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Are all farmers technically inefficient? Evidence from smallholder rice producers in Ghana

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Abstract

This study applied the zero-inefficiency stochastic frontier (ZISF) to analyse the technical efficiency of 333 improved rice-farming households for the 2012/2013 farming season in Ghana. The ZISF accommodates fully efficient rice farms alongside technically inefficient farms under a common production technology. The results revealed that 39% of rice farms were fully technically efficient, with zero inefficiency within a common production frontier. The mean technical efficiency estimate amongst the inefficient farms was 67.8%, implying that these rice farms could increase their output by 32% without changing the levels of inputs used, if they improved their efficiency and operated on the production frontier. There were increasing returns to scale (1.65), with farm size, seed, labour and fertiliser having a positive effect on rice output. Similarly, controlling rice field water levels through levelling and bunding, and weeding the rice field at least two times during the production season, increased technical efficiency. The study recommends cultivation of improved rice varieties, fertiliser application, expanding acreage and easing labour constraints to increase rice output, together with weeding and managing plot water levels to improve efficiency in rice production. Specifically, Ghana's 'Planting for Food and Jobs' programme should expand access to improved rice varieties, fertiliser use, agricultural mechanisation services and other labour-saving technologies to enhance rice output. In addition, the agricultural extension service should be well-resourced to disseminate best practices in rice cultivation to farmers.

Key words: zero-inefficiency stochastic frontier, technical efficiency, rice, Ghana

1. Introduction

Agriculture in Ghana accounts for more than 20% of GDP and offers employment to over 33% of the national labour force (Ministry of Food and Agriculture [MoFA] 2021, 2022). Paddy rice acreage cultivation increased from 216 000 ha to 357 000 ha from 2013 to 2021 (MoFA 2022). Similarly, the production of paddy rice rose from 570 000 Mt to 1 143 000 Mt between 2013 and 2021. The top rice- producing areas in Ghana are the Northern, Volta, Upper East, Oti and Ashanti regions (MoFA 2022). Nonetheless, Ghana's self-sufficiency in rice production has been in decline, as domestic production is able to meet less than 50% of demand due to an increase in consumption (MoFA 2018, 2021). Rice consumption per capita has risen steadily, from 40.38 kg to 51.63 kg, between 2016 and 2020 (MoFA 2021). Currently, the national average rice yield (3.28 Mt/ha) is below the achievable yield of 6 Mt/ha (Ragasa *et al*. 2013; MoFA 2022;). Ketu North in the Volta Region had the highest yield, of 6.24 Mt/ha (MoFA 2021). Ghana imports a large quantity of rice on an annual basis. For instance, 1.3 million tonnes of rice was imported in 2020 compared with one million tonnes produced domestically (Ghana Investment Promotion Centre 2022).

Rice is a very important staple food in Ghana, and raising the productivity of inputs is crucial for improving household nutrition and incomes (Abdulai *et al*. 2013). Nonetheless, rice-farming households in Ghana produce suboptimal yields (Ragasa *et al*. 2013). Many studies (Abdulai *et al*. 2013, 2018) on production efficiency have applied the traditional stochastic frontier models, which do not fully account for the presence of fully efficient farms alongside inefficient ones within a common production technology. Thus, the traditional stochastic frontier estimations assume all farms have some level of inherent technical inefficiency. This assumption in empirical studies – of all farms being technically inefficient – is worrying, because there is the possibility of farms that are fully technically efficient along with inefficient farms under the same production technology. Methodologically, this is wrong, as fully efficient farmers are treated as technically inefficient and policy recommendations based on these estimations may not reflect farm and farmer conditions. Thus, the main contribution of this study is to disaggregate fully technically efficient farms from inefficient farms, rather than to treat all farms as being technically inefficient. This was done by applying the zero-inefficiency stochastic frontier (ZISF) model to a sample of 333 farming households in Ghana planting an improved rice variety. This sample was then used to differentiate fully efficient farm households from inefficient farm households for informed policy decisions regarding rice production in the study area. The zero-inefficiency stochastic frontier produces unbiased estimates of technical efficiency scores because it is able to identify fully efficient rice farms and inefficient farms within the sample, where the former serve as a benchmark for the latter.

