論　説

Technical Efficiency of Rice Farming in the Vietnamese Mekong Delta: A Stochastic Frontier Approach

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Abstract

The study aims to empirically investigate the technical efficiency of rice farming in the Mekong Delta of Vietnam. Observational data were obtained from the in-depth interviews with 352 rice farm households in three provinces of the Mekong Delta. The results from the stochastic frontier analysis reported that the overall mean technical efficiency of rice farming is 77% which implies that, on average, farm households have the potential to increase their rice production by 23% given the same level of inputs and technology. In addition, the estimated return-to-scale computed as the sum of coefficients from the Cobb-Douglass production frontier model is 0.3801 implying that rice farms in the Mekong delta are operating at decreasing returns to scale. Furthermore, the findings revealed that performance of adaptation response, agricultural extension services, the area of farm, and geographical location at both provincial level and micro-level (e.g. access to water source) are key influencing factors of rice farming's inefficiency in the Mekong Delta.
Key words: agriculture, efficiency, rice production, stochastic frontier analysis,

1. Introduction

Rice is the most important crop in agriculture of Vietnam. It occupies more than 89% of total grain food. In 2016, Vietnam is one of five major rice exporters, exporting 4.88 million tons which accounts for 11.3% of the total world rice trade (Vietnam Economic Times, 2018). Particularly, the Vietnam's Mekong Delta encompasses the country's biggest rice

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producing regions — which contribute up to more than 55% of the total rice production of the country (GSO, 2017) — are described as some of the most vulnerable regions to climate change in the world. In addition, rice production is the primary livelihood of approximately 60% of the Mekong Delta's residents.

However, increases in the frequency and intensity of extreme events such as drought, high maximum temperatures, and erratic rainfall are already occurring and expected to accelerate in many regions. According to IPCC (2014), climate change account for a significant reduction in renewable surface water and ground water surface in most dry regions. Climate variability in relation to water scarcity results in serious environmental and social consequences that not only jeopardize agricultural production, but also destabilize rural livelihoods in most of regions in the Mekong Delta.

To maintain food security and manage water resource for a sustainable agriculture should enhance the technical efficiency of rice production, more specifically, the use of irrigation water. There are several studies emphasized the definitions of efficiencies and estimated the technical efficiency in agriculture in developing countries. For example, through data envelopment analysis (DEA) approach, Dhungana *et al.* (2004) measured the average technical inefficiency of rice farms in Nepal to be 0.24, signifying that the farms have the potential to reduce their inputs by 24 per cent and still produce the same level of output. In that study, the allocative inefficiency, economic inefficiency, and scale inefficiency have also been estimated as 0.13, 0.34 and 0.07, respectively. Watkins *et al.* (2014) reported the DEA technical efficiency of rice production in Arkansas, the leading rice-producing state in the United States, to be 0.803 under CRS, 0.875 under VRS, and scale efficiency of 0.92, implying that rice production in Arkansas is significantly efficient at utilizing inputs. In addition, the allocative efficiency and economic efficiency are measured as 0.711 and 0.622, respectively. Technical inefficiency in rice production may come from several sources. For instance, surplus resources such as fertilizer should be re-allocated to increase the yields of other crops and surplus labor could be re-deployed to other economic activities. Also, surplus seed could be re-allocated to supplement food for family demand (Dhungana *et al.,* 2004). By the stochastic frontier analysis (SFA) approach, Kea *et al.* (2016) reported the average technical efficiency of rice production in Cambodia as 78.4%. In addition, the influencing factors including irrigation, production techniques, and the amount of agricultural supporting staff were found to be important determinants of technical efficiency.

Despite the importance of rice production in Vietnamese economy, there has been little study on the efficiency of Vietnamese rice farming. In Vietnam, there are only a few papers that calculate efficiency and determine the factors affecting efficiency of Vietnam's agriculture. For instance, Linh (2012) estimate technical efficiency obtained from both data envelopment analysis (DEA) and stochastic frontier approaches (SFA) using household survey data for rice farming households in Vietnam. More specifically, the mean technical efficiency is 0.704 under CRS, 0.765 under VRS for output-oriented DEA and 0.785 under VRS for input-oriented DEA. Furthermore, the estimate of SFA technical efficiency is 0.634. In terms of influencing factors, technical efficiency is reported to be significantly influenced by primary education and regional factors. Therefore, this study attempts to estimate the technical efficiency and scale efficiency of rice production at farm level in the Vietnamese Mekong Delta.

