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IMPROVED MANAGEMENT PRACTICES ADOPTION AND TECHNICAL EFFICIENCY OF SHRIMP FARMERS IN BANGLADESH: A SAMPLE SELECTION STOCHASTIC PRODUCTION FRONTIER APPROACH

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ABSTRACT

Adoption of improved management practices and technical efficiency can play a crucial role in the growth of aquaculture sector. The present study jointly estimates the determinants of improved management practices adoption and technical efficiency of shrimp farmers using a sample selection stochastic production frontier model. A total of 300 shrimp farmers were interviewed to achieve the objectives. The findings indicate that 41% of the respondents adopted improved practices. Training and extension contact significantly influenced adoption. Adopters received higher yields (343 kg/ha/year) than non-adopters (297 kg/ha/year). Mean technical efficiency was significantly higher for adopters (0.82) than for non-adopters (0.72). Shrimp production of adopters can be increased by 22% by improving technical efficiency level. Policy implications included improvement in current extension facilities to sustain and increase adoption and productivity. Modifying the existing extension approaches would help to improve technical efficiency and adoption of improved management practices.

Keywords: Adoption, technical efficiency, sample selection, shrimp farming

I. INTRODUCTION

Climate change has led to the infiltration of salinity threatening the agricultural farming system in the coastal areas of Bangladesh (Ramachandran, 2013: Khanom, 2016; Alam et al., 2017). Brackish water shrimp farming has been emerged as an adaptation strategy to cope with salinity intrusion. Shrimp farming is one of the major sectors of Bangladesh's economy due to its high export earnings and employment generation

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(Rashid and Chen, 2002; Begum et al., 2013; Akter, 2017). A total of 258 thousand hectares of land was used for shrimp farming in Bangladesh in 2018, compared to just 20 thousand hectares in 1980 (Begum et al., 2013; BBS, 2018). Despite the remarkable expansion of shrimp farming, per hectare productivity and profitability remain very low compared to other countries (Rashid and Chen, 2002; Begum et al., 2013; Shawon et al., 2018). Four types of shrimp culture systems were practiced in Bangladesh: intensive, semi-intensive, extensive, and traditional. The study focused on extensive type of shrimp culture system. Farmers in the study areas practice shrimp cultivation almost all the year round. The culture system involves multi stocking and harvesting throughout the year. A little or no supplementary feeding, water pumping, or water treatment (liming and fertilizers) were applied.

The lack of optimum use of resources was established as a reason for lower profit and productivity (Shawon et al., 2018). Moreover, the sustainability of shrimp farming in Bangladesh has been challenged by a significant outbreak of diseases (Begum et al., 2013). Shrimp farming also has negatively affected cereal crop production, bio-diversity, and agro-ecosystem in coastal Bangladesh (Rasha et al., 2019). Shrimp farms in Bangladesh typically large in size, making it difficult to apply any improved production technology to efficient management (Begum et al., 2013). It is therefore important to find economic and environmentally viable way of cultivating shrimp culture in order to sustainably increase its productivity. Increasing efficient resource utilization is an option that can improve productivity without increasing the use of inputs (Sharma, 1999). Efficiency analysis is useful in assessing the degree to which it is possible to raise productivity by improving efficiency, given the resources and technology (Rashid and Chen, 2002). In order to increase productivity and ensure efficient use of inputs, Bangladesh Fisheries Research Institute (BFRI) introduced few improved management practices for shrimp culture and disseminated these practices through training, field days and demonstrations (BFRI, 2015).

A number of studies have been conducted on profitability aspect of shrimp farming in Bangladesh (Alam, 2007; Karim et al., 2014; Shawon et al., 2018). However, studies on technical efficiency of shrimp farmers are very limited. Rashid and Chen (2002) conducted a study on the technical efficiency of shrimp farmers and found that the mean technical efficiency was ranged from 0.82-0.93. Begum et al. (2013) also found that technical efficiency of the shrimp farmers in Bangladesh was 82%. Rasha et al. (2019) indicated that most of the shrimp farmers inefficiently used their inputs. Most of the earlier studies used the conventional Cobb-Douglas type stochastic frontier production function, ignoring selection bias issues that may occur due to non-randomness in sampling. The presence of selectivity bias may lead to bias and incorrect estimates of technical efficiency (Rahman, 2011; Bravo-Ureta et al., 2012). Moreover, these studies assumed that all the shrimp farmers were similar in terms of management practices and thus, did not estimate technical efficiency of similar group of non-adopting farmers. Comparative efficiency studies using a sample selection approach are confined in Bangladesh or elsewhere. Comparing technical efficiency between adopters and non-adopters will help to enforce policies on the effective use of improved management practices. To fulfill these research gaps, the present study used a sample selection stochastic frontier production function approach to jointly estimates the determinants of improved management practices adoption and to compare the technical efficiency between adopters and non-adopters. The study also identifies the factors affecting technical efficiency of shrimp farmers.

