is the unit production possibility curve represents the upper bound of the production possibilities. Point A, below the production possibility curve represents an inefficient firm. The distance AB represents technical inefficiency, by which the amount of output could be increased without requiring any extra input.

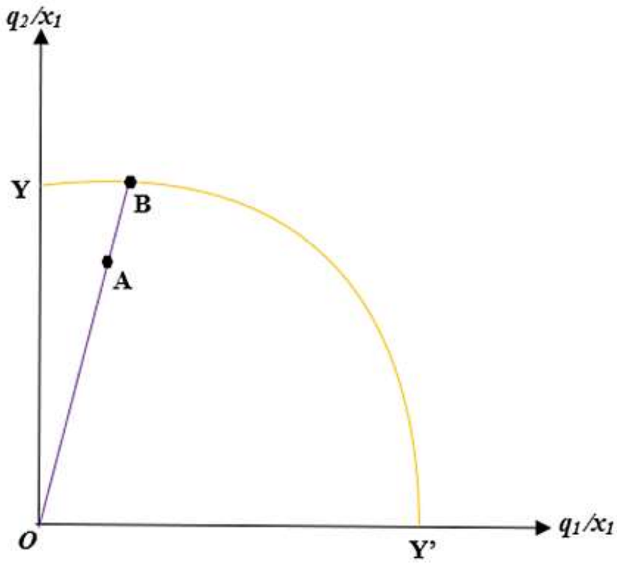

Fig. 1: Output-Oriented Technical Efficiency; Source: Coelli et al., 2005.

Fig. 2 shows the one-input and one-output VRS and CRS production technology. The productivity of firm *H* can be improved by moving from point *H* to point *G*, which is on the VRS frontier. The movement from *H* to *G* removes technical inefficiency while maintaining the same quantity of output. The difference between point EF and EG shows the scale inefficiency. Suppose the firms use variable returns to scale (VRS) technology and G, *K*, and *L* are firms which are all technically efficient and functioning on the production frontier. The productivity of each of these firms is equal to the ratio of their observed output and input quantities, where, in this case, is y/x, and this expression is equivalent to the slopes of ray drawn from the origin through the data points of the firms. Even though all three firms, *G, K,* and *L,* are all technically efficient, they are not all equally productive. This is because the firm can be too small in its operational scale, falling within the production function's increasing returns to scale (IRS) or the firm might be too large and operating at the decreasing returns to scale (DRS) of the production function. In both the case of IRS and DRS, the firms' efficiency can be improved by changing the scale of operation. In Fig. 2, the firm G is operating at IRS of the production frontier and can be more productive by increasing its scale of operation towards point *K*. While firm *L* is operating at the DRS of the production frontier. The firm can be more productive by decreasing its scale of operation towards point *K*. The firm *K* is the reference point for both firm *G* and *L* because it performs at the most productive scale size (MPSS) Hence, firms can be technically, but the operation scale may not be optimal.

Efficiency analysis is often used in agricultural research to measure performance in production. A similar study on rice production among smallholders in Indonesia was evaluated by Wardana et al. (2018). Small-scale rice farmers' technical efficiency was determined using the Data

Envelopment Analysis, which determined Overall Technical Efficiency (OTE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE) based on seven inputs and one output. Only nine and fourteen of the 144 small-scale rice farmers, respectively, were rated as very and weakly efficient, according to the results, with the remaining farmers being classified as inefficient. OTE, PTE, and SE all had average values of 0.41, 0.63, and 0.61, respectively. The observed inefficiency resulted from both failure to operate at an optimal scale (scale inefficiency) and poor input utilization (managerial inefficiency). The performance and profitability of small-scale rice growers can be improved by such technological efficiency analyses. Bich Tho and Umetsu (2022) used the DEA analysis to measure paddy farms' efficiency in the Vietnamese Mekong Delta. Using data from 506 paddy farms, data envelopment analysis was used to look at efficiency scores in the first stage. Input slacks were rather substantial, and the overall efficiency as determined by the slack-based measure was poor at 0.59. This suggested that local farmers had not been producing paddy with their resources effectively. Additionally, farms with less than 2 hectares had higher slack across all input types and a low total efficiency of 54%. Using the DEA approach, Namdari et al. (2024) calculated the economic indicators of sugar beet production in Hamedan, Iran. Using data gathered from 88 farmers in the area, the study calculated efficiency using the CRS and VRS models. According to the analysis, farmers that fit the VRS model are more efficient than those who fit the CRS model, with 19 of the farmers being technically efficient and 55 being purely technically efficient. The average scale efficiency was 0.77 and the average technical efficiency was 0.73. In order to reduce labor costs, farmers should boost production mechanization, according to the DEA models. The cost was reduced by optimizing the inputs used in the manufacturing of sugar beets. The cost was reduced by 51.64% for the CRS model and 28.27% for the VRS model due to the optimization of inputs used in sugar beet production.