2. Study site

The study was conducted in the Mekong Delta, the major agricultural region of Vietnam. This region has been identified as significantly vulnerable to climate change. The Mekong Delta has a flat terrain, mostly of average height of 0.7―1.2 m. Topography along the Cambodia border is the highest with 2.0―4.0 m above from sea level. The lower of the central plains is about 1.0―1.5 m in high. And there is only 0.3―0.7 m in the tidal and coastal areas. Low topography and separated by many irrigation canals and being contiguous to East sea, therefore, salt intrusion and water shortage even become more serious and directly affect rice production (especially the third crop of Spring-Summer) in the delta. Thirteen provinces of the delta have been grouped into four groups at high, moderate, low, and lowest vulnerability levels to climate change. The lowest vulnerability level in An Giang and Dong Thap province are not subjective to projected sea level rise (Thuy and Anh, 2015). Therefore, the study aims at choosing from the rest of three groups. Long An, Ben Tre, and Tra Vinh province are randomly chosen from each of three groups of low, moderate and high levels, respectively. Two districts were then randomly selected from each of the three provinces and two communes from each district.

To cope with climate change and its impacts, especially on agricultural production, adaptation response is necessary for improving the resilience of agricultural production and sustaining rural livelihood (Smit and Skinner, 2002; Bryan *et al.,* 2013). In the study site, local adaptation responses including crop improvement practices, water management practices, diversification practices, and conservation practices are generally employed by rice farmers to cope with risks of climate change related to salinity intrusion and drought.

Climate smart agriculture (CSA) was introduced by the Food and Agricultural Organization (FAO) in 2010, as an innovative cleaner production alternative to conventional farming with the goals of increasing the efficiency of resource uses, productivity of agricultural production system, and enhancing adaptation and resilience in order to reduce greenhouse gas emissions and mitigate climate change for a sustainable agriculture and development. In the study site, the CSA program which are related to either reducing fertilizer and chemical uses or adjusting the amount of seeds for a sustainable agriculture, was introduced to rice farmers by local government and institutions (e.g. Ministry of Agriculture and Rural Development, Department of Agriculture and Rural Development at provincial level) and agricultural companies (e.g. fertilizer company, chemical company). For instance, the CSA pilot program from Binh Dien Fertilizer Joint Stock Company cooperating with the Ministry of Agriculture and Rural Development, which aimed to reduce seeds as well as fertilizer and chemical uses in rice farming, was introduced at thirteen provinces of Mekong Delta since 2016 with the limited number of participants (only five rice farmers at each province). Furthermore, some agricultural companies and Department of Agricultural and Rural Development introduced other CSA pilot programs related to IPM (Integrated Pest Management) and rice variety clange.

3. Materials and method

3.1. Efficiency measurement

Farrell (1957) defined technical efficiency as a measurement of the firm's ability to utilize given inputs in the most effective way. This means that a firm can either produce the optimal output from a given inputs (as output-orientation) or to produce the given level of output from the minimum amount of inputs (input-orientation). Technical efficiency measures the distance from each firm to the frontier, estimated parametrically using stochastic frontier analysis (SFA) and non-parametrically using data envelopment analysis (DEA). DEA allows technical and allocative efficiency to be estimated. However, as DEA is non-parametric, it is sensitive to random error, and does not provide either the impact of individual inputs on the level of outputs or the relationship between the outputs themselves. SFA accounts for the possible influence of random error and has been implemented in several studies in rice production (Villano *et al.,* 2004; Mwajombe and Mlozi, 2015; Kea *et al.,* 2016) or fishery (Kirley *et al.,* 1995, 1998; Grafton *et al.,* 2000; Pascoe and Coglan, 2002; Koundouri and Laukkanen, 2004). Coelli (2005) recommended the SFA approach in most agricultural applications. This method has an important advantage of performing the statistical test of hypothesis associated with the production function and the level of inefficiency. Furthermore, another advantage of the SFA approach is to determine the exogenous factors and shocks (e.g. climate change related to salt intrusion and drought) influencing the level of technical inefficiency of each farm. Therefore, this study aimed at parametrically analyzing technical efficiency of rice production at farm level using SFA approach.

3 . 2 . Stochastic frontier approach

Stochastic production frontier models were introduced by Aigner *et al.* (1977) and Meeusen and Brock (1977). Since then, stochastic frontier models become popular econometric tool in economic field.

Suppose that a farm has a production function $f(X_i, \beta)$. The i^{th} farm would produce $Y_i=f(X_i, \beta)$ in case of no error or inefficiency. Stochastic production frontier model assumes that each farm potentially produces less than it might due to a level of inefficiency. Specifically,

$$Y_i=f(X_i, \beta)\xi_i \tag{1}$$

where, Y_i is output and X_i is input vector of farm i. β_i is the vector of parameter estimates. $f(X_i, \beta)$ is normally assumed either Cobb-Douglass production function or trans-log function. The study aims at choosing the Cobb-Douglass production function to be convenient in testing the return to scale hypothesis. ξ_i represents the level of efficiency of farm i.