II. METHODOLOGY

Data Sources

A farm survey was carried out using multistage random sampling technique for the selection of the shrimp farmers. In the first stage, the three districts[3]: Bagerhat, Khulna, and Cox's bazar were selected on the basis of the highest contributors to shrimp production in Bangladesh. Two of the highest concentrated shrimp production sub-districts were surveyed from each district to collect data. The list of shrimp farmers, who follows extensive shrimp culture technique, in each sub-district was collected from the local fisheries office, which serves as the sampling framework for this study. Then, for each sub-district, 50 shrimp farmers were randomly selected from that list. Thus, a total of 300 shrimp farmers were interviewed to achieve the objectives. BFRI has introduced five improved practices: maintaining appropriate stocking density, provide feed according to body weight, application of lime, change pond water when necessary, and maintain proper drainage facility for efficient use of resources (BFRI, 2015). Based on these improved management practices, we have classified the sample into two groups: adopters, and non-adopters. A shrimp farmer was assigned into adopters' group if he adopted at least any three of the improved management practices. The farmer who did not adopted any or less than three practices was considered as non-adopter. Adoption of improved practices were based on the subjective evaluation of the shrimp farmers. Out of the 300 shrimp farmers, 123 farmers were classified as adopters and rest were non-adopters of improved practices. Three enumerators were hired and trained to collect data from shrimp farmers using a pre-tested interview schedule. Data on shrimp productivity, level of inputs used, production costs, and socio-demographic profile were collected to achieve the objectives.

Analytical Techniques

Descriptive and sample selection stochastic production frontier model were used to analyzed the data. Technical efficiency (TE) of a farm is defined as the ability and willingness of the farm to obtain the maximum possible output with a given technology (Hota and Prodhan, 2012). Assume that the following is a production function used to measure technical efficiency of a farm:

$$Y_i = \beta_i X_i + \epsilon_i \quad (1)$$

[3] Administrative unit in Bangladesh.

Where, Y_i is the shrimp yield of the i^{th} farm, X_i represents explanatory variables, β_i represents parameters to be estimated, and ε_i represents the error terms. The error term ε_i is made of the following two independent components (Aigner et. al., 1977):

$$\varepsilon_i = (v_i - u_i) \tag{2}$$

v_i, capture the effects of measurement errors and random shocks outside the farmer's control, assumed to be independently and identically distributed $N(0, \sigma_v^2)$. u_i, capture the effects of technical inefficiency, are non-negative ($u \geq 0$) one sided random variables with a half normal distribution $(U \sim |N(0, \sigma_u^2)|)$. However, the drawback of this approach is the inability to account for selection biases arising from unobserved sources.

Heckman (1976) proposed a two-step hackman selection model to correct for selection bias by introducing inverse mills ratio (IMR), estimated through first step selection equation, as an additional independent variable. However, Greene (2010) suggests that such an approach is not suitable for non-linear models and therefore, suggested the following internally consistent method of incorporating sample selection into the stochastic frontier model.
Sample selection:

$$d_i = 1\,[\alpha^* z_i + w_i > 0], w_i \sim N(0,1) \tag{3}$$

Stochastic frontier:

$$Y_i = \beta_i X_i + \varepsilon_i \tag{4}$$

(Y_i, X_i) is observed only when $d_i=1$
Error structure:

$$\varepsilon_i = v_i - u_i$$
$$u_i = |\sigma_u U_i| = \sigma_u |U_i| \; where \; U_i \sim N(0,1)$$
$$v_i = \sigma_v V_i \; where \; V_i \sim N(0,1)$$
$$(w_i, v_i) \sim bivariate \; normal \; with \; [(0,1), (1, \rho\sigma_v, \sigma_v^2)]$$

Greene's model assumes that the unobserved characteristics (w_i) in the sample selection model is correlated with the noise term (v_i) in the stochastic frontier function. d is a binary variable equal to one for improved practices adopters and zero for non-adopters. z_i explanatory variables included in the selection model. w_i is the unobservable error term.

