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EFFICIENCY DIFFERENTIAL IN RICE PRODUCTION TECHNOLOGIES IN GHANA: A COMPARISON BETWEEN STOCHASTIC AND BIAS-CORRECTED METAFRONTIER APPROACHES

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Abstract

Productivity in rain-fed and irrigated rice farming ecosystems are very important for Ghana's self-sufficiency in rice. This paper, therefore, provides a synthesis of the irrigated and rain-fed rice farming ecosystems in Ghana using recent advances in the production economics literature. Specifically, the technical efficiency differential in the irrigated and rain-fed rice farming ecosystems are estimated using stochastic and bias-corrected data envelopment metafrontier methods. Technical efficiency drivers of the individual rice farming ecosystems are also examined. Using a sample of 381 for the modelling, the estimated results showed that farms under the irrigated rice farming ecosystem are more technically efficient (71%) compared to those under the rain-fed rice farming ecosystem (59%). However, overall technical efficiency falls short of about 36%, suggesting a substantial level of inefficiency in both rice farming ecosystems. In addition, the results revealed male farmers are more technically efficient compared to female farmers. Also, membership of farming associations has efficiency reducing effect. The study proposes that to improve rice productivity, resources should be invested in improving the managerial skills of farmers operating under the two rice farming ecosystems and in infrastructural development.
Keywords: *Irrigation, rain-fed farming, production economics, efficiency, Ghana*
JEL Codes: *C21, D24, Q12, Q15*

1. Introduction

Over the years, the importance of the agricultural sector in the economic development of poor countries has been recognized (Thiam et al., 2001). For the agricultural sector to contribute effectively to the economic development of these countries, there ought to be higher productivity in the sector. Productivity growth in the agricultural sector is therefore important for the sector to contribute to addressing issues of food insecurity, hunger and poverty (Bravo-Uretha & Pinhiero, 1993; Thiam et al., 2001). However, productivity growth in the agricultural sector in most of these countries is hindered by challenges such as inefficient markets, low technology adoption, and inadequate water supply for production activities, among others. Of critical importance is the availability of water for agricultural production, particularly in this era of climate change.

Currently, in Ghana, promotion of irrigation production system is seen as a pre-requisite for increased productivity with suggestions of improving public investment in irrigation infrastructure (Anang et al., 2017; You et al., 2011; 2014). One of the major crops under irrigation production is rice, which is cultivated mainly as a cash crop and is dominated by small-scale farmers. Rice production under irrigated ecosystem constitutes about 16% of total rice produced in Ghana (Ministry of Food and Agriculture [MoFA], 2010). On the other hand, rain-fed lowland rice production, which is composed of about 78% of total rice cultivable area is the major rice ecosystem in Ghana.

The rain-fed lowland ecology is characterized by frequent flooding from groundwater and precipitation, weed control, water management, unavailability of suitable varieties and adverse soil conditions. Despite challenges of the lowland rain-fed ecosystem, it is still an important part of rice production in Ghana and has a significant role to play in the country becoming self-sufficient in rice production. In fact, conservative estimates indicate that Ghana has over 5 million hectares of unexploited rain-fed lowlands, which when exploited could increase local rice production.

In Ghana, both the rain-fed and the irrigated farming ecosystems are important in ensuring food self-sufficiency in rice production, which will be vital in reducing rice imports that tend to affect the nation's balance of payment. This paper, therefore, aims at providing a synthesis of the technical efficiency of irrigated and rain-fed rice farming ecosystems using an approach that deviates from previous studies (Al Hassan et al., 2008; 2012; Anang et al., 2017; Makombe et al., 2007).

Specifically, a stochastic and bias-corrected data envelopment (hereafter BDEA) metafrontier approaches are employed to compare the technical efficiency of the rain-fed and the irrigated rice farming ecosystems in Ghana. Although there have been many empirical applications of the stochastic metafrontier approach in technical efficiency estimation (Mariano et al., 2010; Assaf et al., 2010; Mitropoulos et al., 2015; Jiang & Sharp, 2013; Matawie & Assaf, 2008), not many are found in the Ghanaian context. In addition, this is the first empirical application of the bias-corrected metafrontier application in the Ghanaian context.

This paper, therefore, adds to the limited metafrontier studies in Ghana using relatively recent advances in the production economics literature. It also seeks to provide policy guidelines for improving rice production in the two ecosystems towards productivity improvements. The econometric modelling revealed that relative to the regional ecosystem frontier, the irrigated rice farming ecosystem achieved a technical efficiency of about 73%, suggesting efficiency could be improved by about 27% within the existing state of input use and technology. The rain-fed farming ecosystem, on the other hand, achieved a technical efficiency of 67%, indicating that efficiency could be improved at 33% within the existing state of input use and technology. Given the overall ecosystem efficiency, rice farms under the irrigated ecosystem are more technically efficient compared to rice farms under the rain-fed ecosystem.