Moreover, by estimating technical efficiency scores and identifying the factors that influence efficiency amongst farmers, it is possible to assess potential gains from improving technical efficiency amongst inefficient farms and identify the determinants of technical inefficiency in order to raise farm performance. Similarly, the fully technically efficient farms will serve as the 'best practice' or 'model farms' to motivate their peers to improve their production efficiency. This study provides unbiased results on the technical efficiency of rice households by separating fully technically efficient farms from inefficient farms to aid the Ministry of Food and Agriculture to enhance rice production. Specifically, the study offers empirical evidence to support the Ministry of Food and Agriculture to target resources to improve rice production amongst inefficient farms, and to continue to motivate fully efficient farms to keep up.

2. Materials and methods

2.1 Description of study area and sampling approach

This study is based on secondary data[1] provided by the International Food Policy Research Institute Ghana office. Proportional and random sampling methods were used to sample a total of 576[2] rice-farming households from 25 rice-producing districts[3] across eight regions (Northern, Upper East, Upper West, Ashanti, Greater Accra, Volta, Western and Eastern regions) during the 2012/2013 cropping season. The eight regions make up 79.29% of Ghana's total land area (MoFA 2016). Proportional sampling gave more sampling weight[4] to districts with higher rice production output,[5] whereas random sampling was used in the final selection of districts, communities and households. The data was collected using semi-structured questionnaires.

2.2 Zero-inefficiency stochastic frontier model

The zero-inefficiency stochastic frontier (ZISF) approach, proposed by Kumbhakar *et al*. (2013) and Rho and Schmidt (2015), accommodates the possibility of fully efficient rice farms with zero inefficiency. The ZISF departs from the assumption in the stochastic frontier literature (such as Aigner *et al*. 1977; Meeusen & Van den Broeck, 1977) that all firms have some level of technical inefficiency, and that inefficiency is non-negative (Rho & Schmidt 2015).

The ZISF identifies fully efficient firms within the same sample, production frontier and common production technology (Rho & Schmidt 2015). The ZISF has some similarity with zero-inflated models, but the abundance of zeros in the ZISF is unobserved (Rho & Schmidt 2015) because inefficiency emanates from the composed error term ($\varepsilon_i = v_i - u_i$). Therefore, the fully efficient firms in the ZISF cannot be directly observed (Kumbhakar *et al*. 2013).

According to Kumbhakar *et al*. (2013), the ZISF model incorporates the neoclassical production function, which assumes that all firms are efficient, and the traditional stochastic frontier, which generalises the existence of inefficiency in production for all firms. Given a fully efficient firm ($u_i = 0$) with zero variance inefficiency, the ZISF is reduced to the neoclassical production function. On the other hand, where inefficiency exists in firms ($u_i > 0$), the ZISF becomes the Jondrow, Lovell, Materov and Schmidt (JLMS) stochastic frontier estimation of firm technical inefficiency. Following Kumbhakar *et al*. (2013), the ZISF is expressed as:

$$ZISF \rightarrow\ y_i = \beta x_i' + v_i \text{ with probability } p \text{ and} \tag{1}$$

$$y_i = \beta x_i' + v_i - u_i \text{ with probability } 1 - p \tag{2}$$

[1] This data comprehensively covered all the well-known rice-growing regions across the country.
[2] These were 333 households who knew about the improved rice varieties out of the 576 who were used for this study.
[3] Districts with more than 1 000 hectares of rice production annually.
[4] A higher probability of being sampled.
[5] The Northern and Upper East Regions are the biggest producers in northern Ghana, whilst the Volta Region is the leading producer in southern Ghana.

Figure 1: A map[6] of Ghana showing the study area

Thus, p^7 represents fully efficient firms, and $1 - p$ is for technically inefficient firms relative to a common production technology, and the probability of a firm being fully efficient or otherwise is

[6] The North East Region and the Savanna Region were carved out of the Northern Region. West Mamprusi is now part of the North East Region. Western North Region was carved out of the Western Region, and Juabeso and Bibiani-Ahwiaso districts are now part of the Western North Region. Oti Region was created from the Volta Region, and Kadjebi District is now under the Oti Region.