A statistically significant value of ρ indicates presence of selection bias from unobserved sources and thus, justify the use of sample selection approach. Details of the model is available in Greene (2010) and Rahman (2011). The econometric software NLOGIT 5 was used to estimate the sample selection stochastic frontier production function model. The Greene's model can be used to assess possible selection bias, but it does not include the determinants of inefficiency (Sumelius et. al., 2011). Therefore, in this study, along with sample selection model, a Tobit regression (Tobin, 1958) was used to identify the factors affecting technical efficiency of the shrimp farmers. The following model was used to identify the factors affecting technical efficiency:

$$Y_i = \alpha_i z_i + \epsilon_i \tag{5}$$

Where, Yi is the technical efficiency scores, α is the parameters to be estimated. The explanatory variables (Table 1) for this study was selected based on previous literatures and expectations (Rahman, 2011; Alam et al. 2012; Begum et al., 2013; Mengui et al., 2019).

Table 1. Description of the explanatory variables

Variable	Notation	Description
Variables in sample selection stochastic production function		
Fingerlings	X_1	Farmers were asked about the number of fingerlings stocked in the survey pond in a year and later it was converted on per hectare basis.
Feed	X_2	Total amount (kg) of feed used in per hectare per year.
Fertilizers	X_3	Total amount (kg) of fertilizers used in per hectare per year.
Lime	X_4	Total amount (kg) of lime used in per hectare per year.
Human labour	X_5	Human labour was calculated on man-day per hectare basis and eight adult male hours were considered equivalent to one man-day.
Yield	Y	Productivity was estimated on kg per hectare per year.
Variables in Probit and Tobit regression		
Family size (No.)	z_1	The total number of people in primary farmer’s family.
Experience (yrs)	z_2	Shrimp farming experience of the primary farmer, a proxy for willingness to adopt.
Education (yrs)	z_3	Total years of schooling, representing the level of knowledge of the primary farmer.
Spouse education(yrs)	z_4	Total schooling years of primary farmer’s spouse.
Training (days)	z_5	Total days in training.
Farm size (ha)	z_6	Total amount of land owned by the primary farmer.
Extension contact (yes/no)	z_7	One if the primary farmer received advise from local extension staff, otherwise 0.
Pond ownership (yes/no)	z_8	One if the primary farmer has own gher/pond, otherwise 0.

III. RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 shows that there are variation exists between adopters and non-adopters of improved management practices in terms of the selected characteristics. Both groups of farmers released more than 32,000 fingerlings per hectare of pond. The average feed application is much higher for non-adopters compared to adopters. The adopters received higher yield compared to non-adopters. Both groups of farmers exhibit similar types of characteristics in terms of socio-demographic profile. About 67% of the adopters have their own pond, while 55% of the non-adopters have their own pond, suggesting that pond owners have adopted improved practices. The findings also indicate that 41% of the respondents were in adopters' group.

Table 2. Descriptive statistics of the variables used in the models

Variables	Adopters		Non-adopters	
	Mean	Standard deviation	Mean	Standard deviation
Fingerlings (No./ha)	32291.95	1590.20	32860.86	1223.73
Feed (kg/ha)	628.90	151.50	752.81	177.29
Fertilizers (kg/ha)	177.98	146.32	132.22	176.05
Lime (kg/ha)	104.65	58.05	92.50	42.53
Human labour (man-day/ha)	76.31	33.07	76.84	29.99
Yield (kg/ha/year)	343.85	113.44	297.53	111.31
Family size (No.)	4.51	1.41	4.39	1.46
Experience (yrs)	13.37	7.91	14.69	7.50
Education (yrs)	7.67	3.99	7.07	3.85
Spouse education(yrs)	6.07	3.38	6.23	3.66
Training (days)	3.30	4.69	3.30	5.02
Farm size (ha)	0.78	0.59	0.58	0.49
Extension contact (yes/no)	0.61	0.49	0.63	0.48
Pond ownership (yes/no)	0.67	0.47	0.55	0.50
Sample size		123		177

