International Journal of Statistical Sciences ISSN 1683-5603
Vol. 24(2), November, 2024, pp 97-108
DOI: https://doi.org/10.3329/ijss.v24i2.77995

Prediction of Technical Efficiency of Aman Rice Farms in Satkhira District of Bangladesh: A Stochastic Frontier Approach

Kazi Julfikar Ali[1*], Md. Abdul Khalek[2] and Md. Abdur Rashid Sarker[1]

[1]Department of Economics, University of Rajshahi, Bangladesh
[2]Department of Statistics, University of Rajshahi, Bangladesh
Email: mak.stat09@gmail.com
[*]Correspondence should be addressed to Kazi Julfikar Ali
(Email: julfikar.eco@ru.ac.bd)

[Received September 29, 2024; Accepted November 15, 2024]

Abstract

This paper aimed to assess the technical efficiency (TE) of *aman* rice farms and analyzed the major factors affecting inefficiency of *aman* rice farms. In doing so, a multistage random sampling method was used to collect primary data from a survey of 455 rice farmers between May and June in 2023 in Kaligonj sub-district of Satkhira district. Stochastic frontier approach (SFA) was employed to predict the efficiency of *aman* rice farms while the Tobit model was used to identify the factors that influence technical inefficiency. The findings of TE ranged from 0.98 to 0.51 with an average score of 0.8469. Technical inefficiency is largely affected by years of schooling, household size, salinity of land, agriculture policy and access to credit variables. The policy implications of this finding is that the government might provide the agricultural extension network so that the extension agent can better engage with targeted farmers rather than just recommendations.

Keywords: Technical efficiency, Returns to scale, Stochastic frontier production function, Bangladesh.

AMS Classification: 60H30, 90B30.

1. Introduction

The agriculture sector plays a crucial role in Bangladesh as it generates highest employment, reduces poverty significantly, and ensures food security. This sector accounts for 40.60% of employment and contributes 11.50% to the nation's GDP (BBS, 2022). The crop agricultural sector in our country heavily relies on rice cultivation, with nearly 13 million farm families engaged in rice farming (BRRI, 2022). In fact, rice production alone contributes to about half of the agricultural GDP, as reported by BRRI in 2023. Rice production is currently facing several challenges, such as climate change, extreme weather, soil erosion, low productivity, etc. These challenges need to be addressed. The issue of low productivity has been tackling through government programs and development partners, which have placed great importance on spreading and implementing agricultural technologies. Nevertheless, the rise in rice productivity is influenced not only by the adoption of technology, but also by the enhancement of farmers' technical efficiency. In a country like Bangladesh, where resources are limited and technological adoption is low, improvements in rice farming through technical efficiency appear to be highly beneficial.

Technical efficiency evaluates farmers' capacity to achieve optimal production levels with a given input level (Farell, 1957). Several studies have been accomplished to analyze the profitability and efficiency in agriculture farming in developing countries including Bangladesh and other nations. Ali et al. (2024) measured technical and scale efficiencies of rice farms in Satkhira district of Bangladesh. They found that the agriculture policy variable positively associated with the technical efficiency of *aman* rice farms. Sarker et al. (2022) compared the technical efficiency of rice production in saline and non-saline environments. Saline areas experienced lower yield despite being more technically efficient. There was more use of irrigation and family labour in saline areas compared to non-saline areas. Roy et al. (2019) analyzed the profitability, yield gap, and inefficiency of *aman* rice production in coastal regions of Bangladesh with findings of yield gaps ranging from 0.134 to 1.014 tons per hectare. They predicted that the average technical efficiency was 81.89%. Rahman et al. (2015) examined the effect of controlling saline water intrusion into the coastal rice field in terms of resource profitability and technical efficiency of rice farmers in Bangladesh. They found that technical efficiency of rice production varied with the controlled of saline water intrusion. This study has the potential to make valuable contributions to the existing body of literature in several ways. Firstly, this study will enrich the existing scanty body of research. Secondly, this study uses a larger data set as compared to previous studies so this study has the potential to produce richer results. Thirdly, there is a scarcity of research that integrates government agricultural policy variable and salinity variable into this particular context. Finally, this study examines the assessment of elasticity of production and returns to scale of *aman* rice farming.