[7] Refers to the probability of a firm being technically efficient.

unobservable. The composed error term (ε_i) in the ZISF (Kumbhakar *et al*. 2013; Rho & Schmidt 2015) is expressed as:

$$v_i - u_i(1 - 1\{u_i = 0\}), \tag{3}$$

where $p = 1\{u_i = 0\}$ for technically efficient firms. Following Kumbhakar *et al*. (2013) and Rho and Schmidt (2015), the probability of a firm belonging to the technically efficient regime is explained by a set of factors, ω_i, and can be expressed using a discrete choice (logit or probit) estimation, as follows:

$$p_i(z_i = 1|\omega_i) = \frac{exp(\omega_i'\gamma)}{1+exp(\omega_i'\gamma)} \tag{4}$$

Alternatively, Equation (4) can also be written as $p_i = \Phi(\omega_i'\gamma)$, for $i = 1, \ldots n$, where z_i indicates a firm's regime (fully efficient or otherwise), ω_i is a $m \times 1$ vector of determinants of firm technical inefficiency or otherwise, γ is an $m \times 1$ vector of parameters, and $\Phi(\cdot)$ is the cumulative distribution function. The variance of the inefficiency distribution is σ_u^2, and the total variance, $\sigma^2 = \sigma_u^2 + \sigma_v^2$; $\lambda = \sigma_u/\sigma_v$; $\sigma_0 = \lambda/\sigma$. Where $\lambda \to 0$, it means firms are producing very close to the production frontier (Kumbhakar *et al*. 2013).

Given a pre-specified cut-off point for firm-specific estimated posterior probabilities, $\check{p}_i$, the zero-inefficiency-Jondrow, Lovell, Materov and Schmidt (ZI-JLMS) scores for inefficient firms are obtained using Equation (5), with $p = 0$.

$$\check{p}_i = \frac{(\hat{p}/\hat{\sigma}_v)\phi(\hat{\varepsilon}_i/\hat{\sigma}_v)}{(\hat{p}/\hat{\sigma}_v)\phi(\hat{\varepsilon}_i/\hat{\sigma}_v) + (1-\hat{p})\frac{2}{\hat{\sigma}}\phi(\hat{\varepsilon}_i/\hat{\sigma})\Phi(-\hat{\varepsilon}_i/\hat{\sigma}_0)} \tag{5}$$

Furthermore, with the value of $\check{p}_i$ and the posterior odds ratio, $R_i = \check{p}_i(1 - \check{p}_i)$, it is possible to calculate the probability of a firm being fully efficient.

Therefore, the conditional expectation for the technical inefficiency distribution for the ZISF (Kumbhakar *et al*. 2013; Rho & Schmidt 2015) is given as:

$$E[u|\varepsilon] = (1 - p)\ \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}\ \left[\sigma_0\ \frac{\phi(\varepsilon/\sigma_0)}{\Phi(-\varepsilon/\sigma_0)} - \varepsilon\right] \tag{6}$$

The conditional distribution of u given ε is normal, with probability p, and truncated normal, $N_+(\mu_*, \sigma_*^2)$, with probability $1 - p$. Where $p = 0$, the distribution becomes the half normal, $N^+(0, \sigma_u^2)$, with $\sigma_*^2 = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$; $\mu_* = -\varepsilon\sigma_u^2/\sigma^2$.

Following Rho and Schmidt (2015), the log likelihood for the ZISF model is expressed as:

$$\ln L(\beta, \sigma_u^2, \sigma_v^2, p) = \sum_{i=0}^{n} lnf_p\,(y_i - x_i'\beta - D_i) \tag{7}$$

$$lnY_i = \beta_0 + \sum_{k=1}^{5} \beta_k\, lnX_{ik} + {}^1\!/_2 \sum_{k=1}^{5}\sum_{j=1}^{5} \beta_{kj}\, lnX_{ik}\, lnX_{ij} + D_i + v_i + u_i\text{s}, \tag{8}$$

where ln represents the logarithm to base $\boldsymbol{e}$; Y is rice output; and X_i represents the five inputs for the translog model. The improved rice varieties cultivated by farmers in the 2012/2013 season were

FARO 15, GR varieties (GR 17 to GR 22), GRUG7, Digang, NERICA varieties, Jasmine 85, Togo Marshall, WITA 7, Jet 3, Aromatic Short, Sikamo, Bumbaz, Bodia, IR20 and Sakai.