The rest of the paper is organised as follows. The next section presents a discussion of the methods of examining efficiency with a special focus on the metafrontier technology and describes the data used in the empirical application. This is followed by the empirical results and discussion in the context of literature. Finally, the paper concludes with policy recommendations for productivity improvement in the rice farming ecosystems in Ghana.

2. Methods

This section presents the empirical model and the data description for the analysis of the technical efficiency differential between irrigated and rain-fed rice farming ecosystems.

2.1 Stochastic Frontier Approach

The stochastic frontier (hereafter SF) is a common parametric efficiency approach often applied in the literature. The model incorporates a composed error structure with a two sided symmetric and a one sided component (Aigner et al., 1977a; Van den Broeck et al., 1994). The one-sided component reflects inefficiency whiles the two sided one captures random effects outside the control of the production unit as well as measurement errors and other statistical noise typical of empirical relationships. Assuming a half-normal distribution for inefficiencies, the model is specified as in Eq. (1):

$$y_i = f(x_i : \beta) - v_i + u_i \tag{1}$$

where y_i is a log of output variable for the farm i, x_i is a vector of explanatory variables and v_i is the stochastic random term (two sided component), which is (i.i.d.) $N(0, \sigma_v^2)$ and u_i is the technical inefficiency term.

2.2 Bias-Corrected Data Envelopment Analysis

The data envelopment analysis (DEA) frontier is constructed using a mathematical programming technique. Although there are different returns to scale models that could be employed, this paper applies the variable returns to scale (VRS) model to predict the technical efficiency. The VRS was selected because it assumes that most farms are not operating at an optimal scale due to imperfect competition, government interventions and credit constraints (Coelli et al., 2005), which is typical of production in developing countries.

The DEA approach specified in Eq. (2) assumes that all farms within a sample have access to the same technology for the transformation of a vector of N inputs denoted by x, into a vector of M, outputs, denoted as y.

$$\begin{aligned}
&\underset{\theta_i, \lambda_i}{Max}\ \theta_i \\
&subject\ to \\
&\theta_i y_i - \lambda_i y' \le 0, \\
&\lambda_i X - x_i \le 0, \\
&j' \lambda_i = 1 \\
&\lambda_i \ge 0, \qquad j = 1, \dots n
\end{aligned} \tag{2}$$

where; y_i is the output quantity for the *i-th* farm, θ is the output technical efficiency measure having a value of $0 \le \theta \le 1$. If $\theta = 1$, then the farm is efficient. x_i is the $N\ x\ 1$ vector of input quantities for the *i-th* farm, X is the matrix of input quantities for all farms, $\emptyset_i$ is a scalar, λ is an $N \times 1$ vector of weights which defines the linear combination of the peers of the *i-th* farm. $X\lambda$ and yλ are efficient projections on the frontier and j is an $N \times 1$ vector of ones. The DEA model in Eq. (2) seeks to maximize output as much as possible relative to the empirically constructed identical and optimal combinations of inputs and output for each decision-making unit (L1 & Nanseki, 2018).

The DEA approach does not account for measurement errors (bias), which makes the method unsuitable for application in developing countries agriculture where data applied are mostly noisy. Simar and Wilson (2007) have proposed a bootstrapping technique to address the bias in the DEA estimator, and that is what was employed in the estimation. For detailed information on the bias-corrected DEA model, see Simar and Wilson (2007).

2.3 Stochastic Metafrontier Specification

In the case of standard stochastic frontier analysis, a key component of the formulation is the production frontier with composed error. For a group q, the stochastic frontier can be formulated as in Eq. (3):

$$Y_{i(q)} = f_{(q)}\left(x_i, \beta_{(q)}\right) = e^{x_i \beta_{(q)} + V_{i(q)} - U_{i(q)}} \tag{3}$$

where: $x_{i(q)}$is the log of the input vector for observation i; $\beta_{(q)}$ unknown parameters to be estimated relative to the *q-th* group; $V_{i(q)}$ is the statistical noise assumed to be independently and identically distributed; and $U_{i(q)}$ represents inefficiency, which is related to the standard measure of technical efficiency (TE) defined as the ratio of actual output to the maximum output possible as in Eq.(4):

$$TE_{i(q)} = \frac{Y_{i(q)}}{e^{x_i \beta^q + V_i{}^q}} = e^{-U_{i(q)}} \tag{4}$$