The objective of this study is to predict technical efficiency and identify the factor affecting variables of *aman* rice farms in Satkhira district of Bangladesh. In order to achieve this objective, SFA method is utilized for the purpose of predicting technical efficiency scores at the farm level and the Tobit model is employed for identifying the factor affecting variable of *aman* rice farms. The rest of the paper is organized as follows: Section 2 discusses the theoretical framework and methodology. The results and discussion are illustrated in Section 4. Finally, the conclusions and policy implications are presented in Section 5.

2. Theoretical framework and methodology of the study

2.1 Selection of the study area, sampling technique and data collection

This study was conducted in eight villages of Kaligonj sub-district in Satkhira district of Bangladesh. The sampled farmers were selected using a multistage sampling technique. In the first stage Satkhira district and Kaligonj sub-district were selected non-randomly due to the severe salinity problems with *aman* rice cultivation. In the second stage, the two *unions* and eight villages were chosen randomly. In the third stage, a sampling frame was prepared from a numbered list of all farmers collected from field level sub assistant agricultural officer. A total of 455 farm households' head were selected with the use of computer generated random numbers. In the final stage, farm households were surveyed randomly using structured questionnaire with use of face to face interview during the months of May and June in 2023. The survey focuses on predicting technical efficiency, elasticity of production, returns to scale and identify the factors for *aman* rice farms.

2.2 Theoretical framework

The stochastic frontier function was separately formulated by Aigner et al. (1977) and Meeusen and Van den Broeck (1977). The stochastic frontier function is a parametric approach because it combines stochastic and deterministic elements. The deterministic component represents the maximum expected output achievable with a given set of inputs, while the stochastic component accounts for random errors or inefficiencies that impact the production process. This function determines the maximum expected output with a given level of inputs and technology that measures the technical efficiency. The stochastic frontier function is specified as Equation no. (1).

$$Y_i = f(X_i, \alpha) + \epsilon_i \tag{1}$$

where $i = 1, 2, \dots, n$ indexes the producers, Y_i represents the scalar output, X_i represents a vector of N inputs and $f(.)$ also represents the production frontier which relies on inputs and a technological parameter vector, α represents an unknown parameter that needs to be estimated, ϵ_i is the composite error term that consists of two sided error term ν_i and one-sided error term μ_i. The two components ν and μ are assumed to be independent of each other across observation. The term ν_i represents statistical noise which is normally distributed, hence, $N(\mu, \sigma^2)$ and μ_i signifies a non-negative error terms that represents technical inefficiency which measures the shortfall of output from its maximum frontier. The term μ_i is crucial in the calculation of inefficiency because the inefficiency is not only sensible to inefficiency terms but also random errors. The output oriented technical efficiency of farm is defined as the ratio of the observed output to the maximum feasible output given inputs and technology (Coelli et al., 2005).

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(X_i, \alpha)\exp(\nu_i - \mu_i)}{f(X_i, \alpha)\exp(\nu_i)} = \exp(-\mu_i) \tag{2}$$

The observed output is Y_i and the frontier output is Y_i^*. Since $\leq Y^*$, the measurement of technical efficiency takes a value between 0 and 1.The technical efficiency of the ith farm can also be calculated as $TE_i = \exp(-\mu_i) \times 100$. The maximum likelihood estimation approach may be used to estimate the parameters of the stochastic frontier production function.

2.3 Tobit model

The Tobit model is intended to represent the linear association between independent factors and a censored dependent variable. The Tobit model is utilized when the dependent variable is censored on either the left, right, or both ends. After calculating scores of inefficiency, the Tobit model was used to identify the sources of inefficiencies. The technical inefficiency of the i^{th} farm is computed by $TIE_i = 1 - \widehat{TE}_i$. The Tobit model is specified in the following equation (Tobin, 1958).

$$TIE_i = TIE_i^* = \delta_0 + \sum_{i=1}^{8} \delta_i Z_i + \omega_i, \tag{3}$$

$$TIE = \begin{cases} 0 & if\ TIE_i^* \leq 0 \\ TIE_i^* & if \quad 0 < TIE_i^* < 1 \\ 1 & if \quad TIE_i^* \geq 1 \end{cases} \tag{4}$$

The TIE_i represents the estimated technical inefficiency of the i^{th} farm which is observed dependent variable, TIE_i^* represents the latent (unobservable) variable and Z_i corresponds to the factors that affect the technical inefficiency. The δ_0 and δ_i represent parameters that are to be estimated. The ω_i represents the error term with mean zero and variance σ^2.