Table 1: Summary definition of variables

Variable	Notation	Description
Stochastic frontier		
Rice output	Y	Rice output (in kg)
Farm size	X_1	Hectares of rice plot
Rice seed	X_2	Quantity of rice seed (in kg) planted
Fertiliser	X_3	Quantity of fertiliser used (in kg)
Farm labour	X_4	Farm labour (person-days) used
Herbicides	X_5	Herbicides (in litres) used on plot
Fertiliser application	D_i	1 = household applied fertiliser on rice farm, 0, otherwise
Technical efficiency		
Sex of household head	M_1	1 = female; 0 = male
Age	M_2	Number of years of household head
Agricultural extension services	M_3	1 = household accesses agricultural extension; 0 = otherwise
Educational Status	M_4	Number of years of formal education of household head
Rice seed priming	M_5	1 = practising seed priming; 0 = otherwise
Row planting	M_6	1 = practising row planting; 0 = broadcasting
Seedling transplanting	M_7	1 = seedling transplanting; 0 = direct sowing
Sawah system	M_8	1= practise sawah system; 0 = otherwise
Land preparation with herbicides	M_9	1 = land preparation using herbicides; 0 = otherwise
Weeding using herbicides	M_{10}	1 = used herbicides for weed control; 0 = hand hoe weeding
Weeding frequency	M_{11}	Number of times rice plot was weeded
Actyva fertiliser use	M_{12}	1 = applied on rice farm; 0 = otherwise
Ammonia fertiliser use	M_{13}	1 = applied on rice farm; 0 = otherwise
Fertiliser rate	M_{14}	1 = if recommended rate of at least 350kg/ha is applied; 0 = otherwise
Rice harvesting method	M_{15}	1 = combine harvester; 0 = sickle
Land preparation	M_{16}	1 = herbicide applied; 0 = otherwise
Pesticide use	M_{17}	1 = pesticide applied; 0 = otherwise

Source: Authors' construction based on survey dataset

2.3 Testing for presence of fully efficient and/or inefficient rice farmers

Unlike the traditional stochastic frontier, in which case the log likelihood ratio is used to test the existence of fully efficient firms, in the ZISF, a pseudo-likelihood ratio (PLR) test is used (Kumbhakar *et al*. 2013). This is because the parameter, p,[8] of the ZISF lies on the boundary (Andrews 2001; Chen & Liang 2010), and it is inappropriate to test the hypothesis on full efficiency or otherwise ($H_0 : p = 1$, or inefficiency, $H_0 : p = 0$). However, Rho and Schmidt (2015) raise identification issues; when $p = 1$ ($H_0 : p = 1$ or $p > 0$), σ_u^2 is not identified, and when $\sigma_u^2 = 0$, p is not identified. Instead, Rho and Schmidt (2015) propose a restriction of the variance parameters (σ_u^2 and σ_v^2), such that $\sigma_u^2 > 0$ and $\sigma_v^2 > 0$ remain in the interior of the parameter space.

Kumbhakar *et al*. (2013) express the PLR test as:

$$PLR = -2(L_N - L_{ZI}), \tag{9}$$

where L_N is the log likelihood obtained from the ordinary least squares estimation, and L_{ZI} is the value of the log likelihood of the ZISF model.

[8] p is the probability of being fully technically efficient.

Nonetheless, in the ZISF model, where $H_0 : p = 1$ is rejected, it does not mean all firms are technically inefficient, as is the case in traditional frontier estimations (Kumbhakar *et al*. 2013), but a proportion of firms in the sample are technically inefficient (Rho & Schimdt 2015). Meanwhile, when p = 1, it implies all firms are fully efficient and σ_u^2 is not identified, and when $\sigma_u^2 = 0, p$ is also not identified (Rho & Schimdt 2015). The test of full efficiency across firms is done using the null hypothesis, $H_0 : \sigma_u = 0$, and where it is rejected, it infers inefficiency across firms for the ZISF, although the focus is estimating the probability of a firm being fully efficient (Kumbhakar *et al*. 2013).

