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Technical efficiency and its determinants in rice production: The case of small-scale rice growers in the Ejisu Juaben Municipality of Ghana

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A B S T R A C T

This study assessed the technical efficiency of smallholder rice growers in the Ejisu Juaben Municipality of Ghana and explained variations using the Stochastic Frontier Approach. Cross-sectional data were collected from 200 rice farmers using a structured questionnaire. The results showed that inefficiency exists as the mean technical efficiency was 55% implying that nearly half (45%) more output could be produced using the existing input levels if farmers were technically efficient. A scope, therefore, exists for increasing rice production. A wide range (11.7% to 98.4%) of technical production efficiency exists among the sampled rice farmers, showing the various levels of improvements expected to bring various farmers to operate on the frontier. Labour cost was revealed as the main constraint hindering the development of the rice sector. The main factors that positively and significantly explain the level of variation in efficiency production were membership to a Farmer-Based Organization (FBO), access to improved varieties, and access to credit. Furthermore, gender, farmer experience, and contact with extension services negatively influence the efficiency performance of farmers. Encouraging farmers to form FBOs is recommended, as this will make credit more available to farmers and improve access to community-based extension services.

1. Introduction

The importance of rice as a cereal in the diet of many households in Ghana cannot be overemphasised. The potential for self-sufficiency in rice production exists in the country. The volume of paddy produced has been on a growth trajectory since 2012 and has increased from 481,134 to 721,465 tons in 2017 (MOFA, 2017). However, the attainment of rice self-sufficiency will not come easy as it requires simultaneous upgrading of the quality of rice as well as the entire value chain (Wailes et al., 2015; Demont et al., 2017). The rice industry has been found profitable in terms of both production and processing (Islam et al., 2017; Bwala & John, 2018; Akter et al., 2019), an enabler of employment creation, poverty reduction, and food security if the right investments are made to address existing constraints (Wongnaa & Awunyo-Vitor, 2018; Linn & Maenhout, 2019). However, profitability levels in the rice industry vary among millers and producers with vulnerable farmers receiving the lowest profit margins.

Rice production output has been driven by intensification, area expansion, and commercialisation (Ogudele & Okoruwa, 2006; Nasrin et al., 2015). However, area expansion is no longer a sustainable option following urbanisation and population growth in most cities. Emerging constraints currently facing rice farmers and productivity includes biotic and abiotic stresses (Balamurugan & Balasubrama, 2017), structural inefficiency of rice value chains due to low investments in infrastructure (Linn & Maenhont, 2019; Bas-ong, 2019), financial constraints and a low share of national budget allocations to the agricultural sector, and difficulties of rice produced locally to effectively compete with imported rice in most markets (Demont et al., 2017). The uncompetitive nature of local rice is partly attributable to the high cost of production associated with locally preferred and or produced varieties, and the failure to tailor rice quality attributes to suit the taste and preferences of consumers (Balamurugan & Balasubrama, 2017; Demont & Ndour, 2017). In addition, other constraints faced by rice value chain actors relate to material supplies, erratic rainfall, distributional bottlenecks, low prices of output, ineffective extension service delivery, and lack of government support (Kavi, 2015). In analysing the factors that impact the technical efficiency of irrigated rice farming, Bas-ong (2019) found environmental support services, climate, cultural management practices and socio-economic issues relevant as they affect rice production. Working to reduce the numerous constraints faced by the rice industry provides a window to boost rice production, reduce rice imports and be self-sufficient (Demont et al., 2017).

The low level of technical efficiency in rice production is well documented by various studies (Pindiriri et al., 2018; Donkor et al., 2018). The technical efficiency performance of rice farmers varies based on farm location, ecological zone, and non-cognitive skills of farmers (Ali et at., 2017; Sinawo & Tolorunju, 2019; Asravor et al., 2019). While northern Ghana is generally noted as a leader in rice cultivation, the same cannot be said of the Ejisu Juaben Municipal which is in the forest belt of the country with potential in rice production. There are currently no known studies that assessed the technical efficiency level of production of rice farmers in the Ejisu Juaben Municipality with the view to improving efficiency in production and this study seeks to bridge this gap. The observed differences in geographical conditions and growing concerns about climate change impacts on production suggest the need for district-specific policy recommendations rather than the usual generalisation which does not offer sound strategies for improving production efficiency (Heriqbaldi et al., 2015; Donkor et al., 2018). In this regard, Anang, Backman, and Sipilainen (2016) called for further investigation into the specific factors that limit farmers' production efficiency and ways to improve them. This study, therefore, contributes to the existing literature by analysing the determinants of smallholder rice growers in the Ejisu Juaben Municipality.