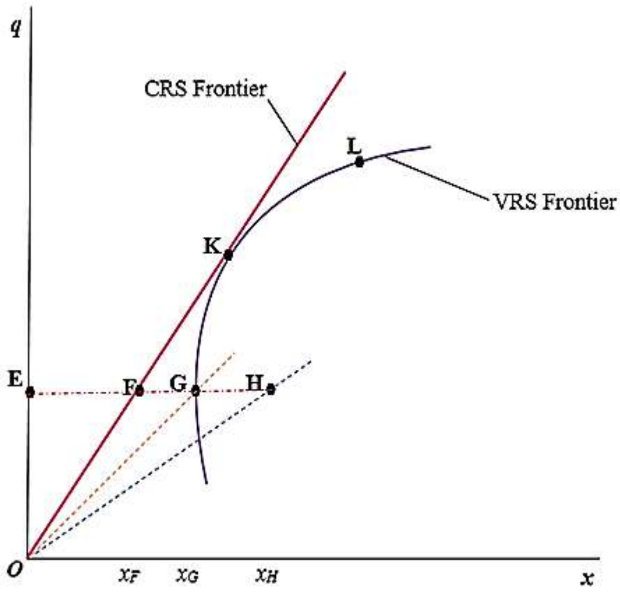

Fig. 2: DEA-CRS and DEA-VRS Production Frontier; Source: Coelli et al., 2005

The long wait for hill paddy recognition has come to an end when the Malaysian National Agrofood Policy 2.0 stating its intention of leveraging the potential of specialty rice. To be able to appreciate in a deeper context, the economic potential has to be explored. In the context of literature, this study makes a novel contribution by providing a region-specific analysis on the determinants of technical efficiency among hill paddy farmers, which is a scope that has been neglected.

The main objective of this study is to determine:

a. the level of technical and scale efficiency,
b. the level of productivity in terms of returns to scale of hill paddy farms, and
c. The determinants of technical efficiency

The evaluation of the efficiency of Sarawak's hill paddy production is crucial to support intervention that targets specific constraints to improve rice productivity and enhance food security in the rural areas of Sarawak. Furthermore, in response to resilient food systems, this research will offer a clear route to comprehending what optimization improvements are required for farmers to endure shocks like climate change and unanticipated shifts in the availability of essential inputs. In the long run, the proper policies will help remove the inefficiency constraints, which will contribute to the Sustainable Development Goals (SDGs) related to eradicating hunger (SGD 2) and safeguarding the environment through sustainable agriculture (SGD 15), even though the effects of these results may not be immediately apparent.

MATERIALS & METHODS

Data Envelopment Analysis

The DEA is a non-parametric method that uses the most stringent input-output vector definitions to design and solve the linear programming function for each farm in order to quantify efficiency. The non-parametric technique used by the DEA does not place any assumptions or limitations on the distribution of data. As inputs or outputs vary, the efficiency assessment is adjusted proportionately. There are two ways to quantify the efficiency scores: the CRS and the VRS, which calculate the farms' individual technical and scale efficiency. The VRS is also commonly referred to as the BCC Model, while the CRS is also commonly known as the CCR Model. The recent adaptation of this method is by Namdari et al. (2024).

DEA measurement begins with the assumption of the farm's production process characteristics. Either maximising the feasible output of production from a given bundle of inputs (output-oriented) or minimising the feasible number of inputs to create a certain level of output (input-oriented) are the two possible assumptions. However, the output-oriented TE measurements are comparable with input-oriented TE under CRS, according to Färe and Lovell (1978). This equivalency, however, disintegrates and loses significance when VRS and other non-constant returns to scale (NCRS) are present (Forsund and Hjalmarsson, 1979; Kopp, 1981).