Determinants of Improved Practices Adoption

Table 3 represent the results of probit model (selection equation) used to estimate the determinants of improved practices adoption. The model χ^2 is statistically significant at the 1% level. Of the 8 explanatory variables, 3 have had a positive influence on the adoption decision. Training and extension contact are significant at 1% level, whereas farm size is significant at 10% level (Table 3). Findings indicate that more days in training increases the likelihood of adoption, confirms the findings of several other studies (Sakib and Afrad, 2014; Prodhan and Khan, 2018). Training is one of the ways of empowering farmers with knowledge, which is a prerequisite for better farming performance. Training helps farmers to learn about improved management practices and encourage them to adopt more. Positive and significant coefficient of extension contact indicates that the likelihood of adoption is higher for the farmers who have extension contact compared to their counterparts. Adoption of improved practices requires technical knowledge and contact with extension officers increases the acquisition of relevant knowledge (DeGraft-Johnson et al., 2014; Mensah-Bonsu et al., 2017). Extension services are crucial in informing and shaping farmers decision to adopt new technologies. Extension services helps to raise awareness and importance of the new technology. Thus, efforts are needed to increase the extension services such as field days, and demonstrations to increase the adoption. Farm size also positively influenced adoption decision. In Bangladesh, large farms typically have more contact with local extension workers, which may encourage the extension workers to select them for trainings, allowing large farmers to gain knowledge and adopt more. In such a situation, extension approaches may need to be modified to put small farmers under the extension coverage in order to further increase the adoption of improved practices in Bangladesh (Table 3). Large farms also generate more income, which in turn may boost farmers to adopt new technology.

Table 3. Determinants of adoption

Variable	Co-efficient	SE	p-value
Constant	0.747**	0.355	0.035
Family size (No.)	-0.005	0.058	0.924
Experience (yrs)	-0.005	0.010	0.964
Education (yrs)	0.007	0.024	0.758
Spouse education(yrs)	-0.001	0.026	0.988
Training (days)	0.091***	0.023	0.000
Farm size (ha)	0.303*	0.157	0.053
Extension contact (yes/no)	0.815***	0.164	0.000
Pond ownership (yes/no)	0.046	0.166	0.780
Log likelihood	-170.00		
χ^2	64.90***		
Pseudo R^2	0.16		
No. of obs.	300		

Note: Dependent variable adoption of improved management practices (adopters =1, Non-adopters=0); *, **, and *** indicates significant at 10%, 5% and 1% level, respectively.

Test of Different Parameters

Likelihood ratio (LR) test was conducted to check the suitability of the Cobb-Douglas type production function relative to less restrictive translog. The results of the LR test indicate that the null hypothesis, Cobb-Douglas production function is an adequate representation, was accepted. In order to justify the use of a stochastic frontier framework, the null hypothesis of no inefficiency component was tested based on the sign of the third moment and the skewness of the Ordinary Least Square (OLS) residuals of the data. Rejection of null hypothesis justify the use of a stochastic frontier framework. We also tested model specification by comparing log likelihood functions using the chi-square value. The null hypothesis was strongly rejected, implying that the use of sample selection framework was valid (Table 4).

Parameter Estimates of Sample Selection Stochastic Frontier Production Function (SFPF)

The empirical results show that both the estimates of $\sigma_{(u)}$ and $\sigma_{(v)}$ are significantly different from zero at the 1% level. The coefficient of the selectivity variable ($\rho_{(w,v)}$) is significantly different from zero for non-adopters at the 10% level, which confirms that selection bias exists (Table 5). This finding also confirms the result of model specification test presented in Table 4. The presence of selectivity bias also implies that the estimates from conventional stochastic frontier model may lead to inaccurate technical efficiency scores (Bravo-Ureta et al., 2012). The empirical results of the sample selection framework reveal that fingerlings and human labour significantly affected the productivity of shrimp. Productivity mainly depends on appropriate use of different inputs and use of quality fingerling can increase the productivity (Prodhan and Khan, 2018).