Following from here, Section two discusses the factors that influence technical efficiency in rice production. Section three focuses on the methodology, data collection procedure, and theoretical and empirical methods applied using the stochastic frontier modelling approach. Section four presents and discusses the main results and how they link up with previous studies. Section five concludes the paper and offers some policy recommendations.

2. Determinants of technical efficiency in rice production

Several empirical studies have analysed production efficiency using the stochastic frontier approach (Donkoh et al., 2010; Khal & Yabe, 2011), meta frontier framework (Donkor et al., 2018; Asravor et al., 2019), data envelopment analysis approach (Watkins et al., 2014; Tun & Kang, 2015), and more recently propensity score matching (Abdulai et al., 2018). All these studies and approaches point to the existence of inefficiency in rice production. For instance, in analysing the efficiency of the rice sector of Ghana, Donkor et al. (2018) showed empirically that rice growers were technically inefficient and that the determinants of technical efficiency vary for the two districts studied. This suggests that the use of general recommendations may not offer a sound solution to improving productivity and efficiency in production.

Donkoh et al. (2010) assessed the factors influencing the efficiency of rice farmers under three production schemes. Their findings suggested that farmers producing under intensive rice schemes had relatively high technical efficiency though the overall mean efficiency was low (42%). The educational level of a farmer, membership of a group, farmer experience, and extension contact were found essential in reducing technical inefficiency in rice production. Meanwhile, Khal and Yabe (2011) found access to irrigation services, and intensive labour more impactful in rice technical efficiency levels. This suggests that when farmers can do all year-round production, their efficiency level of production would likely be higher. This is supported by the finding of Anang, Backman, and Sipilainen (2016) in their analysis of 300 smallholder rice farmers in northern Ghana where irrigation was reported to have led to an upward shift in the production frontier due to double cropping of fields confirming higher productivity with irrigation use. In Zimbabwe, a study by Pindiriri et al. (2018) showed that drought had a detrimental effect on technical efficiency. The authors compared farmers in drought-prone areas and those in wet ecological zones and revealed that farmers in drought-prone areas were 19% less efficient than their counterparts operating in wet ecological zones. Irrigation, drought experience, and modern methods of forecasting weather impact positively technical efficiency.

Furthermore, various studies have documented the positive role of technology adoption and improved production and processing practices on technical efficiency (Fofana et al., 2011; Dandedjrohoun et al., 2014; Ali et al., 2017; Donkor et al., 2018; Abdulai et al., 2018). For instance, Ali et al. (2017) reported that the decision to adopt, technical efficiency (TE) in production and returns from adoption are directly linked to the non-cognitive skills of farmers and that the magnitude of adoption impacts are higher than measures obtained from traditional human capital. Abdulai et al. (2018) showed that farmers who adopted improved rice cultivation practices were 2% more technically efficient than those who did not. While the mean TE for adopters was high (58%), that for non-adopters was low (48%). The observed gap in TE between non-adopters and adopters is indicative of the effect of technology adoption on farmers' efficiency performance. In the area of rice processing, the adoption of improved parboiling technology led to a 17% reduction in heat-damaged grains, a lower ratio of cracked milled grains, and higher returns (Fofana et al., 2011).

Demographic and social factors are also linked to technical efficiency. Idiong (2007) estimated the level of technical efficiency and the factors influencing rice production in Nigeria using a sample of 112 farmers. While rice farmers were technically inefficient, level of education, access to credit and membership in farmer associations were significant factors that influence farmers' production efficiency. Younger farmers were more technically efficient while funding source, income, and land size had a positive impact on technical efficiency (Heriqbaldi et al., 2015). In analysing the performance of irrigated rice schemes in the Volta Region of Ghana, Kavi (2015) found that irrigation cost, equipment, age, farming experience and membership in a Famer-Based organisation (FBO) were statistically significant in explaining technical efficiency. Family labour and access to farm machines/tools contribute significantly to rice production efficiency (Tun & Kang, 2015). In the Mfanteman Municipality of Ghana, Essilfie et al. (2011) showed that years of formal schooling and off-farm income impact on technical efficiency of rice production. Soil fertility status and household size also influence the efficiency of smallholder farmers engaged in rice cultivation (Magreta et al., 2013). Distance to the trading centre and the use of an ox plough significantly affect allocative efficiency (Okello et al., 2019). The use of tractor service (mechanisation) and large family size reduces technical inefficiency while age and intercropping increase inefficiency (Ayedun & Adeniyi, 2019). Male maize farmers are technically more efficient than females and that membership in a farmer association is directly related to technical efficiency (Wongnaa & Awunyo-Vitor, 2018).