2.4 Estimating the determinants of technical efficiency of the ZISF using fractional probit

The traditional stochastic frontier analysis, which assumes farms have some level of inefficiency, estimates the production function and the determinants of technical inefficiency using a one-step approach. This is not the case for the ZISF, because the ZISF identifies fully efficient farms along with inefficient ones within a common production technology. For fully efficient farms, ($u_i = 0$) and σ_u^2 is not identified (Rho & Schimdt 2015). The stochastic frontier outputs vary about the deterministic part of the model, $exp(X_i\beta)$, and are what determine the farm-specific technical efficiency scores (Coelli *et al*. 1998).

Therefore, factors within the control of the farm are responsible for its efficiency/inefficiency. Thus, to estimate the determinants of technical efficiency for the whole sample, which consists of both fully efficient and inefficient farms, the fractional regression was applied. The traditional stochastic frontier analysis (SFA) only estimates the determinants of output and technical efficiency scores for inefficient farms, but the interest is in the efficient farms as well, hence the use of the two-stage approach involving the ZISF and fractional regression.

Many studies (Coelli *et al*. 2002; Isik & Hassan 2003; Hauner 2005; Havrylchyk 2006; Rezitis 2006; Ji & Lee 2010; Abdulai *et al*. 2018) have analysed the determinants of technical efficiency using the tobit model. Nonetheless, this model cannot be applied to fractional responses with a continuous distribution, unless there is an abundance of zeros and ones in the dataset of the dependent variable (Wooldridge 2002). It also requires the dependent variable to be normal and homoscedastic (Ramalho *et al*. 2011). Maddala (1991) argues that observations at the lower and upper bounds of a fractional dataset are themselves choices individuals make, and not because of any type of censoring.

The technical efficiency scores obtained from the ZISF estimation are continuous variables, with an upper bound of one and a lower bound greater than zero. The fractional response model accommodates the bounded nature (0, 1) of the dependent variable (technical efficiency scores) and the nonlinearity of the dataset, and ensures that the predicted values remain within the interval of the dependent variable (Gallani & Krishnan 2017). A fractional response model is able to handle estimations with continuous variables between zero and one employing a probit, logit, heteroskedastic probit as well as beta regression (Wooldridge 2002).

A fractional probit regression is based on the Bernoulli distribution and estimated by quasi-maximum likelihood, which yields consistent estimates of $\hat{\beta}$, irrespective of the distribution of y_i and conditional on m_i (Papke & Wooldridge 1996), as:

$$E(y_i|m_{i_i}) = \Phi(m_i\beta), \tag{10}$$

where y_i is the dependent fractional variable, m_i is a vector of explanatory variables in Table 1 that explains technical efficiency, and $\Phi(m_i\beta)$ is a probit function that ensures the predicted values of the dependent variable remain within the interval of y_i. The Bernoulli log-likelihood function proposed by Papke and Wooldridge (1996) is given as:

$$l_i(b) \equiv y_i \log[\Phi(m_i\beta)] + (1 - y_i)log[1 - \Phi(m_i\beta)] \tag{11}$$

The quasi-maximum likelihood is a linear exponential estimator from which β is obtained by maximisation as follows:

$$\max_b \sum_{i=1}^{N} l_i(b) \tag{12}$$

The estimated parameters of the fractional probit regression are interpreted as average partial effects (APEs) on the mean response and not as probabilities, as would be the case for a probit model (Papke & Wooldridge 1996).

3. Results and discussion

3.1 Determinants of rice output

This section discusses the determinants of rice output using the zero-inefficiency stochastic frontier. The results of the pseudo-likelihood ratio in Table 2 reject the null hypothesis that all rice farms are fully technically efficient.

Table 2: Testing for presence of fully efficient firms, p = 1

Sample	Null hypothesis	Log likelihood function (H_0) OLS	Test statistic	Critical value	Decision
Adopters	$H_0 : p = 1$	-343.066	16.677	3.841 (1)	Reject H_0: All farms not fully efficient

Notes: Critical value is at the 5% significance level and obtained from the χ^2 distribution table; the figure in brackets is the number of restrictions; $PLR = -2(L_N - L_{ZI})$

The first-order coefficients of the inputs are partial production elasticities because they were normalised against their geometric mean values before the translog estimation (Coelli *et al*. 2003). The coefficient (0.596) of farm size had a positive and statistically significant effect on rice output at the 1% level of significance. This means that when farm size is increased by 100%, holding all other inputs constant, rice output would increase by nearly 60%.