Table 4. Test of different parameters for model selection

Hypothesis	LR test statistics	χ^2 critical value 1% /p-value	Outcome
a. Functional form test			
H_0: Cobb-Douglas H_1: Translog	22.42	29.92	Cobb-Douglas is adequate
b. Frontier test			
H_o: No inefficiency component	4.23	0.020	Frontier not OLS
c. Model specification test			
H_o: Sample selection bias is not present	294	5.41	Sample selection bias is present

Table 5. Parameter estimates of sample selection SFPF

Variable	Adopters		Non-adopters	
	Coefficient	SE	Coefficient	SE
Constant	4.124***	0.892	4.576***	0.431
Fingerlings	0.152***	0.056	0.033***	0.035
Feed	0.042	0.030	0.066	0.023
Fertilizers	-0.017	0.015	-0.006	0.020
Lime	0.010	0.021	-0.005	0.014
Human labour	0.086	0.094	0.203***	0.057
Model diagnostics				
Log likelihood	-125.309	--	-102.138	--
$\sigma_{(u)}$	0.566***	0.061	0.247**	0.101
$\sigma_{(v)}$	0.122**	0.053	0.251***	0.039
$\rho_{(w,v)}$	-0.032	0.695	0.546*	0.288
Sample size	123		177	

Note: ***, ** and * indicate significant at 1%, 5%, and 10% level of significance, respectively. '--' indicates not applicable. Dependent variable = Yield (kg/ha/year)

Technical Efficiency Distribution

Technical efficiency analysis suggested that both adopters and non-adopters of improved practices exhibited a wide variety of technical efficiency scores, which is similar to the findings of previous studies (Bravo-Ureta et al., 2007; Rahman, 2011; Karim et al., 2013). Not a single farm was found to be entirely technically efficient from both groups of farmers. The mean technical efficiency of adopters appears to be similar to other studies (Begum et al., 2013). The finding indicates that adopters of improved practices were technically more efficient than non-adopters and the difference was significant at 1% level (Table 6). Although the findings indicate that adopters are technically more efficient than non-adopter, there is still sufficient room for increasing the level of technical efficiency. The mean technical efficiency of the adopters was calculated at 82%, which implies that improved practices adopters could increase the production of shrimp by 22% by only improving the technical efficiency.

Table 6. Farm specific technical efficiency estimates

Technical efficiency	Adopters	Non-adopters
Maximum	0.93	0.95
Minimum	0.48	0.33
Mean	0.82	0.72
Mean difference	0.10***	

Note: *** indicates significant at 1% level; t-test was used to test mean difference

Factors Affecting Technical Efficiency

Findings reveal that the technical efficiency of the adopters was significantly influenced by training, extension contact, and pond ownership, while technical efficiency of the non-adopters significantly influenced by farm size and extension contact (Table 7). The pooled model, considering all the sample, indicates that technical efficiency level of shrimp farmers was positively influenced by training and extension contact, whereas farm size negatively influenced technical efficiency (Table 7). Earlier studies reported mixed results on farm size and technical efficiency (Boubacar et al., 2016; Zhang and Chen, 2016). In this study, we found a negative relationship, which implies that the small farms were technically more efficient than the large ones. More days in training significantly improve the technical efficiency level. General belief that training improves knowledge and technical knowhow holds validity in this context. Training increases the ability to perceive, and respond to new events and improves the skills of farmers, including the efficient use of inputs. The positive and significant coefficient of extension contact implies that farmers who have maintain communication with extension agents tend to be more efficient (Onumah et al., 2010; Mengui et al., 2019). The coefficient of ownership of the pond/gher was found to be significant and positive for adopters. This finding indicates that lease farmers are technically less efficient than the farmers who have their own pond/gher. The owners of pond/gher tend to better manage their farm management activities, particularly when innovative technologies are being applied (Onumah et al., 2010). The coefficient of experience, education, spouse education, farm size, and pond ownership are statistically insignificant, which means that these variables have no effect on technical efficiency. However, their inclusion in the efficiency model increases the explanatory power of the model.

Table 7. Factors affecting technical efficiency

Variable	All sample		Adopters		Non-adopters	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	0.801***	0.037	0.797***	0.053	0.826***	0.031
Family size (No.)	0.014	0.326	0.025	0.019	0.004	0.005
Experience (yrs)	-0.001	0.001	-0.001	0.002	-0.001	0.001
Education (yrs)	0.000	0.003	-0.002	0.004	-0.001	0.002
Spouse education(yrs)	-0.002	0.003	-0.001	0.005	0.000	0.002
Training (days)	0.003*	0.002	0.006**	0.003	0.001	0.001
Farm size (ha)	-0.014**	0.006	0.006	0.022	-0.025*	0.014
Extension contact (yes/no)	0.034*	0.018	0.032*	0.017	0.030**	0.014
Pond ownership (yes/no)	0.011	0.017	0.045*	0.027	0.008	0.013
Log likelihood	155.19		69.67		148.85	
LR χ^2	13.71*		14.26*		13.59*	

Note: ***,**, and * indicates significant at 1%, 5%, and 10%level, respectively.