Both environmental and institutional factors impact rice production efficiency which highlights the need for the provision of irrigation infrastructure, especially in drought-prone areas (Pindiriri et al., 2018). Previously, Anang et al. (2016) revealed that gender, years of financial education, and specialisation in rice production impact production efficiency. Yang et al. (2016) analysed the link between production risk and technical inefficiency of sampled rice farms in China. Risk function results show that labour and good soil quality reduce the risk in rice production while the use of machines increases production risk significantly. Extension services access and use, as well as off-farm income, were found to be statistically significant in influencing technical efficiency levels. To reduce variability in yields and technical inefficiency in rice production, knowledge of input choice combinations by farmers is relevant.

In analysing environmental-technology gaps and production efficiency of rice-producing households in Ghana, Asravor et al. (2019) found farmers in the forest-savannah transition more technically efficient (56%) than those in the guinea savannah zones (42%), highlighting the need for geographic targeting. Dandedjrohoun et al. (2014) used the average treatment effect framework and estimated the actual adoption rate of an improved parboiling technology to be 67% with an estimated potential adoption rate of 75% in Benin. Members' participation in video training as well as belonging to the parboilers association were statistically significant and positively related to the knowledge and adoption of the technology which impacts efficiency. Previously, Ogundele and Okoruwa (2006) estimated TE differentials for farmers who planted traditional rice varieties and those that cultivated improved varieties using a sample of 302 rice growers. The results show that area expansion (farm size) contributes to increases in rice output while herbicides, seeds and hired labour contributed positively to TE. Farming experience and education are relevant in traditional technology rice farms as they impact positively TE. For the poultry sector, Osinowo and Tolorunju (2019) found farm location to be an important driver of technical efficiency although high feed cost, unstable power supply and incidence of diseases remain major constraints hampering the efficient operation of the sector.

3. Methodology

3.1 The study area and sample

The study was conducted in the Ejisu Juaben Municipality in the Ashanti Region of Ghana. The Municipality has a total land area of 637.2 km^2 with an estimated population of over 143,762. The Municipality is centrally situated in the Ashanti Region and enjoys a bimodal rainfall pattern with great potential in food production. About 62.5% of the population is engaged in subsistence agriculture with crop farming being dominant (96.8%). This study utilised a multistage sampling procedure in choosing the sample farmers. Purposive selection of five communities was done based on the prevalence of rice production in the Municipality. Within each community, a random sample of 40 rice farmers was selected, making a total of 200 farmers for the study. The sample size was determined by following Yamane's (1967) proposed formula,

$$n = \frac{N}{1 + N(e)^2}$$

Where n = sample size, N = Population size, and e = margin of error (5%). Data was collected using semi-structured questionnaires and the scope covered the socioeconomic characteristics of the farmers, production information, output levels and constraints hampering rice production.

3.2 Variables and measurement

The volume of rice harvested (total output) for the 2018 cropping season was used as the dependent variable in this study. Four main variables (fertiliser, improved seed, family labour, and hired labour) were included in the production function likely to influence rice output and the efficiency performance of farmers. The main variables considered, and their measurements are contained in Table 1.

Table 1: Variables and measurement

Variable	Measurement	Expected sign
Yield (YLD)	Quantity of rice harvested in 2018 (kg/ha)	
Seed (SEED)	Quantity of rice seed planted (kg/ha)	-/+
Fertiliser (FERT)	Quantity of chemical fertiliser applied (kg/ha)	+
Family labour (FLAB)	Total family labour used (man-days)	+
Hired labour (HLAB)	Total hired labour used (man-days)	+
Gender (GEN)	1 if male, 0 if female	-/+
Education (EDC)	Number of years of formal schooling	-/+
Household size (HHS)	Number of people in the household	+
Farmer experience (EXP)	Number of years engaged in rice cultivation	+
Extension contacts (EXT)	Number of times a farmer has engagements with extension agents for the 2018 season	+
Farmer based Organization (FBO)	1 if a farmer belongs to any FBO, 0 otherwise	+
Off-Farm Income (OFI)	1 if a farmer is engaged in off-farm income activities, 0 otherwise	-/+
Land ownership (LND)	1 if the farmer owns the land, 0 otherwise	-/+
Improved variety (VAR)	1 if a farmer cultivated improved rice variety for 2018, 0 otherwise	+
Access to credit (CRA)	1 if a farmer has access to credit for the 2018 season, 0 otherwise	-/+
Age	Number of years	-/+

Source: Authors' compilation from various literature

The main justifications and supportive evidence for using these variables are discussed here. *Fertiliser* encompasses the total quantity of chemical fertiliser applied by a rice farmer during the 2018 cropping season. The productivity of rice farmers has been linked to the judicious application of chemical fertilisers and the adoption of fertiliser-based technologies (Kavi, 2015; Abdulai et al., 2018; Ayedun & Adeniyi, 2019). The quantity and quality of *improved rice seed*s planted impact positively farmers' technical efficiency performance and output (Ayedun & Adeniyi, 2019). However, access to improved seeds by smallholder farmers especially those in remote areas coupled with the high cost of such seeds remains a constraint in using improved seeds and as such increasing rice production and productivity. Moreover, rice production is a *labour-intensive* task and most peasant farmers still rely heavily on family labour to carry out farm operations. The use of hired labour is growing especially among absentee farmers (people with financial resources and interest in farming whose farms are managed by others due to distance and time) with a commercial focus. The positive effects of both family and hired labour on the technical efficiency performance of rice farmers are well documented (Abdulai et al., 2018; Ayedun & Adeniyi, 2019).