This research focuses on the output-oriented concept for production and uses CRS and VRS measurements to gauge efficiency. It is assumed that n farms are generating one output, h, which represents hill paddy, using m distinct inputs ($m = 1,2, \ldots 5$), which are labor, fertilizer, pesticides, and herbicide, to build an empirical model using the non-parametric framework. The column vectors x_i and q_i, respectively, reflect the input and output data of the ith farm. The input matrix X (dimension: $h \times n$) and output matrix Z (dimension: $m \times n$) represent the data of all n. The following is the expression for the output-oriented DEA model adapted from Coelli et al. (2005) that is used to measure technical efficiency:

$Max\ \theta, \lambda{:}\ \theta$

$Subject\ to{:}\ -\theta qi\ +\ Z\lambda\ \geq\ 0,$

$\theta\ xi -\ X\lambda\ \geq\ 0,$

$N1'\lambda\ =\ 1$

$\lambda \geq\ 0,$

With λ being a n×1 vector of constants and θ being scalar. Convexity constraint $N1'\lambda = 1$ is applied for VRS, where $N1$ is a n×1 vector of 1. It is the most efficient farm on the frontier, with $\theta_i = 1$, $\lambda_i = 1$,, and $\lambda_j = 0$ for $i \neq j$. It is possible to estimate each farm's output technical efficiency measure as $TE_i^{DEA} = 1/\theta_{i.}$. The predicted technical efficiency of each farm unit in the output-oriented VRS DEA (TE_i^{VRS}) will be greater than or equal to that of the output-oriented CRS DEA (TE_i^{CRS}). The estimated scale efficiency (SE) for the ith farm can be written as follows:

$SE = \left(\left(TE_i^{CRS}\right)/\left(TE_i^{VRS}\right)\right),$

A farm is said to be scale inefficient when SE is less than one, which could be the result of either growing or shrinking returns to scale. The farm is presumably operating at optimal scale when SE equals one. The estimation of non-increasing returns to scale will be aided by the extra restriction $N1'\lambda \leq 1$. The estimation indicated decreasing returns to scale (DRS) if TE_{NIRS} is equal to TE_{VRS}. If TE_{NIRS} is not equal to TE_{VRS} then the estimation indicates increasing returns to scale (IRS), and if TE_{VRS} is equal to TE_{CRS} then constant returns to scale (CRS) are shown by the estimation (Coelli et al., 2005).

The factors influencing the efficiency of hill paddy farms in Belaga, Sarawak, are determined by regressing the predicted efficiency scores with the sociodemographic variables education, age, experience, household size and distance to farm. Since the dependent variable has a range of 0 to 1, its distribution is suppressed. A Tobit regression is employed to estimate the factors that influence technical efficiency. The vector of explanatory variables affecting farm efficiency is represented by X, and the efficiency scores for farm i are represented by I_i. The Tobit model in the form of an econometric specification can be described as follows:

$$I_i\ =\ \begin{cases} I_i^*\ if\ I_i^* > 0 \\ 0\ otherwise \end{cases}$$

The observed variable $I_i$is thought to be related to the latent variable I_i^*, and $I_i^*\ =\ X_i\beta\ +\ \vartheta_i$

Data

The district of Belaga in the Kapit Division in Sarawak contributed 2,977 tonnes out of the total output of 10,693 tonnes in the Kapit Division (Department of Agriculture Sarawak, 2022). It is the second-largest district in hill paddy production in Kapit. The majority of the population is of the Orang Ulu tribe, an Indigenous people group of Borneo Dayaks.

The instrument for the study were designed using a set of selected variables from previous study. Primary data were gathered from the farmers from August to October 2024, using the non-probability convenience sampling. The survey was conducted in the Belaga District of Kapit Division in Sarawak (Fig. 3), as the majority of hill paddy farms are located there. 148 respondents who worked as hill paddy farmers in Belaga provided the data. The questionnaires were all interviewer-administered using non-probability convenience sampling. The data collected was then analysed using the R 4.4.0 software.