The metafrontier enveloping all group frontiers is assumed to have a similar functional form but a different set of parameters as in Eq. (5):

$$Y_i^* = f(x_i, \beta^*) = e^{x_i' \beta^*} \tag{5}$$

where: Y_i^* is the metafrontier output and β^* is a vector of metafrontier parameters satisfying the constraints $x_i, \beta^* \geq x_i, \beta_{(q)}$. The efficiency of this actual output against the metafrontier output can be decomposed into group technical efficiency (GTE) and meta-technology ratio (MRT). It is easy to show the decomposition mathematically by rewriting the output equation in Eq. (1) as in Eq. (6):

$$Y_{i(q)} = e^{-U_{i(q)}}\ x\ \frac{e^{x_i \beta_{(q)}}}{e^{x_i \beta^*}}\ x\ e^{x_i \beta^* + V_{i(q)}} \tag{6}$$

The group technical efficiency (GTE) measures technical efficiency of observations relative to the stochastic frontier that applies to the *q-th* group, or as in Eq. (7):

$$GTE_{i(q)} = \frac{Y_i}{e^{x_i \beta_{(q)} + V_{i(q)}}} = e^{-U_{i(q)}} \tag{7}$$

The meta-technology ratio (MRT), on the other hand, measures group production function output relative to the potential output defined by the metafrontier function, and is given by Eq. (8):

$$MRT_{i(q)} = \frac{e^{x_i \beta_{(q)}}}{e^{x_i \beta^*}} \tag{8}$$

The overall technical efficiency of the *i-th* observation or unit relative to the meta-frontier is referred to as meta-technical efficiency (MTE_i^*) and compares observed output relative to metafrontier output, adjusted for the corresponding random error as in Eq. (9):

$$MTE_i^* = \frac{Y_i}{e^{x_i \beta^* + V_{i(q)}}} \tag{9}$$

In other words, MTE_i^* is the product of group technical efficiency and meta-technology ratio given in Eq. (10):

$$MTE_i^* = TE_i^q \ x \ MRT_i^q \tag{10}$$

2.4 Model Estimation

Although Cobb Douglas functional form is the common production function often applied in the empirical literature, the translog functional form is assumed for both the group and metafrontiers because of its flexibility. The Translog functional form may be specified as in Eq. (11):

$$\ln y_i = \beta_o + \sum_{j=1}^{m} \beta_{ij} \ln x_{ij} + \frac{1}{2} \sum_{j=1}^{m} \sum_{q=1}^{n} \beta_{jq} ln \, x_{ij} \, ln x_{iq} + v_{i(q)} - u_{i(q)} \tag{11}$$

where: β is a vector of parameters to be estimated; y is output and x is a vector of inputs; $v_{i(q)}$ is the symmetric noise or error term which might be distributed as half-normal or exponential; and $u_{i(q)}$ is a non-negative inefficiency term.

The estimation of the metafrontier is a two-step process. In the first step, group frontiers are estimated, and the metafrontier with decomposition into technology gap and meta-technical efficiency are estimated in the second step. For the stochastic metafrontier, the two rice farming ecosystem frontiers were estimated using a stochastic frontier approach in a maximum likelihood framework. After the stochastic group frontier estimations, the stochastic metafrontier was estimated using the average expected values of the group frontiers (O'Donnell et al., 2008). The standard errors of the metafrontier were generated using bootstrapping techniques.

In the case of the bias-corrected DEA model, the output oriented model under variable returns to scale was estimated both for the group frontiers and the metafrontier using linear programming with bootstrapping techniques (Simar &Wilson, 2007) to correct for bias in the DEA estimator. The group frontiers were estimated separately for the rain-fed and irrigated rice farming ecosystems. The estimation of the metafrontier was done by estimating a pooled frontier for the two rice farming ecosystems. The technology gap was obtained by the ratio between the group technical efficiency and the pooled technical efficiency.

3. Data and Variable Definition

The paper uses a farm household production data of rain-fed and irrigated rice farmers collected in 2014 from the Northern and Upper East regions of Ghana. The selection of the regions was based on volume of rice produced and closeness to the major rice market, Ashanti region. The study focused on irrigated and rain-fed farming ecosystems because those ecosystems are the major rice production systems in Ghana (MoFA, 2010).