The coefficient (0.124) of quantity of rice seed planted had a positive and statistically significant effect (at 10%) on output. This implies a partial production elasticity of 0.124 on rice output given a unit increase in the quantity of seed planted.

The coefficient of quantity of inorganic fertiliser was positive and statistically significant at 1%. Thus, the partial production elasticity of fertiliser application on rice output was 0.739 for a unit increase in the quantity of fertiliser applied.

Table 3: Results of the zero-inefficiency stochastic frontier

Variable	Coefficient	Standard error
Constant	8.810***	0.107
Farm size (ha)	0.596***	0.071
Seed (kg)	0.124*	0.068
Fertiliser (kg)	0.739***	0.063
Labour (person days)	0.103*	0.053
Herbicides (litres)	0.088	0.068
Farm size squared	0.365	0.228
Seed squared	0.056	0.149
Fertiliser squared	0.332**	0.146
Labour squared	-0.060	0.070
Herbicides squared	0.243**	0.122
Farm size*seed	-0.120	0.154
Farm size*fertiliser	0.263**	0.124
Farm size*labour	-0.152	0.096
Farm size*herbicides	-0.006	0.119
Seed*fertiliser	-0.223*	0.126
Seed*labour	0.027	0.085
Seed*herbicides	-0.065	0.115
Fertiliser*labour	-0.027	0.102
Fertiliser*herbicides	-0.102	0.121
Labour*herbicides	0.017	0.079
Lambda (λ)	1.071	0.519
Sigma-u	0.922***	0.083
Sigma-v	0.383***	0.083
Zero inefficiency problem	0.390**	0.152
Mean efficiency	0.678	
Returns to scale	1.650	
Log-likelihood function	-334.728	
No. of observations	333	

Note: ***, ** and * indicate values that are statistically significant at 1%, 5% and 10%, respectively.

The coefficient of the quantity of labour (in person days) had a positive and statistically significant influence at 10% on rice output. However, herbicide application had no statistically significant effect on rice output.

In fulfilment of the monotonicity condition (Sauer *et al*. 2006), the coefficients of farm size, seed, fertiliser, labour and herbicides all had positive signs. The returns to scale value was 1.650, which implied increasing returns to scale in rice production.

The coefficients of the square of fertiliser and herbicides were positive and statistically significant, at 5%. This is contrary to the *a priori* expectation (a negative sign of the coefficient of the square of an input) of diminishing marginal productivity of the conventional inputs.

The coefficient of the interaction term of farm size and fertiliser was positive and statistically significant, at 5%. The positive sign implies that farm size and fertiliser were complementary inputs in rice production. Meanwhile, the negative coefficient (-0.223) of the interaction term of seed and fertiliser means the two inputs were substitutes in rice production.

The probability of fully technically efficient rice farms was 0.390. This means that 39% of rice farms were fully technically efficient, with zero technical inefficiency. The zero-inefficiency stochastic frontier identified fully technically efficient rice farms within the same sample and production frontier (Kumbhakar *et al*. 2013; Rho & Schmidt, 2015). Therefore, the zero-inefficiency stochastic frontier produced unbiased estimates of technical efficiency scores, as there are some fully efficient rice farms within the sample. Meanwhile, the mean technical efficiency estimate was 0.678.

3.2 Distribution of technical efficiency estimates for the ZISF

The results of the distribution of technical efficiency scores in Table 4 reveals less than half (47.75%) of rice farms were fully technically efficient, and the rest were technically inefficient.

Table 4: Distribution of technical efficiency for the ZISF

Category	Frequency	Percent (%)
Fully efficient	159	47.75
Technically inefficient	174	52.25
Total	333	100

Source: Authors' computation based on survey data

In addition, the distribution of efficiency scores for the technically inefficient rice farms in Table 5 reveals about 28% of rice farms had a score of less than or equal to 0.50. Meanwhile, more than 62% had a technical efficiency score within the 0.51 to 0.70 range.