2.4 Output elasticity and returns to scale (RTS)

The elasticity of output measures the extent to which output responds to a unit change in input used. The coefficient of independent variables of the Cobb-Douglas function shows the output elasticity of production. Returns to scale reveals the rate of increase in production provided that all other inputs are equally increased. The rate of return on production may be determined by adding up all of the individual elasticity, which also provides an indication of the stage of production.

$$RTS = \sum_{i=1}^{8} \alpha_i \tag{5}$$

Where, RTS represents returns to scale; $\alpha_1, \alpha_2, \ldots, \alpha_8$ signifies coefficient parameters that need to be estimated.

2.5 Model specification

In this study, Cobb-Douglas stochastic frontier production function was used to predict the efficiency at farm levels for the following reasons: first we are interested in comparing the production effect of various inputs on *aman* rice production. Second, random errors are crucial in our calculation because the inefficiency of *aman* rice production is sensible not only to inefficiency term but also to random errors. The Cobb-Douglas stochastic frontier production function model is specified as Equation (5).

$$\ln Y_i = \alpha_0 + \alpha_1 \ln X_{1i} + \alpha_2 X_{2i} + \alpha_3 X_{3i} + \alpha_4 X_{4i} + \alpha_5 X_{5i} + \alpha_6 X_{6i} + \alpha_7 X_{7i} + \alpha_8 X_{8i} + \nu_i - \mu_i \tag{6}$$

where ln = natural logarithm; X_{1i} = land; X_{2i} =labour; X_{3i} = capital; X_{4i} = seed; X_{5i} = irrigation; X_{6i} = NPK fertilizer; X_{7i} = organic fertilizer; X_{8i} = pesticide; ν_i = random error term; μ_i = non-negative error term; α_0 = intercept; $\alpha_1, \alpha_2, \ldots, \alpha_8$ = coefficient of inputs.

2.6 The Tobit model

The stochastic frontier approach (SFA) is a statistical framework used for estimating and quantifying the level of efficiency in production processes. The Tobit model for *aman* rice farms is specified in following equation.

$$TIE_i = \delta_0 + \delta_1 Z_{1i} + \delta_2 Z_{2i} + \delta_3 Z_{3i} + \delta_4 Z_{4i} + \delta_5 Z_{5i} + \delta_6 Z_{6i} + \delta_7 Z_{7i} + \delta_8 Z_{8i} + \omega_i \tag{7}$$

The TIE_i = estimated technical inefficiency of the i^{th} *aman* rice farm ; Z_{1i} = age ; Z_{2i} = education; Z_{3i} = experience; Z_{4i} = household size ; Z_{5i} = extension contact; Z_{6i} = salinity of land; Z_{7i} = agricultural policy; Z_{8i} = access to credit and ω_i= the random error term.

2.7 Variables for predicting of technical efficiency of *aman* rice farms

To predict efficiency, eight inputs were employed in the stochastic frontier model: land, labour, capital, seed, irrigation, NPK fertilizer, organic fertilizer, and pesticide while *aman* rice production was kept as the output variable which is shown in Table 1.

Table 1: Description of variables for predicting technical efficiency

Variable	Description	Expected sign
Output		
Aman rice	Total *aman* rice production per *bigha* in Kg (1 *bigha*=33 Decimal)	
Input		
Land	Total land under *aman* rice cultivation (Decimal)	+
Labour	Total number of man days (Days)	+
Capital	Monetary worth of equipment and machinery (BDT)	+
Seed	Total amount of seeds used (Kg)	+
Irrigation	Groundwater used for *aman* farming (Number)	+
NPK fertilizer	Amount of NPK fertilizer used (Kg)	+
Organic fertilizer	Number of *van* (Roughly 1 van = 100Kg)	+
Pesticide	Amount of pesticide used (Milliliters)	+

2.8 Variables for the technical inefficiency effect for *aman* rice farms

The explanatory variables such as age, education, experience, household size, extension contact, salinity of the land, agricultural policy and access to credit that were employed to identify factors affecting variables for *aman* rice farms. The list of the explanatory variable for Tobit model is shown in Table 2.