For the determinants of technical efficiency, the study included relevant socio-economic factors. *Education* which reflects in the managerial ability of farmers and its impact on technology adoption leads to higher technical efficiency in production (Donkor et al., 2010; Khal & Yabe, 2011; Wongnaa & Awunyo-Vitor, 2018). On the contrary, significant negative effects of education on rice production efficiency have been reported by other studies also (Tun & Kang, 2015). The effect of education on technical efficiency performance is therefore anticipated to be mixed. *Access to credit* impacts positively technical efficiency as farmers can buy the needed inputs timely for use. However, access to credit remains a key hindrance to commercialising smallholder agriculture in most developing countries. The financing of irrigated rice farmers is inversely related to rice output due to climatic and management-related constraints (Bas-ong, 2019). Similarly, access to credit affects the allocative efficiency performance of rice farmers (Magreta et al., 2013; Okello et al., 2019).

In most rural farming communities, *household size* is a good indicator of labour availability for farm operations. Larger households are likely to be more efficient in production due to family labour availability (Dhungana et al., 2004). Intensive labour use in rice cultivation, as well as the use of family labour, has a positive impact on the technical efficiency of rice production (Khal & Yabe, 2011; Tun & Kang, 2015; Abdulai et al., 2018; Okello et al., 2019). Furthermore, *farming experience* reflects the number of years of involvement in rice production and older farmers are more likely to be technically efficient due to learning curve effects (Owuor & Shem, 2009). *Age* is a significant determinant of rice production efficiency and younger farmers are more efficient (Kavi, 2015). Older farmers could also be more conservative in adopting new technologies and hence technical inefficiency could result (Coelli, 1996).

The adoption and use of *improved rice varieties* with shorter maturity periods, high yielding, drought, and pest resistance are likely to meet the needs of farmers with dramatic positive effects on technical efficiency. Following the right recommendations, hybrid rice varieties have been found to impact positively technical efficiency (Sherlund et al., 2002) as well as the adoption and use of improved production practices by rice farmers (Donkor et al., 2018). The *land tenure system* (land ownership) can adversely affect the efficiency performance of smallholder rice farmers. For farmers working under a long-term lease arrangement, the likelihood that they will put in more effort to meet their contractual obligations is high (Coelli et al., 2002) with positive effects on production efficiency. On the contrary, agency problem which is characterised by high monitoring costs could negatively impact on efficiency performance of smallholder farmers who do not own land. Paltasingh, Basantaray and Jena (2022) argued that a secured land tenure system enhances farm efficiency, but fixed rents make no difference. Mixed effects are therefore anticipated.

Gender has significant effects on rice output levels and the efficiency performance of farmers. Women rice farmers are more efficient in allocating resources than men (Kavi, 2015). Farmers' *access to extension services* is critical in technology adoption and increasing production. Extension contact with farmers increases their technical efficiency performance (Donkor et al., 2010). Membership in a *Farmer Based Organisation (FBO)* has positive effects on production efficiency. Through bulk purchases, FBO members enjoy discounts, training on input use, and access to guaranteed markets, leading to efficiency in their farm operations. *Off-farm income* is the income generated outside farm business activities and it includes income from pensions, wages and salaries from off-farm jobs, and investment income. In the absence of formal credit for smallholder farmers, access to off-farm income has grown in importance in financing farm operations. However, the effect of off-farm income on technical efficiency performance has been mixed. While positive effects in compensating labour constraints, food security and nutrition have been reported (Abdulai & Eberlin, 2001; Babatunde & Qaim, 2010), the negative effects of off-farm income on farming efficiency exist (Tun & Kang, 2015).

3.3 Theoretical framework and estimation

The Cobb-Douglas functional specification is utilised, and it remains the most used in the estimation of production frontiers as evidenced by recent studies on efficiency analysis (Essilfie et al., 2011; Awuni et al., 2018). Its logarithmic nature makes it attractive, and the estimation of parameters is less complex (Murthy, 2002). The fact that rice production in Ghana is characterised by less perfect competitive producers also lends much credence to the choice of this functional form (Coelli & Perelman, 1999). Furthermore, a likelihood ratio test conducted provides a firm base for the choice of the Cobb-Douglas functional form as against the translog functional form which is attractive due to its non-restrictive assumptions. However, one weakness in using this functional form as pointed out in the literature is that it does not meet regularity conditions (of monotonicity and curvature properties) to adequately represent a production technology (see Sauer et al., 2006). The translog functional form equally suffers from issues of multicollinearity in its application. Recent studies revealed that functional specification does not impact greatly measured efficiency estimates (Bravo-Ureter et al., 2015).