A multistage sampling procedure was applied in the data collection. In the first stage, I used the stratified sampling method to categorize the regions into districts and later communities. The random sampling technique was then employed to select the farmers based on names provided by the Department of Agriculture. The instrument used for the data collection was a structured questionnaire composed of questions relating to socio-economic characteristics of the farm households and details of inputs and output of the production process. For the empirical estimation, a total of 381 observations comprising 202 rain-fed farms and 179 irrigated farms were used in the estimation.

Consistent with the production economics and efficiency literature, four inputs and a single output were considered. Output was measured as an amount of paddy rice produced per hectare of rice farm. The inputs include farm size, labour, fertilizer quantity, and other variable costs. Farm size (X1) was measured as the total area cultivated to rice in hectares. Labour (X2), total person-days committed to the production process by both family and hired. The family labour who counted are persons of the family unit that reside in the house and are actively involved in the production process. Fertilizer input (X3) is the quantity of NPK and sulphate of ammonia in kilograms used in the production process and other variable costs (X4): This is an aggregation of other production costs such as harrowing, ploughing, herbicides in monetary terms, and cost of water for irrigation in Ghana Cedis[1].

Table 1 Sample Descriptive Statistics of Data

	Pooled		Rain-fed ecosystem		Irrigated ecosystem	
Variables	Mean	SD	Mean	SD	Mean	SD
Variables in the production function						
Yield (kg/ha)	1415	745	1425	774	1404	712
Farm size (ha)	1.63	1.04	2.15	0.987	1.05	0.754
Labour (man-days)	168	39	173	47	163	28.29
Fertilizer (kg/ha)	157	94	193	103	115.45	59.35
Other variable costs (GHS/ha)	265[2]	104	299	84.6	226	111
Variables in the inefficiency model						
Farmer based organization	0.44	0.49	0.569	0.49	0.285	0.45
Non-farm income	0.60	0.49	0.574	0.50	0.631	0.48
Gender	0.17	0.37	0.173	0.379	0.162	0.369
Farming experience	10.6	5.64	11.4	5.43	9.75	5.76

Table 1 presents summary statistics of variables used in the empirical model. From the table, the average farm size is about 2 hectares. This is indicative of the small-scale nature of the rice production system and typical of production in developing countries (Owusu & Hailu, 2014; Abatania et al., 2012). Per the rice farming ecosystem, farm sizes in rain-fed farms are double the sizes in irrigated farms. An independent sample t-test conducted on the variables revealed a significant difference in all the input quantities between the rain-fed and irrigated farms.

4. Results and discussion

Prior to the estimation, standard tests for the choice of functional form and justification of inefficiency approach were conducted. Concerning the structure of the production, the translog functional form was found an adequate restriction compared to the Cobb-Douglas model for rain-fed and irrigated ecosystem frontiers. A second test for the null hypothesis of no inefficiency effect is rejected for both groups of farms. Hence, the average production function is not an adequate representation of the production technology. Finally, a hypothesis

[1,2] 2.8 Ghana Cedis is equivalent to 1 USD

test of identical technology across farms is rejected. Therefore, the metafrontier approach is suitable for the sample data under consideration. The results of the preliminary diagnostic tests are presented in Table A.1 in the Appendix.

Following the justification of the method, a translog stochastic production function was estimated for each rice farming ecosystem-irrigated and rain-fed. The input variables were measured as a deviation from the means so that the estimated coefficients for the first order terms could be interpreted directly as production elasticity at the sample mean. The estimates of the empirical model are now presented and discussed starting with the group frontiers. The parameter estimates of the group frontiers are reported in Table 2. For the rain-fed rice farming ecosystem frontier, the estimates of the production elasticities are 0.085 for land, 0.403 for labour, 0.212 for fertilizer input and 0.315 for other variable inputs. Given the parameter values, labour and other variable inputs contribute greatly to the production process.