Table 2: Description of explanatory variables of Tobit model

Variable	Description	Expected sign
Age	Total age of the farmers (Years)	-
Education	Farmers have received formal education (Years of schooling)	-
Experience	Experience in rice farming (Years)	-
Household size	Total family member (Number)	-
Extension contact	Dummy variable which takes 1 if the *aman* rice farmer receives extension service and 0 otherwise.	-
Salinity of the land	Dummy variable which takes 1 if the *aman* rice farmer faces salinity problem and 0 otherwise.	+
Agricultural policy	Dummy variable which takes 1, if farmers have bank account of 10 BDT and 0 otherwise	-
Access to credit	Dummy variable which takes 1,if farmers have access to credit and 0, otherwise	-

3. Results and discussion

3.1 Results of Cobb-Douglas stochastic production function model for *aman* rice farms

The estimated parameters are summarized and displayed in Table 3. The key indicators of the results of the MLE estimation are the variance (σ^2) and gamma (γ) values. The gamma (γ) value indicates the extent to which inefficiency variance affects the production function and the importance of the gamma (γ) parameter highlights the role of inefficiency in the model. Both the parameters variance and gamma were significant with values 0.04 and 0.82, respectively. This finding aligns with the research conducted by Wadud (2003) and Coelli and Battese (1996). Estimated parameters are used in the stochastic frontier production function to evaluate the factors affecting the production of *aman* rice farms.

Table 3: Maximum likelihood estimates of stochastic frontier model for *aman* rice farms of technical efficiency

Variable	Estimate	SE	*z*-value	*p*-value
Intercept	4.1965	0.2291	18.3206	0.000
Land	0.0159	0.0094	1.6857	0.092
Labour	0.1554	0.0454	3.4207	0.001
Capital	0.0156	0.0196	0.7921	0.428
Seed	0.1088	0.0277	3.9222	0.000
Irrigation	0.0710	0.0197	3.5997	0.000
NPK fertilizer	0.1100	0.0286	3.8461	0.000
Organic fertilizer	0.0805	0.0180	4.4628	0.000
Pesticide	0.1576	0.0235	6.7168	0.000
Sigma squared	0.0403	0.0053	7.6789	0.000
Gamma	0.8181	0.0652	12.5481	0.000

Source: Authors' calculation based on the field survey, 2023

The coefficient for land was found to be significant at 10 percent level with $p < 0.10$. The estimated coefficient was 0.0159 which indicates that there is a positive association with land and rice output. The expansion of agricultural land by 1% will result in a corresponding increase of 0.02% in *aman* rice production. The result is consistent with the study of Barokah et al., 2022, Chandio et al., 2019, and Itam et al., 2015.

The coefficient of the labor variable was 0.1553 and has a high level of significance with $p < 0.01$. This positive correlation between the quantity of labor and rice output indicates that as the amount of labor increases, the production of rice also increases. The majority of farmers in the study region are smallholder farmers who mainly depend on physical labor for their farming operations. This finding is consistent with Khondaker and Baba 2023, Barokah et al., 2022, Ojo et al., 2020, Chandio et al., 2019, Hasnain et al, 2015, Sikdar et al., 2008.

The coefficient of seed variable was 0.1088 indicating its statistical significance at $p < 0.01$. The seed variable has a positively influence on *aman* rice production. Specifically, for every 1% increase in seed, there will be a corresponding 0.11% increase in production. The result aligns with the findings of Rondhi et al., 2024,Barokah et al., 2022, Itam et al., 2015, Hasnain et al., 2015.

The coefficient of the irrigation variable was estimated to be 0.0710 at the statistically significant with $p < 0.01$. The strong correlation between irrigation and technical efficiency indicates that the farmers in this study are effectively utilizing irrigation water in their *aman* rice farms. The result aligns with the findings of Sikdar, at al., 2008.

The coefficient for NPK fertilizer variable was estimated to be 0.1100 at the significance with $p < 0.01$. The NPK fertilizer variable has a strong correlation with technical efficiency. By increasing the amount of fertilizer used to 0.11%, producers have the potential to boost the rice yield by 1%. The finding aligns with the findings of Rondhi et al., 2024, Sikdar et al., 2008.

The coefficient of organic fertilizer was 0.0805, indicating its significance with $p < 0.01$. It was evident that organic fertilizer had a notable impact on increasing rice production. The finding suggests that a mere 1% increase in the use of organic fertilizer can result in an estimated 0.08% increase in rice production, all other factors remaining constant. It is evident that the use of organic fertilizer in their *aman* rice farms has resulted in a significant increase in output.

The coefficient of the pesticide variable was 0.1576 and statistically significant with $p < 0.01$. There is a clear correlation between pesticide use and rice production, suggesting that the use of pesticide can enhance overall technical efficiency. It is worth noting that a mere 1% increase in pesticide usage leads to a corresponding 0.16% increase in rice production, all other factors remaining constant.