Following the framework independently proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) for the stochastic frontier analysis, the production function is stated as:

$$InY_i = In\, f(X_i\, , \beta) + \, v_i - u_i \qquad (1)$$

Where Y_i is the output, X_i represents input vectors, β is the coefficient of parameters to be estimated, v_i represents random events over which the farmer has no control, and u_i captures technical inefficiency. The assumption is that v_i and u_i are Independent and Identically Distributed (IID) as random factors and u_i is assumed to have half-normal distribution (Aigner et al.,1977) due to its usefulness compared with other parameterisations (such as the gamma, exponential, and truncated normal).

Technical efficiency (TE) is defined as the ratio of the observed output (y) to the corresponding frontier output (y*), based on the level of inputs used in production. The TE of an individual farm is expressed as:

$$TE = \ln y_i / ln y^* = (f\ (x_i; \beta) \exp\ (v_i - u_i) / f(x_i\, ; \beta) \exp(v_i) = \exp(-u_i) \qquad (2)$$

such that, $0 \leq \text{TE} \leq 1$.

Technical inefficiency, u_i is, however, unobservable, and only the difference ($\varepsilon_i = v_i – u_i$) can be observed. Jondrow et al. (1982) derived the predictor for u_i as:

$$E\left[\frac{u_i}{\varepsilon_i}\right] = \sigma\lambda \frac{[\emptyset(z)-Z]}{1} + \lambda^2\ 1 - \emptyset(z) \quad (3)$$

where $z = \frac{\varepsilon_i}{\sigma}\lambda$, and ϕ is obtained from normal distribution Tables. The unknown parameters are then substituted with the maximum likelihood estimates to generate the predictor of u_i. For u_i = 0, implies the technical efficiency of the i^{th} rice farmer; and u_i > 0, or u_i < 0 means the farmer is technically inefficient.

The inefficiency model was empirically specified as:

$$u_i = \delta_0 + \sum_{m=1}^{N} \delta_m z_i \quad (4)$$

where z_i is a vector of farmer characteristics that impact efficiency and δ are parameters to be estimated. Following the one-step procedure, both the maximum likelihood estimates, and inefficiency model were simultaneously estimated using the empirical model below:

$$\ln YLD = \beta_0 + \beta_1 \ln SEED + \beta_2 \ln FERT + \beta_3 \ln FLAB + \beta_4 \ln HLAB + \delta_1 AGE + \delta_2 EDC + \delta_3 EXP + \delta_4 FBO + \delta_5 OFI + \delta_6 EXT + \delta_7 CRA + \delta_8 GEN + \delta_9 LND + \delta_{10} VAR + v_i - u_i \quad (5)$$

3.4 Hypothesis test

A likelihood ratio test was conducted to establish the relationship between rice output (dependent variable) and inputs use as well as the link between the farm-specific, institutional, and socioeconomic variables (explanatory factors) on the other hand. The form of the generalised likelihood test is presented as:

$$k = -2\left[\frac{\ln\{L(H_A)\}}{\ln\{L(H_o)\}}\right] = -2[\ln\{L(H_A)] - \ln\{L(H_o)\}] \quad (6)$$

where $L(H_A)$ = value of the livelihood function under the alternative hypothesis; $L(H_o)$ = value of the livelihood function under the null hypothesis; k = value of the mixed chi-square distribution (degree of freedom equals the number of parameter differences between the null and alternative hypotheses. Equation (6) was also used to test the choice of the Cobb-Douglas model against the translog functional form.

The null hypothesis (H_o) for this study is that: there are no differences in technical efficiency among the sampled rice farmers and that any variation in output is due to random factors ($_\gamma$>0). The generalised likelihood ratio statistic (α) will have a mixture of Chi-square (X^2) distribution provided $_\gamma = 0$ (Coelli, 1995). For a one-sided likelihood ratio test of size (α), the decision rule is to reject the null hypothesis in favour of the alternative if γ exceeds X^2 2(α).