Table 2 Estimated Parameters of the Group Stochastic Production Frontier

	Rain-fed farming ecosystem		Irrigated farming ecosystem	
	Coef.	SE	Coef.	SE
Constant	0.372***	0.102	0.298***	0.069
lnx1	0.085	0.099	0.047	0.080
lnx2	0.403**	0.002	0.458*	0.203
lnx3	0.212**	0.078	-0.341***	0.092
lnx4	0.315*	0.130	0.775***	0.078
$0.5(\ln x1)^2$	-0.015	0.266	0.201	0.139
$0.5(\ln x2)^2$	0.986	0.766	1.975*	1.129
$0.5(\ln x3)^2$	-0.417*	0.213	-0.052	0.313
$0.5(\ln x4)^2$	-2.319***	0.871	0.370	0.233
lnx1.lnx2	-0.191	0.287	1.173***	0.275
lnx1.lnx3	0.027	0.151	-0.433*	0.182
lnx1.lnx4	0.571*	0.347*	0.228	0.188
lnx2.lnx3	-0.503	0.256*	-0.873*	0.437
lnx2.lnx4	0.549	0.423	-1.331**	0.430
lnx3.lnx4	0.253	0.259	0.082	0.143
Sigmasq	0.877**	0.276	0.725*	0.305
Gamma	0.916***	0.039	0.958***	0.021
Non- farm income	-0.072	0.261	-0.199	0.406
Gender	-0.557*	0.299	-1.203*	0.577
Membership of FBO	1.796***	0.391	1.453**	0.504
Farming experience	-0.103*	0.061	0.162*	0.102
Observation	202		179	

Note: FBO, farmer-based organization; X1=Farm size, X2=labour use, X3=fertilizer input use; X4=other variable inputs use, SE. Standard errors

For the irrigated rice farming ecosystem frontier, the input elasticities are 0.047 for land, 0.458 for labour, -0.341 for fertilizer input, and 0.775 for other variable inputs.

The determinants of the technical efficiency of the rice farming ecosystems were examined by incorporating non-farm income, gender, farming experience and farmer group membership variables into the modelling. Since the models were estimated in one stage, positive coefficients have efficiency reducing effects and negative coefficients have efficiency increasing effects. From the estimated parameters in the second block of Table 2, it is observed that membership of farmer association reduces farmer efficiency, greater farming experience in the case of the irrigated farming ecosystem also reduce farm efficiency. This finding is consistent with Danso-Abbeam and Donkoh (2017) study on technical efficiency in Northern Ghana.

The gender variable gives an indication that male farmers in both ecosystems are more technically efficient compared to female farmers. The farming experience variable is negative and significant in the rain-fed farming ecosystem frontier, indicating that higher farming experience reduces inefficiency in the farming ecosystem. This finding is consistent with previous studies (Nwaru, 2007) that have identified that experienced farmers are more technically efficient compared to inexperienced farmers. The possible explanation for the efficient nature of experienced farmers could emanate from the practical knowledge they have gained over the years in addressing production related problems, which further suggests that policies and programmes aimed at improving technical efficiency of farmers in the rain-fed rice farming ecosystem should target experienced farmers.

Now, I proceed to discuss the metafrontier results. Table 3 presents the metafrontier estimates obtained from the stochastic metafrontier (SMF) approach and the bias-corrected data envelopment analysis (BDEA). The results show that other variable inputs use has the greatest effect on the metafrontier, and this is followed by labour input use. In terms of the performance indices- group technical efficiency (GTE), meta-technology ratio (MRT) and meta-technical efficiency (MTE) are presented in Table 4. Before discussing the results in detail, the distributions of the technical efficiency of the farming ecosystems are compared using the two methodologies.

Table 3 Bootstrapped Metafrontier Estimates

Variable	Mean	SE
Constant	0.348	0.001
lnx1	0.064	0.001
lnx2	0.221	0.015
lnx3	0.082	0.013
lnx4	0.581	0.013
$0.5(\ln x1)^2$	0.036	0.020
$0.5(\ln x2)^2$	0.140	0.036
$0.5(\ln x3)^2$	0.077	0.017
$0.5(\ln x4)^2$	-0.033	0.031
lnx1.lnx2	0.476	0.075
lnx1.lnx3	-0.044	0.036
lnx1.lnx4	-0.189	0.053
lnx2.lnx3	-0.057	0.024
lnx2.lnx4	-0.057	0.031
lnx3.lnx4	0.430	0.062

Notes: X1=Farm size, X2=labour use, X3=fertilizer input use; X4=other variable inputs use, SE, Standard errors

Figure 1 shows the boxplot of the technical efficiency for the rain-fed and irrigated rice farming ecosystems from the Stochastic frontier (SF) and BDEA approaches. It can be observed from the figure that the technical efficiency obtained from the SF model is higher compared to the BDEA model. The estimates from the BDEA model are also highly variable compared to those obtained from the SF model. The boxplots, therefore, suggest of a variation in the efficiency of the two approaches used in estimating the technical efficiency of the two ecosystems.