3.2 Results of elasticity and returns to scale

The output elasticity and returns to scale are presented in Table 4. The finding of output elasticity shows that the highest elasticity of output is for pesticide which implies that pesticide is the prime factor of production. Labour is the next important factor followed by pesticide. Elasticity of output with respect to land, seed, irrigation, organic fertilizer and (NPK) fertilizer are also significantly positive. Furthermore, the last column of the Table 4 gives the returns to scale. The returns to scale is 0.699 which shows that farms operate in the region of decreasing returns to scale and signify the presence of diseconomies of scale. In this case, farmers have scope to boost up their scale of *aman* rice production without adding additional inputs.

Table 4: Output elasticity and returns to scale

Variable	Mean	Elasticity	Returns to scale
Land	120.620	0.016	
Labour	16.330	0.155	
Capital	9.978	0.016	
Seed	6.287	0.109	0.699
Irrigation	5.325	0.071	
Organic fertilizer	55.640	0.110	
NPK fertilizer	2.404	0.080	
Pesticide	404.700	0.158	

Source: Authors' calculation based on the field survey, 2023

Returns to scale of the *aman* rice production is less than unity which implies that *aman* rice producers operate in the region of decreasing returns to scale. It suggests that output grows at a slower rate than input increases, resulting in inefficiency.

3.3 Farm level technical efficiency

The frequency distribution of technical efficiency and their descriptive statistic of *aman* farms are presented in Table 5.

Table 5: Frequency distribution of technical efficiencies for *aman* rice farms

Efficiency Index	Number of farm	Percentage of farm
50-60	6	1.32
60-70	50	10.99
70-80	73	16.04
80-90	165	36.26
90-100	161	35.38
Total	**455**	**100**
Maximum	0.98	
Minimum	0.51	
Mean	0.847	
SD	0.096	

Source: Authors' calculation based on the field survey, 2023

The frequency distribution table of efficiency score of *aman* farms is created by the exclusive method. This is because this method can easily create histogram than inclusive method. Table 5 illustrates that the technical efficiency of the majority of the *aman* farms falls within the range of 51 and 98. Out of 455 sampled farms 35.38% of farms have technical efficiency than 90 while only 1.32% of the *aman* farms lies between 50 and 60. The mean technical efficiency of the *aman* farms is estimated at 0.85 with a minimum of 0.51 and a maximum of 0.98. It means that no farm is fully efficient. So, there is considerable scope for improvement in productivity through increased technical efficiency.

4. The determinants of inefficiency

The Tobit model is used to assess the factors affecting variables for *aman* rice farms in the study area.

4.1 Results of Tobit model for *aman* rice farms

Table 4 presents the results of Tobit model. It can be concluded that the coefficients for the explanatory variables in our model are not equal to zero. The model's dependent variable was inefficiency, and a part from salinity variable the negative signs imply that an increase in the explanatory variable would decrease the corresponding level of inefficiency. The parameter estimates showed that factors such as age, salinity, were positively related to inefficiency, while education, farming experience, household size, extension contact, agricultural policy, and access to credit were negatively related to inefficiency.

Table 6: Results of Tobit model for *aman* rice farms

Variable	Coefficient	SE	*z*-value	*p*-value
Intercept	0.1833	0.0213	8.62	0.000
Age	0.0004	0.0005	0.74	0.461
Education	-0.0025	0.0009	-2.69	0.007
Experience	-0.0008	0.0005	-1.64	0.101
Household size	-0.0037	0.0017	-2.14	0.032
Extension contact	-0.0118	0.0068	-1.73	0.083
Salinity of the land	0.0136	0.0080	1.71	0.088
Agricultural policy	-0.0203	0.0070	-2.89	0.004
Access to credit	-0.0164	0.0073	-2.24	0.025

Source: Authors' calculation based on the field survey, 2023

The coefficient of education was a statistically significant at 1% level. The coefficient of education -0.0025 was negative, indicating that there was a negative relation between education and inefficiency. It appears that a higher level of education is connected with a decrease in technical inefficiency. It also suggests that farming does require a high level of education for better rice farming activities in the study area This result aligns with the research conducted Piya et al., 2012 and the study by Sharif and Dar in 1996. Nevertheless, this outcome differs from the findings of Rondhi et al., 2024, Wadud (2003), Wadud and White (2000), and Coelli and Battese (1996).