Table 5: ZISF technical efficiency distribution

Technical efficiency range	Frequency	Percent (%)
≤ 0.50	49	**28.2**
0.51-0.60	54	**31.0**
0.61-0.70	55	**31.6**
0.71-0.80	14	8.1
0.81-0.90	2	1.1
0.91-0.99	0	0.0
Total	174	100.0

Source: Authors' computation based on survey data

3.3 Determinants of technical efficiency in rice production for the ZISF

A fractional response model was employed to estimate the determinants of technical efficiency using the zero-inefficiency stochastic frontier efficiency scores. The efficiency scores are continuous variables with an upper bound of one and a lower bound greater than zero. A fractional response model is able to handle estimations with continuous variables between zero and one, employing a probit or logit (Wooldridge 2002). The parameters of the fractional probit regression are average partial effects on the mean response, and not probabilities – as is normally the case for a probit model (Papke & Wooldridge 1996).

Table 6 shows that a variable with a positive sign has a positive effect on technical efficiency, and vice versa. The practise of the sawah system (1 if practised, 0 if not practised) and weeding frequency statistically influenced technical efficiency in rice production.

The practising of lowland rice plot water management strategies, such as levelling and bunding – collectively known as the sawah system (Buri *et al*. 2012; Ragasa *et al*. 2013; Abdulai *et al*. 2018) – increased technical efficiency in rice production.

Table 6: Fractional probit results of determinants of technical efficiency for the ZISF

Variable	Coefficient	Standard error
Constant	0.066	0.201
Sex of household head	-0.093	0.115
Age of household head	0.000	0.004
Agricultural extension	0.103	0.097
Education of household head	0.010	0.009
Rice seed priming	0.039	0.111
Transplanting seedlings	0.090	0.117
Row planting	-0.095	0.101
Sawah system	0.252*	0.102
Land preparation using herbicide	0.115	0.095
Weeding using herbicide	0.149	0.096
Weeding frequency	0.147***	0.056
Use of Actyva fertiliser	0.008	0.278
Use of ammonia fertiliser	0.051	0.125
Fertiliser rate	-0.014	0.148
Method of rice harvesting	0.088	0.164
Pesticide use	-0.134	0.101
Log pseudolikelihood	-172.859	
No. of observations	333	

*** and * indicate values statistically significant at 1% and 10%, respectively.

The coefficient of weeding frequency was positive, implying that farmers who weeded their rice farms more than once were more technically efficient than those who did not. The recommended practice in Ghana is weeding twice during the cultivation period (Ragasa *et al*. 2013).

4. Conclusion and recommendations

This study used the zero-inefficiency stochastic frontier (ZISF) to assess the technical efficiency of 333 households that cultivated improved rice varieties in the 2012/2013 farming season. The ZISF produced unbiased estimates of technical efficiency scores alongside fully efficient farms within the sample. The probability of rice farms with zero technical inefficiency was 0.390, implying that 39% of rice farms were fully technically efficient under the same production frontier. The mean technical efficiency estimate amongst the inefficient farms was 0.678. This means rice farms were producing at 68% of their potential output, and could raise their output by 32% without changing the levels of inputs used if they improved their efficiency and operated on the production frontier. The returns to scale value of 1.65 indicated increasing returns to scale. Thus, rice production in Ghana was in stage one of the production function, implying an increase in the use of conventional inputs would lead to a more than proportionate increase in output. Farm size, seed, labour and fertiliser had a positive and statistically significant effect on rice output. Similarly, controlling rice field water levels through levelling and bunding, known as the sawah system, and weeding the rice field at least two times during the cultivation season, increased technical efficiency. This study recommends the cultivation of improved rice varieties, use of fertilisers, expanding farm size, and easing labour constraints during cultivation to raise rice output, alongside weeding and managing rice plot water levels to increase production efficiency. Specifically, phase two of the 'Planting for Food and Jobs' programme of Ghana's Ministry of Food and Agriculture should facilitate easy access to improved rice seed varieties and fertiliser to increase output. Government land reforms should facilitate access to farmlands, as farm size had a positive effect on rice output.

Moreover, the agricultural extension service in Ghana should be strengthened and resourced to offer advisory services to farmers on best practices in rice cultivation. To this end, targeted support can be extended to the inefficient farms to assist them to close the productivity gap. Lastly, the Ministry of

Food and Agriculture should support farmers to have easy access to agricultural mechanisation services and other labour-saving technologies to enhance rice productivity.

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