IV. CONCLUSIONS

The present study jointly estimates the determinants of improved management practices adoption and technical efficiency of shrimp farmers in coastal areas of Bangladesh using cross-sectional data collected through face-to-face interviews. The results of the study suggested that 41% of the respondents adopted improved practices. Adopters received higher productivity compared to non-adopters. Adopters were technically more efficient than non-adopters. Training and extension contact have had a significant influenced on adoption as well as on technical efficiency. These findings indicate that extension delivery system should be given the necessary attention by policy makers. There is a need to provide more extension services, such as training, and demonstrations, to increase the adoption and level of technical efficiency. This could be done by delivering in-house training, and recruiting more field level extension workers. Modification of the existing extension approach by targeting not only large farmers but also small farmers can help with widespread adoption of improved management practices. Pond/gher owners were more efficient than the lease farmers. Emphasis should be put on lease farmers to bring them into training and extension facilities in order to improve their technical efficiency. More visits to villages by extension workers will ease the process of adopting improved management practices and can improve the level of technical efficiency.

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REFERENCES

Aigner, D. J., Lovell, C.A.K. and Schimidt, P. (1977). Formulation and estimation of stochastic frontier production models. *Journal of Econometrics*, 6: 21–37.

Alam, M.F., Khan, M.A. and Huq, A.S.M.A. (2012). Technical efficiency in tilapia farming of Bangladesh: a stochastic frontier production approach. *Aquaculture International*, 20(4): 619–634.

Alam, M.Z., Carpenter-Boggs, L., Mitra, S., Haque, M., Halsey, J., Rokonuzzaman, M., Saha, B. and Moniruzzaman, M. (2017). Effect of salinity intrusion on food crops, livestock, and fish species at Kalapara coastal belt in Bangladesh. *Journal of Food Quality*, 2017: 1–23.

Alam, S.M.N. (2007). Economic returns of disease-affected extensive shrimp farming in southeast Bangladesh. *Journal of food and aquatic science*, 15(5): 363–370.

Akter, F. (2017). The export trend of shrimp industries in Bangladesh: an analysis. *Scientific Research Journal*, 5(9): 80-95.

BBS. (2018). Yearbook of Agricultural Statistics of Bangladesh. Bangladesh Bureau of Statistics, Statistical Division, Ministry of Planning, Government of the People's Republic of Bangladesh, Dhaka.

Begum, M.E.A., Hossain, M.I. and Papanagioto, E. (2013). Technical efficiency of shrimp farming in Bangladesh: An application of the stochastic production frontier approach. *Journal of the World Aquaculture Society*, 44(5): 641-654.

BFRI. (2015). Improved shrimp farming system in ghers. Retrieved from http://www.fri.gov.bd/site/page/c5044b3e-8964-4688-bd93-dd076bcb0332/-

Boubacar, O., Hui-qiu, Z., Rana, M.A. and Ghazanfar, S. (2016). Analysis on technical efficiency of rice farms and its influencing factors in south-western of Niger. *Journal of Northeast Agricultural University*, 23(4): 67-77.

Bravo-Ureta, B.E., Solis, D., Lopez, V.H.M., Maripani, J.F., Thiam, A. and Rivas, T. (2007). Technical efficiency in farming: a meta regression analysis. *Journal of Productivity Analysis*, 27: 57–72.

Bravo-Ureta, B.E., Greene, W. and Solis, D. (2012). Technical efficiency analysis correcting for biases from observed and unobserved variables: an application to a natural resource management project. *Empirical Economics*, 43: 55–72.

DeGraft-Johnson, M., Suzuki, A., Takeshi, S.T. and Otsuka, K. (2014). On the transferability of the Asian rice green revolution to rainfed areas in sub-Saharan Africa: an assessment of technology intervention in northern Ghana. *Agricultural Economics*, 45(5): 555–570.