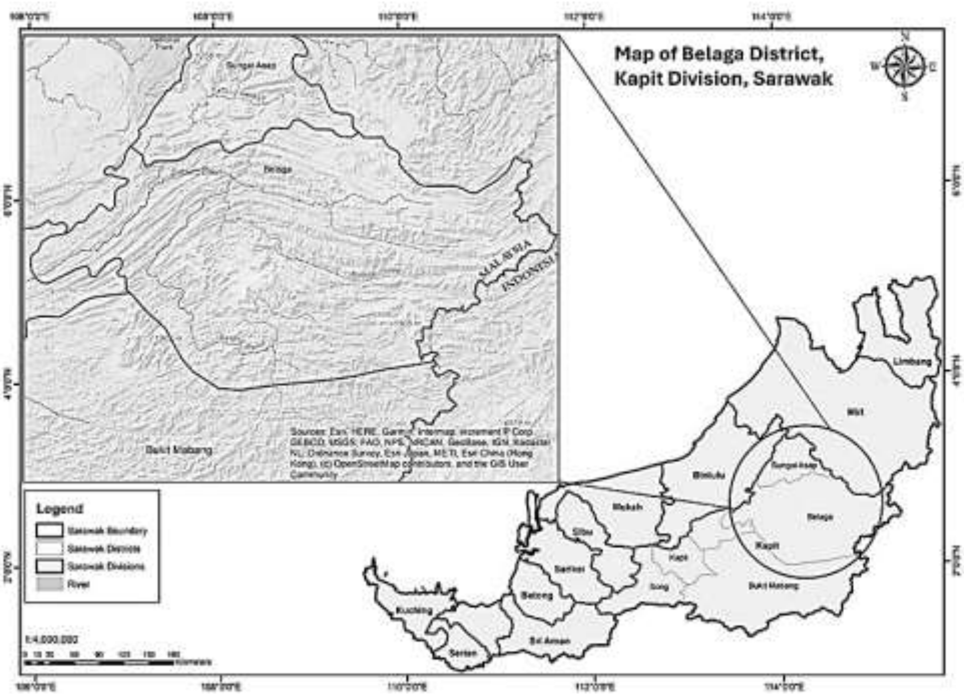

Fig. 3: Map of Belaga District, Kapit, Sarawak.

RESULTS & DISCUSSION

Descriptive Analysis

Table 1 shows the descriptive statistics for the variables used in the efficiency measurement. The data has been generalized to per hectare for one season or cycle for all the variables. There are four input variables – labor, seed, fertilizer, and herbicide. The inputs are categorised into two sections – unit measurement and prices in ringgit. The maximum number of man-days was 208 days per hectare costing RM12,800, and the minimum was 97 days per hectare costing RM2,895 in a season. The mean number of man-days was 154 days per hectare costing RM6810 in a season with a standard deviation of 27.75 man-days. The maximum seed used is 54kg per hectare costing RM375 per season and the minimum seed used is 7.2kg per hectare costing RM50 per season. The mean seed used for cultivation per season is 25.2kg per hectare costing RM175 per season. The standard deviation is 11.7kg per hectare. The maximum fertilizer used for hill paddy cultivation per season is 495.05kg per hectare costing RM1,485.15 per season and the minimum fertilizer is 10kg per hectare costing RM28 per season. The mean fertilizer used was 60kg costing RM144 per season. The maximum herbicide used per hectare was 14L, costing RM420 per season, and the minimum use of herbicide was 3.5L, costing RM42 per season. The average use of herbicide per hectare was 7L costing RM126 per season. A total of four input expressed in unit measurement and price are used in estimating the efficiency model.

Table 1: Descriptive Statistics Summary for Efficiency Measurement Variables

Variables	Mean	Max	Min	Standard Deviation
Input/hectare				
Hired Labor (man-days)	154.00	208.00	97.00	27.75
Seed (kg)	25.20	54.00	7.20	11.70
Fertilizer (kg)	60.00	495.05	10.00	121.25
Herbicide (ℓ)	7.00	14.00	3.50	2.63
Input Prices/hectare				
Hired Labor (RM)	6,810.00	12,800.00	2,895.00	2,476.25
Seed (RM)	175.00	375.00	50.00	69.77
Fertilizer (RM)	144.00	1485.15	28.00	163.99
Herbicide (RM)	126.00	420.00	42.00	59.56
Explanatory				
Education (rank)	2.62	6.00	1.00	1.27
Association Membership (dummy)	0.26	1.00	0.00	0.44
Distance to farm (km)	15.80	121.00	0.02	22.36
Household size (person)	5.07	12.00	1.00	2.31
Age (years)	56.13	90.00	20.00	12.38
Experience (years)	20.57	55.00	2.00	11.13
Output/hectare				
Paddy Yield (kg)	868.30	3712.90	83.30	662.82
Paddy Yield (RM)	4211.30	18,007.50	404.17	3,214.66