The coefficient for farming experience is negative and statistically significant at 10 % level. The coefficient of farming experience -0.0008 was negative, indicating that there was a negative relation between experience and inefficiency. It is evident that farmers who have a higher level of expertise are generally more effective in their *aman* rice production. This indicates that technical inefficiency decreased due to rice farmers' skill in timing and using inputs properly. One possible explanation for the remarkable decrease in technical inefficiency due to experience could be that farmers who have been in the field for a longer time have likely become more skilled through hands-on experience in a challenging production setting. Several studies have also reached similar conclusions (Bozoglu and Ceyhan, 2007; Idiong 2007; Onyenweaku and Nwaru 2005; Huffman 2001; Kalirajan and Flinn, 1983).

The household size coefficient was a negative and statistical significance at 5% level. The coefficient for household size was - 0.0037 which indicated a negative correlation between household size and the inefficiency of *aman* rice farming. Therefore, family labor plays a crucial role during the farming period. This result is consistent with the study of Etefa et al., 2022.

The coefficient of extension contact was negative and statistically significant at 5% level. Visits to the extension had a significant adverse association with technical inefficiency. The findings revealed that regular extension visit created to reducing technical inefficiency. The extension visits can also serve as a valuable policy tool for the government to boost agricultural productivity. These visits enable farmers to gain insights into enhanced agricultural management practices and the more efficient use of scarce resources. The findings are in agreement with the research that was conducted by Sikdar et al., 2008.

The coefficient of salinity is was positive and significant at 5% level as expected. The salinity coefficient was 0.0136 which demonstrates a positive impact on inefficiency of *aman* rice farms. Considering the circumstances, the growth and yield of a rice plant in this study area are negatively impacted by salinity. Salinity leads to adverse environmental and hydrological conditions that hinder the *aman* rice production. The management of saline water significantly affected the agricultural productivity of T. *aman* rice cultivators (Rahman et al., 2015).

One of the key factors considered in the Tobit model was the inclusion of agricultural policy operationalized as an access to bank account to receive agricultural assistances. The coefficient of agricultural policy variable was highly significant at 1 % level. The coefficient of agricultural policy variable was - 0.0203which demonstrates a negative impact on technical inefficiency. The coefficient's negative value indicates a negative correlation between agricultural policy and inefficiency of *aman* rice farming.

The coefficient of access to credit was statistically significant at 5 % level. The credit access coefficient was -0.0164 and indicting that access to credit negatively influenced on the technical inefficiency. The coefficient's negative value suggests a negative correlation between access to credit and inefficiency in *aman* rice farming. Having access to credit, the rice farmers can greatly improve the efficiency of rice farms. When producers have access to credit, it enhances their ability to obtain inputs, leading to improved technical efficiency. This finding aligns with prior research (Yabi, 2009) that demonstrated a positive correlation between credit accessibility and the technical efficiency of agricultural operations. This is because farmers can purchase inputs in a timely manner and avoid any delays in their farming activities.

5. Conclusion and policy implications

The objective of this study was to predict technical efficiency and identify the factor affecting variables of *aman* rice farms in Satkhira district of Bangladesh. The technical efficiency of *aman* rice farms was investigated through the application of a stochastic frontier technique. The findings of the study revealed that the average scores of technical efficiency were 0.85, with 0.98 being the highest efficiency level and 0.51 representing the lowest efficiency level. The findings implied that it is possible to boost rice production by 15% without adding more input levels. The finding of output elasticity showed that the highest elasticity of output was for pesticide which implied that pesticide was the prime factor of production. The results of returns to scale revealed that *aman* farms operate in the region of decreasing returns to scale and signify the presence of diseconomies of scale. As a result, *aman* rice farmers can increase their output without increasing their inputs. The Tobit model was employed for identifying the factor affecting variable of *aman* rice farms The findings of Tobit model suggested that various factors, including education, experience, household size, extension contact, agricultural policy, and access to credit significantly impact on the inefficiency of *aman* rice farmers. These factors have significant policy implications for addressing the current inefficiency of *aman* rice farms. Based on these findings, the followings policy implications emerge in this study: The results of this study show that government can enhance the agricultural extension network. Instead of merely delivering recommendations, the government can also provide useful assistance to the crop agricultural sector by encouraging interactions between targeted farmers and extension agents. Moreover, salinity of the land was found to have a positive and significant influence on inefficiency of *aman* rice farms. Thus, the findings of this study hold significance for policymakers seeking to enhance technical efficiency of *aman* rice farms. Addressing the salinity problem in this study area is of utmost importance as it greatly impedes the efficiency of *aman* rice production. So, the government could provide salinity-tolerant *aman* rice varieties such as BRRI*dhan* 52, BRRI*dhan* 47, BRRI*dhan* 44, and BRRI *dhan*54 to farmers for mitigating the salinity induced *aman* rice loss and enhancing the productivity of *aman* rice farms. Field-level sub assistant agricultural officers (SAAOs) could be a good avenue for disseminating information on salinity- tolerant *aman* rice varieties among farmers.