Greene, W. (2010). A stochastic frontier model with correction for sample selection. *Journal of Productivity Analysis*, 34: 15–24.

Heckman, J. (1976). The common structure of statistical methods of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals* of *Economic and Social Measurement*, 5: 475-492.

Hota, K.S. and Prodhan, K.K. (2012). An economic analysis of technical efficiency in rice production: data envelopment analysis (DEA) approach. *International Journal of Advanced Research in Science and Technology*, 1(2): 109-119.

Karim, M.R., Rashid, M.A. and Rahman, M.S. (2013). Comparative study of IPM and non-IPM technology in selected vegetables growing areas in Bangladesh. Research Report, NATP-SPGR Project, BARC, Dhaka, Bangladesh.

Karim, M., Sarwer, R.H., Philips, M. and Belton, B. (2014). Profitability and adoption of improved shrimp farming technologies in the aquatic agricultural systems of southwestern Bangladesh. *Aquaculture*, 428-429: 61–70.

Khanom, T. (2016). Effect of salinity on food security in the context of interior coast of Bangladesh. *Ocean and Coastal Management*, 130: 205–212.

Mengui, K.C., Oh, S. and Lee, S.H. (2019). The technical Efficiency of smallholder irish potato producers in santa subdivision, Cameroon. *Agriculture*, 9: 259.

Mensah-Bonsu, A., Daniel, B.S., Ramatu, H., Samuel, A.B., Irene, S.E., John, K.M.K. and Yaw, B.O. (2017). Intensity of and factors affecting land and water management practices among smallholder maize farmers in Ghana. *African Journal of Agricultural and Resource Economics*, 12(2): 142-157.

Onumah, E.E., Brummer, B., Horstgen-Schwark, G. (2010). Elements which delimitate technical efficiency of fish farms in Ghana. *Journal of the World Aquaculture Society*, 41(4): 506-518.

Prodhan, M.M.H., and Khan, M.A. (2018). Management practice adoption and productivity of commercial aquaculture farm in selected areas of Bangladesh. *Journal of Bangladesh Agricultural University*, 16(1): 111-116.

Rahman, S. (2011). Resource use efficiency under self-selectivity: the case of Bangladeshi rice producers. *The Australian Journal of Agricultural and Resource Economics*, 55: 73–290.

Ramachandran, N. (2013). Gender, climate change and household food security: A south Asian perspective. In: M. Behnassi, O. Pollmann, & G. Kissinger (Eds.), Sustainable Food Security in the Era of Local and Global Environmental Change. Dordrecht: *Springer*, pp. 69-84.

Rasha, R.K., Rahman, M.R., Huq, A.S.M.A. and Jalil, G.M.A. (2019). Productivity and resource use efficiency of tiger shrimp farming in some selected areas of bagerhat district in Bangladesh. *Asia-Pacific Journal of Rural Development*, 29(1): 7-19.

Rashid, M.H.A. and Chen, J. (2002). Technical efficiency of shrimp farmers in bangladesh: a stochastic frontier production function analysis. *Bangladesh Journal of Agricultural Economics*, 25(2): 15-31.

Sakib, M.H. and Afrad, M.S.I. (2014). Adoption of Modern Aquaculture Technologies by the Fish Farmers in Bogra District of Bangladesh. *International Journal of Agriculture Innovations and Research*, 3(2): 414-421.

Sharma, K.R. (1999). Technical efficiency of carp production in Pakistan. *Aquaculture Economics and Management*, 3(2):131–141.

Shawon, N., Prodhan, M.M.H., Khan, M.A. and Mitra, M. (2018). Financial profitability of small-scale shrimp farming in a coastal area of Bangladesh. *Journal of Bangladesh Agricultural University*, 16(1): 104-110.

Sumelius, J., Islam, K.M.Z. and Sipilainen, T. (2011). Access to Microfinance: Does it Matter for Profit Efficiency Among Small Scale Rice Farmers in Bangladesh, Paper presented at EAAE 2011 congress, Zurich, Switzerland.

Tobin, J. (1958). Estimation of relationship for limited dependent variables. *Econometrica*, 26(1): 24-36.

Zhang, X.M. and Chen, S. (2016). The influence factors of the quality of the new generation migrant workers and the countermeasures to improve the quality. *Academic Exchanges*, 1: 141-144.