There are six explanatory factors used to analyze how far these factors affect the efficiency of the decision-making unit (DMU). The explanatory variables that were taken are education, association membership, distance to farm, household size, age and experience. The association membership status of the farmers is the only explanatory factor expressed in the dummy, where the maximum is one, the minimum is zero and the mean is 0.26. Whereas education is expressed in rank, where the highest is six indicating university-level education, the minimum is one indicating no education, and the mean is 2.62 suggesting a primary education. The distance to the farm is expressed in kilometres, where the longest distance is 121km, the shortest distance is 20 metres, and the average distance is 15.8km from their residential area. The household size is expressed in the number of people, where the maximum number of people per household is twelve people, the minimum number of people per household is one and the average size of the farmer's household is 5.07. The maximum age of hill paddy farmers is 90 years old, the minimum age is 20 years old, and the average age of the population surveyed is 56.13 years. The experience in hill paddy cultivation is expressed in years, where the maximum is 55 years, the minimum is two years, and the average is 20.57 years. A total of six explanatory variables are used in estimating the efficiency model.

Meanwhile, in terms of output produced by the farms, it is measured in the form of paddy (unhusked rice). The maximum paddy production by hill paddy farmers was 3,712kg per hectare with a value of RM18,007.43 per season. The minimum production was 83.3kg per hectare with a value of RM404.17 per season. The average production was 868.3kg per hectare with an average value of RM4,211.30 per season.

Data Envelopment Analysis

Table 2 presents the results of overall technical, pure technical, and scale efficiency for the hill paddy farms, analyzed using data envelopment analysis (DEA). There are two approaches to presenting technical efficiency (TE): the variable returns to scale (VRS), also known as pure technical efficiency, and the constant returns to scale (CRS), also known as overall technical efficiency. The mean technical efficiency of CRS is 0.856 and the mean technical efficiency for VRS is 0.901. The production for the given input is only at 85.6% (for CRS) and 90.1% (for VRS), respectively. The results suggested room for improvement in production, ranging from 14.4 to 9.9%. At the same time, the TE_{CRS} has 11 decision-making units (DMU) and the TE_{VRS} has 15 DMUs scoring a ratio of one. These two results comparisons show that the TE_{CRS} model scores lower than the TE_{VRS} model, indicating that the DEA_{VRS} model shows much affability compared to the DEA_{CRS} model. The DEA_{VRS} model envelopes the data better than the DEA_{CRS} model.

Table 2: Overall Technical, Pure Technical, and Scale Efficiency Scores Data Envelopment Analysis

Efficiency level	TE_{CRS}	TE_{VRS}	SE
0.499 and below	0	0	0
0.599 to 0.500	1	1	0
0.699 to 0.600	3	0	0
0.799 to 0.700	33	12	0
0.899 to 0.800	74	61	15
0.999 to 0.900	26	59	115
1.000	11	15	18
Mean	0.856	0.901	0.950
Standard deviation	0.082	0.077	0.040
Minimum	0.531	0.581	0.823
Maximum	1.000	1.000	1.000

Scale efficiency expresses whether a firm is functioning at its optimal scale. The scale efficiency is calculated by dividing TE_{CRS} by TE_{VRS}. The scale efficiency of the sampled farms had a mean efficiency of 0.950, with minimum efficiency and maximum efficiency at 0.823 and

1.00. Of 148 farms, only 18 were found to be functioning at full-scale efficiency. None of the farms were operating below 80% scale efficiency. When the decision-making units are found to be functioning below the optimal scale (which is at 1.000), the analysis of returns to scale is necessary for further perspective.

Returns to Scale

The returns to scale are classified into three categories: increasing returns to scale (IRS), which is sub-optimal; constant returns to scale (CRS), which is optimal; and decreasing returns to scale (DRS), which is super-optimal. Table 3 shows the number of sampled farm which falls in each category. From the results, 69.6% (103) of the farms were producing at sub-optimal levels, where a small rise in input can result in larger output. Another 7.4% (11) and 23% (34) of the farms were producing at optimal and super-optimal levels. The higher number of farms producing at increasing returns to scale in DEA shows a result parallel to the stochastic frontier analysis, where the elasticity of the Cobb-Douglas production function was 1.149, indicating increasing returns to scale. The farms categorized as sub-optimal were producing higher yields compared to the optimal farms and super-optimal farms. The mean yield difference between the sub-optimal farms with optimal and optimal with super-optimal farms was 55.71kg and 263.91kg. The farms at the super-optimal level should implement strategies to increase the efficiency of their farm to gain higher returns in terms of profit and yield.