4 Results and discussion

4.1 Descriptive statistics

From the production statistics, the mean rice yield per hectare was 974.80 kg which is a little below the 1029 kg/hectare recorded in 2011 (MoFA, 2011). This was achieved through the combination of various levels of variable inputs. On average, 12.39kg of rice seed; 45.92 kg of chemical fertiliser; 71.73 man-days of family and hired labour combined were employed in producing the stated output (Table 2). These statistics are much lower than that reported by Ragasa et al. (2013) who found the seeding rate for direct planting to be 45 kg/ha and fertiliser rate of 375 kg/ha when NPK is combined with Urea. This points to the under-utilisation of inputs with a potential effect on production efficiency. Smallholder rice farmers in the area are getting older as revealed by the mean age (42 years). The productive age for rice farmers is reported to be between 20 and 40 years since it constitutes the early life and peak performance time of every individual (Ogundele & Okoruwa, 2006). Age could, therefore, account for production inefficiency as reported by Ayedun and Adeniyi (2019) for rice farmers in Nigeria.

The majority (67.5%) of the farmers covered were males as anticipated since males tend to dominate in production activities. Farmers' access to extension services is an issue as 68.5% indicated that they had no engagements with extension agents during the year. This could be attributed to inadequate logistics which hamper the movement of extension staff to conduct farm and home visits. Membership to FBO in the study area is also an issue as only 40.5% were members of such groups. This suggests that farmers may not be deriving the needed benefits such as group marketing and access to inputs associated with group belongingness. The percentage of rice growers that accessed credit was low (31%) and the majority (69.5%) do not own land for permanent rice cultivation. Only 42.5% of farmers were using improved rice varieties. These statistics have implications for sustainable rice production and suggest the need to strengthen existing extension systems and group dynamics.

Table 2: Descriptive statistics of the model variables

Variable	Mean	Std. Dev.	Min.	Max.
Rice output (kg/ha)	974.80	437.50	540.10	1580.79
Seed (kg/ha)	12.39	6.31	7.04	19.69
Fertiliser (kg/ha)	45.92	26.72	22.33	60.12
Family labour (man-days)	86.50	33.70	50.21	121.4

Hired labour (man-days)	56.50	26.49	36.42	92.61
Age (years)	42.14	14.11	23	70
Education (years)	4.79	2.53	3	10
HHS (number)	11.05	3.61	1	18
Farmer Experience (years)	12.30	5.78	2	75
Extension contacts (EXT)	6.232	5.092	0.0	15.0
Credit access (CRA)	0.310	*0.501*	0.0	1.0
Improved variety (VAR)	0.425	0.386	0.0	1.0
Land ownership (LND)	0.305	0.480	0.0	1.0
Off-Farm Income (OFI)	0.595	0.492	0.0	1.0
Farmer Based Organization (FBO)	0.360	0.458	0.0	1.0
Gender (GEN)	0.675	0.321	0.0	1.0

Source: Authors' computation from field data, 2018

The mean years of schooling achieved by rice farmers were about five years. Through education, farmers can acquire technical knowledge in production and improve their decision-making processing (more efficient). Farmers with more than four years of education are technically efficient in production (Sharma & Leung, 2000). The mean number of years of farming experience was (12 years), which is needed by farmers to learn and master rice production techniques and practices for efficient production. Good managerial skills gained through field practical experience enable farmers to better cope with risk and uncertainties in production (Ellis, 2003).

4.2 Tests of hypotheses

The outcome of the likelihood ratio tests for the functional form and the presence of inefficiency (Table 3) shows that the Cobb-Douglas function is preferred over the translog specification for this study. It also confirms that inefficiency exists among the sampled rice farmers.

Table 3: Results of hypothesis tests for Cobb-Douglas and coefficients of the technical inefficiency models

Null Hypothesis	**Log-likelihood function (H_o)**	**Test Statistic (α)**	**Critical Value**	**Decision**
$H_o:\beta_{ij} = 0$	-75.32	8.45	18.24	Accept H_o
$H_o: \delta_1 = ... = \delta = 0$	19.01	12.59	14.067 (7)	Accept H_o

Note: *Figures in parenthesis are the number of restrictions. The critical value is at 5% obtained from the chi-square distribution Table.*

4.3 Parameter estimates of stochastic frontier production function

Table 4 presents the estimated parameters of the stochastic frontier production function. The variable inputs (seed, fertiliser, family labour, and hired labour) included in estimating the production function had positive and statistically significant parameters, suggesting that they directly influence rice yields obtained in the area. Thus, unit increases in input quantities will increase rice output in the study area. To understand how changes in the various inputs affect rice output, the elasticity of each factor was analysed. As evident in Table 4, a one percent increase in the adoption and use of improved rice seed could increase output by 0.74% (*P = 0.000*) *ceteris paribus*. Also, a 1% increase in the quantity of fertiliser applied results in a 0.40% increase in rice output (*P = 0.093*). Again, a 1% increase in family and hired labour will probably increase rice yield by 0.11% (*P = 0.001*) and 0.05% (*0.000*) respectively. Interestingly, the rice production system in the area exhibits increasing returns to scale and the adoption of improved varietal seeds has the greatest effect in increasing rice yields.