References

[1] Aigner, D., Lovell, C. K. and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. Journal of Econometrics. 1977 Jul 1;6(1):21-37.

[2] Ali, K. J., Khalek, M. A. and Sarker, A. R (2024). An analysis of overall technical, pure and scale efficiencies of rice farms in Satkhira district of Bangladesh: A data envelopment approach. Khulna University Studies. 2024 June; 21(1):380-392

[3] Bäckman, S., Islam, K. Z. and Sumelius, J. (2011). Determinants of technical efficiency of rice farms in North-Central and North-Western regions in Bangladesh. The Journal of Developing Areas. 2011 Oct 1: 73-94.

[4] BBS (2023). Household Income and Expenditure Survey 2022, Bangladesh Bureau of Statistics, Ministry of Planning, Dhaka, Bangladesh.

[5] BBS (2023). Yearbook of Agricultural Statistics 2022, Bangladesh Bureau of Statistics, Ministry of Planning, Dhaka, Bangladesh.

[6] BBS (2022). Yearbook of Agricultural Statistics 2021, Bangladesh Bureau of Statistics, Ministry of Planning, Dhaka, Bangladesh.

[7] BRRI (2023). Bangladesh Rice Knowledge Bank, Bangladesh Rice Research institute, Gazipur, Bangladesh.

[8] BRRI (2022). Bangladesh Rice Knowledge Bank, Bangladesh Rice Research institute, Gazipur, Bangladesh.

[9] Barokah, U., Rahayu, W., Agustono, A. and Antriyandarti, E. (2022). Determinants of rice farming efficiency in Karanganyar Central Java in the period of one decade after reformation. Journal of Environmental Science and Sustainable Development.2022 July; 5(1):109-29.

[10] Battese, G. E. and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics. 1995 Jun; 20:325-32.

[11] Bozoğlu, M. and Ceyhan, V. (2007). Measuring the technical efficiency and exploring the inefficiency determinants of vegetable farms in Samsun province, Turkey. Agricultural Systems. 2007 Jun 1; 94(3):649-56.

[12] Chandio, A. A, Jiang, Y, Gessesse, A. T. and Dunya, R. (2019). The nexus of agricultural credit, farm size and technical efficiency in Sindh, Pakistan: A stochastic production frontier approach. Journal of the Saudi Society of Agricultural Sciences. 2019 Jul 1; 18(3):348-54.

[13] Coelli, T. J., Rao, D. S., O'donnell, C. J. and Battese, G. E. (2005). An introduction to efficiency and productivity analysis. Springer science & business media; 2005 Dec 6.

[14] Coelli, T. J. and Battese, G. E. (1996). Identification of factors which influence the technical inefficiency of Indian farmers. Australian Journal of Agricultural Economics. 1996 Aug;40(2):103-28.

[15] Etefa, T., Rahmeta, O. and Bekele, Y. (2022). Resource use efficiency of smallholder maize producers' in Bilo Nopa district, IIu Abador Zone, Oromia Region, Ethiopia: An application of stochastic frontier analysis. Ethiopian Journal of Applied Science and Technology. 2022 Jun; 13(1): 94-103.

[16] Farrell, M. J. (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society: Series A (General). 1957 May; 120(3):253-81.

[17] Huffman, W. E. (2001). Human capital: Education and agriculture. Handbook of Agricultural Economics. 2001 Jan 1; 1:333-81.

[18] Idiong IC. Estimation of farm level technical efficiency in small scale swamp rice production in cross river state of Nigeria: a stochastic frontier approach. World Journal of Agricultural Sciences. 2007;3(5):653-8.

[19] Itam, K.O., Ajah, E. A., Ofem, U. I. and Abam, O. E. (2015). Technical efficiency analysis of small scale cassava farmers in Cross River State, Nigeria: A stochastic production frontier approach. Applied Economics and Finance. 2015;2(4):10-8.