Table 3: Summary of Returns to Scale

Returns to Scale	Number of farms	Mean yield (kg)
Increasing returns to Scale (IRS) - Sub-optimal	103	1026.68
Constant returns to scale (CRS) – Optimal	11	970.97
Decreasing returns to scale (DRS) – Super-optimal	34	762.77

Determinants of Technical Efficiency

The difference in production among firms that produce identical products within a territory is primarily due to differences in managerial decisions. The decision-making unit, which is the hill paddy farmers in this case study, decides hill paddy cultivation practices. The decisions made by farmers are influenced by multiple factors which could lead to the farms' efficiency or inefficiency. Rosli et al. (2020) described that farm inefficiency is not solely due to inefficiency in input usage, but also internal and external factors. The second stage of the efficiency analysis is to identify the determinants of the inefficiency. This analysis will assist in policy articulation for future developments in the hill paddy production industry. Six explanatory variables – education, experience, age, household size, association membership, and distance to farm were used as the determinants of efficiency. At this stage, the Tobit regression model is used to examine the relationship between the six explanatory variables and the efficiency of the decision-making units, independently.

a. Education

According to the technical efficiency Tobit regression model, farmers' educational attainment was found to be negatively correlated and statistically insignificant. It is not surprising that there is a negative correlation between the technical efficiency of hill paddy farms and the educational attainment of farmers. Since the highly educated population concentrates on other profitable endeavours and views hill paddy farming as a marginalized cultural activity, the arduous cultivation of hill paddy is frequently linked to farmers' low levels of formal education. To put it another way, farmers with more formal education do not view hill paddy as a crop with significant earning potential; instead, they only devote a small portion of their attention, energy, and resources to it. Education had a favorable effect on technical inefficiency, according to comparable findings by Wadud (2003), who examined the efficiency of rice production in Bangladesh, Coelli and Battese (1996), who examined the efficiency of rice farms in India, and Prabowo et al. (2025), who studied rice technical efficiency of rice farms in Indonesia.

b. Experience

The number of years spent producing hill paddy is the second explanatory variable that has been observed. The majority of farmers were discovered to possess a considerable amount of experience, with a collective average of almost 20 years. However, optimal efficiency is not guaranteed by the vast amount of years of experience. Table 4 shows a negative and statistically significant Tobit regression coefficient of 1% for the years of agricultural experience in connection with the DEA's technical efficiency.

Table 4: Determinants of Technical Efficiency Using Tobit Regression

Explanatory Variable	DEA- TE_{VRS}		
	Coefficient	Standard Error	P-value
Intercept	0.9782	0.0386	0.000***
Farmers' Education Level	-0.0041	0.0052	0.429
Farmers' Experience	-0.0015	0.0005	0.002***
Farmers' Age	-0.0007	0.0005	0.211
Farmers' Household Size	-0.0008	0.0026	0.751
Farmer's Association Membership Status	0.0415	0.0143	0.003***
Distance From Farmers' House to Hill Paddy Farm	0.0001	0.0003	0.943

Notes: ***Significant at 1%

The inverse relationship suggests that farms' technical efficiency decreases with increasing farmer experience. These results run counter to those of Ali and Murtaza (2022) and Okoh et al. (2022). However, even though farmers' cumulative experience may seem efficient by default, El-Ramady et al. (2015), who conducted a thorough investigation into farmers' experience and efficiency, noted that this could be found to be the opposite in many situations where the sample is skewed by the predominance of older farmers (which is applicable in this research).This is because older farmers are less likely to strive for efficiency since they may have reached a point when they feel their life experiences have forced them to stop developing their agricultural practices and instead value other aspects of life over monetary gain. El-Ramady et al. (2015) supported the claim with Gloy et al. (2002) and McBride and El-Osta (2002), who conducted a thorough investigation into farm experience, age, and farm earnings, concluding that there is no statistical correlation between the three factors.

c. Age

Technical efficiency in relation to farmer age is shown to have a negative and statistically insignificant coefficient in the Tobit regression model. Technical efficiency decreased by 0.0141% when farmers' ages increased by 1%. Wadud (2003), Berkhout et al. (2010), Nyagaka et al. (2010), El-Ramady et al. (2015), Rosli et al. (2020), Sahara et al. (2021), Okoh et al. (2022) all obtained similar results.