The variance parameters, lambda (λ) and sigma-squared (σ^2) are 1.48 and 0.65 respectively. The statistical significance of σ^2 at 1% shows a good fit and that the distributional assumptions specified are correct. The variance ratio shows that variations in observed rice output are mainly attributable to differences in farmer practices. Gamma (γ) values usually range between 0 and 1 and measure the level of inefficiency. The estimated value of γ was 0.6909, indicating that 69% of the total variation in rice output resulted from technical inefficiency. The mean Variance Inflation Factor (VIF) of 1.125 is small, signifying that multicollinearity is not an issue in the model.

Table 4: Maximum likelihood estimates of technical efficiency and determinants

Variable	**Parameter**	**Coefficient**	**Z-value**
Intercept	β_0	7.0972	3.64

Ln (SEED)	β_1	0.7444***	9.73
Ln (FERT)	β_2	0.4008**	1.75
Ln (FLAB)	β_3	0.1134***	7.27
Ln (HLAB)	β_4	0.0508***	3.39
Inefficiency model			
Age (AGE)	δ_1	0.0028	0.33
Gender (GEN)	δ_2	-0.4320*	-1.68
Education (EDC)	δ_3	-0.0681	-0.94
Household size (HHS)	δ_4	-0.0111	-0.67
Farmer Experience (EXP)	δ_5	-0.0834***	-3.41
Farmer-based organization (FBO)	δ_6	0.3805*	1.73
Off-Farm Income (OFI)	δ_7	-0.0127	-0.06
Land ownership (LND)	δ_8	-0.2933	-1.17
Improved variety (VAR)	δ_9	1.4517***	4.91
Extension Contact (EXT)	δ_{10}	-1.2416***	-3.44
Credit Access (CRA)	δ_{11}	0.8272***	3.06
Variance Parameters			
Sigma Squared	σ^2	0.6516***	3.44
Gamma	γ	0.6909**	2.42
Lambda	λ	1.48	
Log Likelihood function		19.69	
Mean efficiency		0.549	
Mean VIF (multicollinearity)		1.125	
Minimum		0.117	
Maximum		0.984	

Source: Computation from field survey data, 2018. *Note: ***, **, * represent P<0.01, P<0.05, and P<0.10 levels of significance respectively.*

The inefficiency model (Table 4) revealed that gender is negative and significantly influences the technical inefficiency of rice farmers at 5%. This implies that technical inefficiency decreases with male rice producers compared with females. Thus, male farmers are less technically inefficient in rice production. The observed closeness of males to the production possibility frontier could be attributed to the fact that males still dominate the production process and have more control over resources. They are also well placed to best meet the labour-intensive requirements needed for the successful production of the crop. This result concurs with the findings of Wongnaa and Awunyo-Vitor (2018), Abdulai et al. (2017) and Kibaara (2005) that being a male farmer decreases technical inefficiency. Furthermore, the likelihood of male farmers participating in agricultural extension training is high (Kibaara, 2005) which enhances their production efficiency.

The coefficient of farmer experience is negative and statistically significant at 1%. This means that the technical inefficiency of farmers decreases as they accumulate farming experience over time. This is in line with a priori expectations due to learning curve effects. As farmers carry out the same operations over time, they can minimise the number of mistakes made relating to input combinations and the use, and timing of farm operations. This eventually, decreases their technical inefficiency level in rice production and moves them closer to the frontier. This result is in line with the findings of Donkoh et al. (2010), Abdulai et al. (2017), and Wongnaa and Awunyo-Vitor (2018). Farmer experience also influences the intensity of adoption of improved rice production technologies (Awuni et al., 2018) with a likely positive impact on technical efficiency.

The coefficient for FBO is positive and statistically significant at 10%. Group membership is an important element in reaching out to farmers with extension information and in shaping their productivity levels, especially in the face of a dwindling extension-to-farmer ratio in the country. Farmer belongingness to an FBO has also been shown to enhance their access to production inputs, output markets and production efficiency (Idiong, 2007). The observed low number of farmers that belong to FBOs is a point for advocacy since the results show clearly that membership in FBOs increases technical inefficiency. This outcome contradicts that of Donkoh et al. (2010), Kavi (2015) and Wongnaa and Awunyo-Vitor (2018) who found that group membership is significant in reducing farmers' inefficiency in Ghana.

Similarly, the coefficient of improved varietal seeds is positive and statistically significant at 1%. This suggests that improved varietal use by rice farmers increases technical inefficiency. This could be explained by the low number of farmers that cultivated improved rice varieties in the sample during the period. Other factors such as the timely application of fertilisers could also account for this observation. This result is in line with the finding of Wongnaa and Awunyo-Vitor (2018) who found the use of improved maize seeds to impact positively on farmers' technical inefficiency.