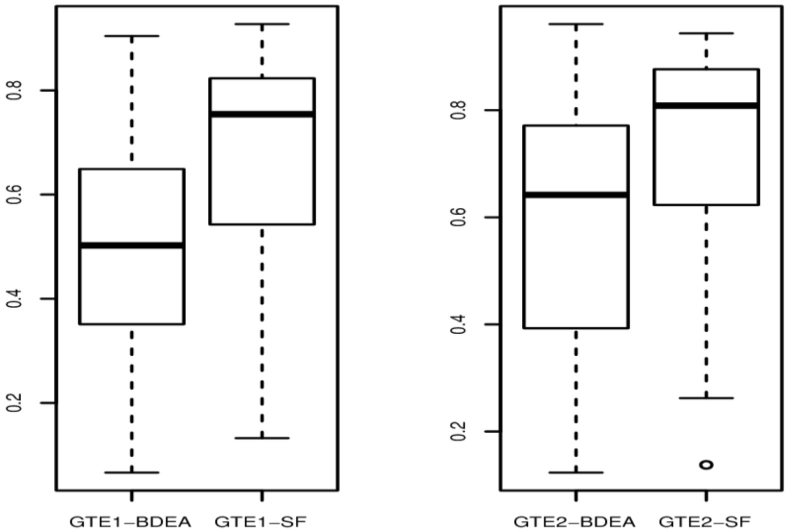

Figure 1 Boxplots of Regional Ecosystem Technical Efficiency for Rain-Fed Ecosystem (Left) And Irrigated Ecosystem (Right)

Table 4 reveals the results for the performance indicators under the group frontiers. Regarding the irrigated rice farming ecosystem, the technical efficiency ranges from 0.138 to 0.943 with an average of 0.732. The average technical efficiency for the rain-fed rice farming ecosystem ranges from 0.132 to 0.927 with a mean of 0.665. This implies that on average, the rain-fed rice farming ecosystem is producing about 67% of the output that could be produced from the observed input quantities. Similarly, the irrigated rice farming ecosystem is producing 73%.

The results show that farms under the irrigated rice farming ecosystem could improve efficiency by about 27% within the existing state of resources and technology. Those under the rain-fed rice farming ecosystem could also improve their technical efficiency by about 33% within the existing state of resources and technology. The results, therefore, imply that within the short-term, improvement upon the managerial skills of farmers operating under both farming ecosystems would be more beneficial with a potential higher return to investment. In the long run, the introduction of new technologies would be relevant in improving the technical efficiency of the rice farming ecosystems.

Table 4 Summary Statistics for Technical Efficiency and TGRS for The Rice Ecology Systems

Stochastic frontier model estimates					Bias-corrected DEA model estimates			
Group	Mean	Min	Max	SD	Mean	Min	Max	SD
Rain-fed farming ecosystem								
GTE1	0.665	0.132	0.927	0.216	0.492	0.066	0.904	0.202
MRT1	0.880	0.549	1	0.100	0.435	0.063	0.926	0.207
MTE1	0.587	0.094	0.894	0.207	0.248	0.005	0.780	0.186
Irrigated farming ecosystem								
GTE2	0.732	0.138	0.943	0.184	0.587	0.123	0.961	0.215
MRT2	0.964	0.763	1	0.034	0.570	0.122	0.941	0.212
MTE2	0.706	0.138	0.930	0.181	0.380	0.015	0.904	0.234
TE	0.696	0.132	0.943	0.204	0.537	0.066	0.961	0.214
MRT	0.919	0.549	1	0.087	0.50	0.063	0.941	0.220
MTE	0.643	0.094	0.930	0.204	0.310	0.005	0.904	0.220

Note: GTE-Group technical efficiency, MRT-Meta-technology Ratio, MTE-Metafrontier technical efficiency

As far as MRT is concerned, the values range from about 0.549 to 1 with a mean of 0.880 for the rain-fed ecosystem, while the MRT for the irrigated ecosystem ranges from 0.763 to 1 with a mean of 0.964. The results imply on average, irrigated farms produce 96% of the potential output given the technology available to the industry. The rain-fed farms, on the other hand, produce about 88% of the potential output. Compared to the stochastic metafrontier (SMF) estimates, the MRT values obtained from the BDEA model are low with wider variations (see Figure 2). This gives an indication that the type of frontier methodology used in estimating the technology gap has an effect on the magnitude of the values.

Now as the meta-technical efficiency (MTE) estimates of the rain-fed and irrigated rice farming ecosystems are measured on the same production frontier, we can compare the technical efficiencies. The mean technical efficiency of the rain-fed ecosystem with respect to the metafrontier (MTE1) ranges from 0.094 to 0.894 with an average of 0.587. The irrigated ecosystem (MTE 2) on the other hand ranges from 0.138 to 0.930 with a mean of 0.706 in respect to the meta-technology available. The findings show that for the sample under study, the irrigated rice farming ecosystem is more technically efficient as opposed to the rain-fed rice farming ecosystem. This finding is consistent with previous study outcomes (Al-Hassan et al., 2012; Anang et al., 2017).