d. Household Size

A household's size is the fourth explanatory variable for hill paddy farmers. According to the technical efficiency model's Tobit regression coefficient, the household size is negative and not statistically significant. Technical efficiency is not impacted by the size of a farmer's household, according to the results. Similar findings were found by Ebers et al. (2017), who studied the efficiency of Cambodian and Thai rice farms.

e. Association Membership Status

At 1%, the technical efficiency Tobit regression coefficient for association membership status was positive and statistically significant. Technical inefficiency will decrease by 0.0415% for every 1% increase in membership participation. The findings were comparable to those of studies by Nyagaka et al. (2010), Rosli et al. (2020), Okoh et al. (2022), Muteti et al. (2024).

Distance from Farmers' House to Hill Paddy Farm

The distance between farmers' homes and farms has a positive and statistically insignificant association with technical efficiency. This suggests that efficiency rises with distance. When the distance to return home is great, Belaga farmers often spend days or weeks managing and protecting their hill paddy farms by staying overnight at their farms. This led to a favourable outcome. Farmers often travelled 15 kilometres on average, with a maximum distance of 121 kilometres, primarily on unpaved and damaged roads. In their study, Berkhout et al. (2010) and Ebers et al. (2017) reported similar results.

Policy Implications

1. Technical efficiency is negatively and significantly correlated with farmers' age. The average farmer was 56 years old. This suggests that farmers' degree of efficiency declines with age. The majority of farmers are unable to regularly provide the rigorous labor needed for hill paddy farming as they get older. Younger, more active individuals must work in hill paddy cultivation in order to provide the necessary labor. However, due to other opportunities that offer larger wages, only a small portion of the younger generation is interested in it. Echoh et al. (2017) also mentioned how little the younger generation in Sarawak is involved in agriculture, particularly paddy production. By raising knowledge of food security and making rice as profitable as possible, the younger generation can be encouraged to get involved. Through the educational systems in schools, the involvement can be effectively fostered.
2. Efficiency is frequently positively correlated with education and experience. However, the study discovered a negative correlation between technical efficiency and the education and experience of hill paddy farmers. Due to ignorance, Belaga's hill paddy farmers have continued to run their farms traditionally. Technical inefficiency results from a lack of new knowledge about farm management and procedures. Increasing efficiency requires educating farmers about new technologies and providing them with practical demonstrations. Farmers will improve their cultivation performance if new information on farm management is periodically made available through campaigns and programs.
3. Cooperatives should be strongly promoted to increase production because farmers' technical efficiency is positively correlated with their association membership status. Input costs are reduced via teamwork and planning, particularly when it comes to paid labor. The practice of reciprocal labor by hill paddy farmers expedites and lowers the expense of the task. The local agriculture department ought to think about offering cooperative perks and incentives to entice additional farmers to become members.
4. The local agriculture agency must recognize the importance of training for the hill paddy farming community. Farmers can gain first-hand information and experience of implementation through training. Farmers are more inclined to implement at the farm level when they have tried it on their own and seen the results. Implementation increases both the productivity and efficiency of farms. Farmers are urgently requesting pest management training to mitigate crop losses, which is contributing to major financial losses.

Limitations of the Study

The study was conducted in the Belaga District, which contributes to a region-specific finding. The author would like to recommend widening the area studied for stronger generalizability. In addition, the study is limited to one season of the hill paddy cycle. The future study should explore using two seasons at least for comparison in productivity and weather influence on production decisions. Stochastic frontier analysis and panel data analysis are also recommended for future study, as these findings are limited to non-parametric and cross-sectional data analysis.

Conclusion and Recommendation

The study's findings showed that the mean of overall technical efficiency and pure technical efficiency has a gap for improvement by approximately 14.4 and 9.9%. The average scale efficiency was found to be 95%. According to scale efficiency, just 45 of the decision-making units were found to be functioning at an ideal production level. Experience and association membership status were found to have a strong relationship in the determination of efficiency. The rural hill paddy farmers, extension service agents, and the government will be able to improve the performance of the farms by working together in the specific areas addressed and implementing policies suggested by the study. Besides the Data Envelopment Analysis method, the study recommends that the analysis be further conducted using the Stochastic Frontier Analysis and Panel Data Stochastic Frontier Model analysis methods. Some examples of this method are used by Rosli et al. (2020), Paul and Shankar (2020) and Muteti et al. (2024).

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