Extension contact has a negative and statistically significant effect on technical inefficiency. This suggests that the involvement of extension agents in the rice production value chain is not yielding the right results. The low number of extension agents coupled with logistical challenges which are manifested in poor extension contact with farmers explains the increases in technical inefficiency performance. This outcome strengthens the findings of Donkoh et al. (2010), Abdulai et al. (2017), and Wongnaa and Awunyo-Vitor (2018) that extension contact is relevant in reducing farmers' inefficiency.

The coefficient for credit access is positive and statistically significant at 1%, suggesting that increases in credit access will result in an increase in technical inefficiency in production. This contradicts a priori expectation and could be explained by the observation that only a few farmers (31%)

assessed credit in the area. The data also points to credit diversion as some farmers who accessed credit did not apply all to the production of rice. Other crops such as maize benefited from fertiliser inputs received on credit meant for rice cultivation. This result contradicts the finding of Idiong (2007) and Pindiriri et al. (2018) that access to credit positively influences rice farmers' technical efficiency. Heriqbaldi et al. (2015) revealed that the source of funding is a significant determinant of rice production efficiency in Indonesia.

4.4 Distribution of technical efficiency scores

The distribution of the predicted efficiency scores varies substantially among the rice farmers considered. The mean technical efficiency score obtained was 55% and the distribution ranged from a minimum of 12% to a maximum of 98% (Table 4). The mean technical efficiency score suggests that about 45% more output could have been achieved with the same input quantities provided farmers were operating on the frontier. The mean figure though low is similar to other studies that analysed production efficiency in the rice sector. For instance, Magreta et al. (2013) reported 65%, Wongnaa and Awunyo-Vitor (2018) reported 58.1%, Ayedun and Adeniyi (2019) found 61% for rice farmers in Benue and Nasarawa states in Nigeria, Abdulai et al. (2018) found 58% and 48% for adopters and non-adopters of rice cultivation technologies in Ghana, and Asravor et al. (2019) recently reported 56% and 42% for the forest and guinea savannah zones of Ghana respectively. These statistics tend to suggest that input use efficiency among rice farmers across various zones is an issue which needs to be addressed for increased productivity.

From the distribution of efficiency scores for all the farms considered (Table 5), only a few farmers (7%) had technical efficiency scores above 80% with almost half (49.5%) recording efficiency levels below 50%. This also shows the various levels of improvements required for farmers to produce on the frontier. This has policy implications in terms of targeting and the level of support needed by individual farmers. Thus, more scope exists in terms of improving the technical efficiencies of smallholder rice farmers in the area and beyond.

Table 5: Distribution of technical efficiency scores of smallholder rice farmers

Efficiency category	Number of farmers	Percentage (%)
Less than 0.50	99	49.5
0.51-0.60	17	8.5
0.61-0.70	43	21.5
0.71-0.80	27	13.5
0.81-0.90	9	4.5
0.91-1.00	5	2.5
Total	200	100

Source: Computation from field data, 2018

5 Conclusion and policy implications

Using cross-sectional data collected from five villages for the 2018 rice production season, estimated results from the stochastic frontier analysis show that inefficiency exists in the rice production system as the overall mean technical efficiency achieved was 55%. This means that given the current input levels and technology available, the potential to increase output by 45% exists. Rice farmers in the municipality do not have the same level of technical expertise in production. The revealed range of technical efficiencies ranged between 12% minimum to 98% maximum, indicating the variable shortfalls/improvements required to bring all producers to produce closer to the frontier. This outcome has implications in terms of efficiently targeting rice farmers in the Municipality for improved productivity. Also, at the broader level, geographic targeting of rice farmers with specific intervention support may help yield the desired results of achieving increased productivity and efficiency in resource use. Increasing returns to scale in production exist which farmers need to exploit for higher incomes. Among all the conventional factors of production considered, the adoption and use of improved rice seeds have the highest effect on yields. One implication is for the government, research institutions, and seed out-grower schemes to focus more on developing seed systems for improved productivity.

The main significant factors that influence the technical efficiency of rice farmers are gender, farming experience, membership to a Farmer-Based Organisation, use of the improved varietal seed, extension contact with farmers and credit access. Improving efficiency in rice production would mean working to minimise the constraints associated with the provision of these services to farmers. Increasing female farmers' access to production resources, strengthening extension services delivery and farmer education, and improving credit support to smallholder farmers through public-private partnerships are recommended policy options aimed at improving smallholder farmer productivity and efficiency.

6 Limitations and directions for future research

The current study has some limitations which are worth noting. First, though the study found no multicollinearity among the variables used, some of the variables could be endogenous. Future studies using such variables could test for potential endogeneity to deal with possible bias and ensure consistency in the estimates. Secondly, the current study included land ownership in the inefficiency model as it impacts production efficiency. Future studies could consider including land in the production model since it is a primary input in production.

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