In terms of model comparison, it is observed that the estimates from the SMF are higher compared to the BDEA model estimates (see Figure 3). However, both models give a consistent result of irrigated ecosystems being more technically efficient compared to rain-fed ecosystems.

The differences in the distributions of the performance indicators were further investigated by conducting a Kolmogorov-Smirnov test (Table 5). The null hypothesis is rejected at all the three conventional levels, implying that the distributions of the performance indicators vary for all models and therefore, the samples are not drawn from the same distribution.

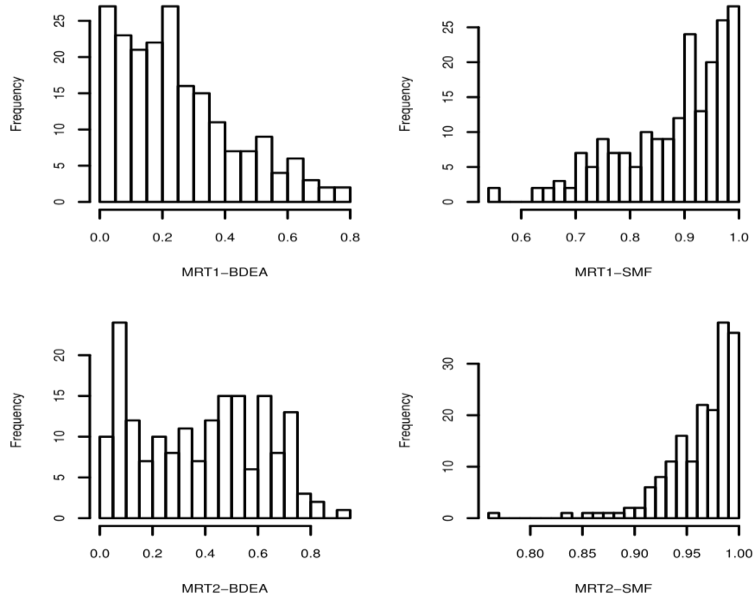

Figure 2. Frequency Distributions of Meta Technology Gap for The Rain-Fed Farming Ecosystem (Top) and Irrigated Farming System (Bottom) for the SMF (Right) and BDEA (Left) Models

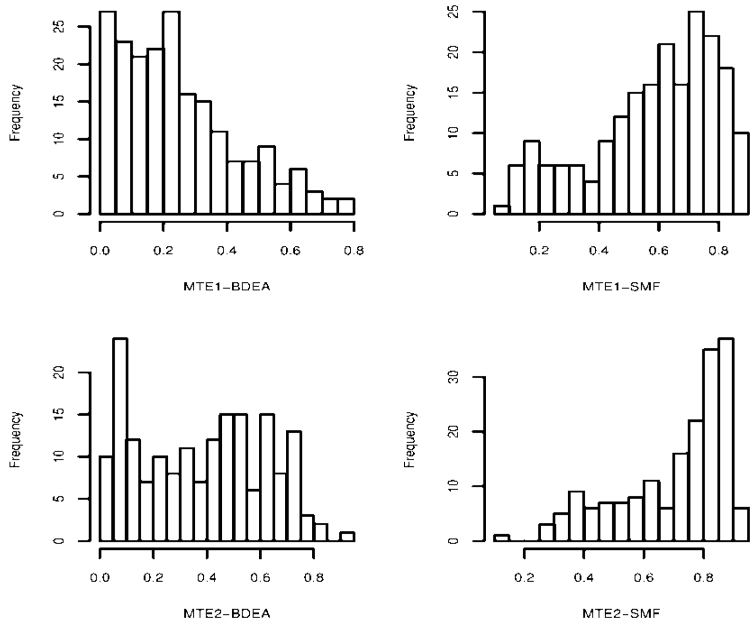

Figure 3. Frequency Distributions of Meta Technical Efficiency for the Rain-Fed Farming Ecosystem (Top) and Irrigated Farming System (Bottom) for the SMF (Right) and BDEA (Left) Models