[20] Kalirajan, K.P. and Flinn, J. C. (1983). The measurement of farm specific technical efficiency. Pakistan Journal of Applied Economics. 1983;2(2):167-80.

[21] Khan, S., Shah, S. A., Ali, S., Ali, A., Almas, L. K. and Shaheen, S. (2022). Technical efficiency and economic analysis of rice crop in Khyber Pakhtunkhwa: A stochastic frontier approach. Agriculture. 2022 Apr 2;12(4):503.

[22] Khondaker, M. E. and Baba, M. U. (2023). An empirical study of Middle-income Farmers on Millet Production in Kano South Nigeria: A Stochastic Frontier Analysis Approach. International Journal of Statistical Science. 2023 November; 23(2): 39-46.

[23] Mathijs, E. and Vranken, L. (2000). Farm restructuring and efficiency in transition: Evidence from Bulgaria and Hungary 2000.

[24] Meeusen, W., van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. International Economic Review. 1977 Jun 1:435-44.

[25] Ojo, T. O., Ogundeji, A. A., Babu, S. C. and Alimi, T. (2020). Estimating financing gaps in rice production in Southwestern Nigeria. Journal of Economic Structures. 2020 Dec; 9:1-8.

[26] Onyenweaku, C. E. and Nwaru, J. C. (2005). Application of a stockastic frontier production function to the measurement of technical efficiency in food crop production in Imo State, Nigeria. Nigeria Agricultural Journal. 2005; 36:1-2.

[27] Piya, S., Kiminami, A. and Yagi, H. (2012). Comparing the technical efficiency of rice farms in urban and rural areas: a case study from Nepal, Trends in Agricultural Economics, 2012; 5: 48-60.
[28] Rahman, M. C., Hussain, C. N., Hossain, M. R., Rahman, M. S. and Chowdhury, A. (2015). Comparative profitability and efficiency analysis of rice farming in the coastal area of Bangladesh: The impacts of controlling saline water intrusion. IOSR Journal of Agriculture and Veterinary Science. 2015; 8(10):89-97.
[29] Rondhi, M., Suherman, S. J., Hensie, C. B., Ulum, S., Suwandari, A., Mori, Y. and Kondo, T. (2024). Urbanization Impacts on Rice Farming Technical Efficiency: A Comparison of Irrigated and Non-Irrigated Areas in Indonesia. Water. 2024 Jan;16(5):651.
[30] Roy, A. C., Rahman, and Khan, M. A. (2019). Yield gap, profitability and inefficiency of Aman rice in coastal areas of Bangladesh. Progressive Agriculture, 2019; 30(4):395-404.
[31] Sarker, J. R., Rolfe, J. and Ananda, J. (2022). Analysis of technical efficiency of dry season rice production in saline and non-saline areas of Bangladesh. Journal of Environmental Management. 2022 Aug 15; 316:115256.
[32] Sharma, V. and Datta, K. (1997). Technical efficiency in wheat production on reclaimed alkali soils. Productivity. 1997. 38 (2).;334.
[33] Sharif, N. R. and Dar, A. A. (1996). An empirical study of the patterns and sources of technical inefficiency in traditional and HYV rice cultivation in Bangladesh. The Journal of Development Studies. 1996 Apr 1;32(4):612-29.
[34] Sharif, N. R. and Dar, A. A. (1996). Stochastic frontiers and technical efficiency distributions: An analysis based on rice farming data for Bangladesh. The Canadian Journal of Economics/Revue Canadienned Economique. 1996 Apr 1;29: S582-586.
[35] Sikdar, M. M., Alam, M. A. and Hossain, M. I. (2008). Factors affecting the technical efficiency of Boro rice production in Bangladesh a Cobb-Douglas stochastic frontier analysis. Journal of the Bangladesh Agricultural University. 2008; 6(1):215-26.
[36] Tobin, J. (1958). Estimation of relationships for limited dependent variables. Econometrica.1958; 26:24-36.
[37] Wadud, M. A. (2003). Technical, allocative, and economic efficiency of farms in Bangladesh: A stochastic frontier and DEA approach. The Journal of Developing Areas. 2003 Oct 1:109-26.
[38] Wadud, A. and White, B. (2000). Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. Applied Economics. 2000 Oct 1;32(13):1665-73.
[39] Yabi, A. J. (2009). Efficiency in rice production: evidence from gogounou district in northen of Benin. Annales des Sciences Agronomiques. 2009;12(2).