Table 5. Results of Kolmogorov-Smirnov and Wilcoxon-Mann- Whitney Rank Sum Tests

Index	Null Hypothesis	K-S value	P-value
GTE $_{SMF}$	Distribution MTE1= distribution MTE2	0.336	0.000
MRT $_{SMF}$	Distribution MRT1 = distribution MRT2	0.489	0.000
GTE $_{BDEA}$	Distribution MTE1= distribution MTE2	0.306	0.000
MRT $_{BDEA}$	Distribution MRT1 = distribution MRT2	0.345	0.000
		Z value	
GTE $_{SMF}$	Mean MTE1=Mean MTE2	-6.316	0.000
MRT $_{SMF}$	Mean MRT1=Mean MRT2	-9.434	0.000
GTE $_{BDEA}$	Mean MTE1=Mean MTE2	-5.413	0.000
MRT $_{BDEA}$	Mean MRT1=Mean MRT2	-5.846	0.000

Note: SMF=Stochastic metafrontier, GTE=Group technical efficiency, MRT=Meta technology ratio

I also performed a Wilcoxon-Mann-Whitney rank sum test to determine whether there is any significant difference in the performance indicators. The results are presented in Table 5. All the null hypotheses are rejected in favour of the alternatives at all three conventional levels, a clear indication that the rank differences in the indicators are significant and providing further evidence of the heterogeneity between the two ecosystems.

Furthermore, I examined the correlation between the performance indicators using Spearman correlation coefficient (Table A.2 in the Appendix) and found a positive correlation among indicators of the same ecosystem across models. However, there is a negative correlation between the MRT and MTE between the ecosystems, which suggest that to be on the same metafrontier, as one group's contribution increases, another's decreases.

5. Conclusion

In this study, technical efficiency differential between irrigated and rain-fed rice farming ecosystems in Ghana was investigated using a cross sectional data collected in the 2013/2014 production season. The study employed both parametric and non-parametric metafrontier approaches to examine the technical efficiency differences between the two rice farming ecosystems. Specifically, the stochastic and the bias-corrected data envelopment metafrontier approaches were employed to compare the technical efficiency of rice farms under irrigated and rain-fed ecosystems.

The empirical results revealed that labour and other variable inputs use have greater effects on rice output. Labour is an essential part of increasing farm productivity; therefore, investment should be made in improving the skills of farm labour to increase their productivity. The factors identified to drive the technical efficiency of farmers include membership of farmer-based organization, farming experience and gender. Specifically, the findings revealed that male farmers are more technically efficient compared to female farmers. The less efficiency level of female farmers could be attributed to cultural norms and practices that ban female farmers from access to land. If some of these practices are addressed by policymakers, female farmers are likely to equal their male counterparts in efficiency in farm production.

The results further revealed that irrigated rice farming ecosystems are more technically efficient compared to rain-fed rice farming ecosystem. Specifically, the efficiency of the irrigated rice farming ecosystem is about 15% higher than the efficiency of rain-fed rice farming ecosystem. This finding suggests that more investment should be made in irrigation infrastructure in Ghana in improving rice production. However, since rain-fed rice farming ecosystem constitutes a greater percentage of land cultivated to rice, and its efficiency could be increased by 33% within the existing state of resources and technology, managerial abilities of farmers in that system of rice production should be improved. Both rice farming ecosystems would require new technologies to move them beyond the existing rice production frontier and such technology should consider farmers in the inception, planning and implementation to improve adoption.

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Appendix

Table A.1 Likelihood Ratio Test of Hypothesis

Null hypothesis	Model	Log likelihood	Chisq	P-value	Decision
Ho: $\boldsymbol{\beta}_{\mathbf{ij}} = \mathbf{0}$	Cobb Douglas	-409.280	56.702	0.000	Reject *Ho*
	Translog	-43.63			
Ho: $\boldsymbol{\gamma} = \mathbf{0}$	There is no inefficiency			0.000	Reject *Ho*
	OLS	-480.230	141.91		
	Translog	-409.280		0.000	Reject *Ho*
	Groups nested in Pooled		101.79	0.000	Reject *Ho*
	Irrigated	-87.261			
	Rain-fed	-252.137			
	Pooled	-409.280			

Table A.2 Correlations between Performance Indicators

	MRT $_{Stochastic}$	MTE $_{Stochastic}$	MRT $_{BDEA}$	TE $_{BDEA}$	MTE $_{BDEA}$	
TE $_{Stochastic}$	1					
MRT $_{Stochastic}$	0.1743	1				
MTE $_{Stochastic}$	0.9672	0.3529	1			
MRT$_{BDEA}$	0.8741	0.2457	0.8692	1		
TE $_{BDEA}$	0.869	0.1069	0.8384	0.9448	1	
MTE $_{BDEA}$	0.8859	0.1909	0.8705	0.9908	0.9786	1

Note: BDEA=Bias-corrected Data Envelopment Analysis