Output is also assumed to be subject to random error v_i, suggesting that

$$Y_i=f(X_i, \beta)\xi_i\exp(v_i) \tag{2}$$

where v_i is assumed to be independently and identically $N(0; \sigma^2{}_v)$.

The natural logarithm of the production function is expressed as

$$\ln Y_i=\ln[f(X_i, \beta)]+\ln(\xi_i)+v_i \tag{3}$$

Assume that there are k inputs and that the production function is linear in logs, and define technical inefficiency effect $u_i=-\ln(\xi_i)$ which is assumed to be independently exponentially distributed with $\sigma^2{}_u$, the production frontier function in equation (3) becomes

$$\ln Y_i=\beta_0+\sum_{k=1}^{k}\beta_k\ln X_{ik}+v_i-u_i \tag{4}$$

The technical inefficiency effect can be expressed as

$$u_i=\alpha_0+\sum_{j=1}^{j}\alpha_j Z_{ij}+\omega_{ij} \tag{5}$$

where ω_{ij} is the stochastic noise, Z_{ij} is exogenous factors that are affecting rice production, α are parameter estimates, if α_j is negative that indicates a positive relationship between exogenous factors and technical efficiency of rice production, and vice versa. Technical efficiency (TE) under output-oriented of i^{th} farm is measured as $\xi_i=\exp(-u_i)$ and is defined as a ratio of observed output and frontier output. ξ_i must be in the interval (0,1]. If ξ_i is equal to 1, the farm is considered as operating at the optimal output with the

Table 1 Description of output and input variables in the production frontier model

Variables	Description	Mean	S. D.	Min	Max
Output					
Yield	Total average yield of rice per crop (ton/ha)	5.3629	1.6584	1	12
Inputs					
Seeds	Total amount of seeds using for rice production per crop (kg/ha)	144.969	51.3838	10	360
Fertilizer	Total amount of fertilizer uses per crop (kg/ha)	236.233	140.846	20	785
Chemical	The cost of chemical use per crop (million VND/ha)	1.7649	1.7853	0.250	13.065
Irrigation	The cost of irrigation water use per crop (million VND/ha)	0.6681	0.4719	0.1	3.417

technology embodied in the production frontier.

3.3. Data

3.3.1. Data collection

The main objective of field survey in this study is to understand how rice farmers observe that climatic conditions related to salt intrusion and drought are changing as well as the efficiency of their rice production. A field survey was conducted in February 2018 in three provinces of Mekong Delta including Long An, Ben Tre, and Tra Vinh province. The cross-section data of 361 households via face-to-face interviews with the structured questionnaire were selected. More specifically, these interviewed households have different access to water resource. It is divided into three levels of near, medium and far access to water resource based on the distance to main, secondary and small irrigation systems, respectively. And only one individual from a household (mainly head of household) was surveyed. The structured questionnaire included four sections: household characteristics, climate change awareness, climate change adaptation behavior, and agricultural production. We dropped nine observations due to incomplete information and outliers. The efficiencies are calculated using the final sample of 352 rice farm households.

3.3.2. Data description

Variables for the efficiency measurement by stochastic production frontier model

Four input variables are included in the stochastic production frontier model: seed, fertilizer (expressed in kilogram per hectare per crop), chemical (expressed as cost in million VND per hectare per crop), and irrigation (expressed as cost in million VND per hectare per crop). The output in the production frontier model is constructed by rice yield (expressed in ton per hectare per crop) (Table 1).

More specifically, seeds input, with an average of 145 kg per hectare, is expected to be positively to rice yield. Fertilizer input is measured as the total amount of chemical and

Table 2 Description of exogenous variables in the technical inefficiency effects model

Variables	Description
Farmer characteristics	
Education	Number of year of formal schooling
Experience	Number of year of farming rice
CSA	Dummy variable, 1 denotes farm household participates in climate smart agriculture pilot program and 0 denotes otherwise
Adaptation	Dummy variable, 1 denotes farm household performs adaptation response to climate change and 0 denotes otherwise
Extension	Dummy variable, 1 denotes farm household participates in agricultural extension services and 0 denotes otherwise
Belief in climate change	Using 1-5 Likert scales, from strongly disagree to strongly agree with the statement "Climate change is influencing my livelihood"
Farm characteristics	
Farm area	Total area of rice farming (hectare)
Access to water (Near)	Distance to water source intuitively estimated by rice farmer — dummy variable, 1 denotes farm locates in near and 0 denotes otherwise
Access to water (Medium)	Distance to water source intuitively estimated by rice farmer — dummy variable, 1 denotes farm locates in medium and 0 denotes otherwise
Region (Long An)	Farm location — dummy variable, 1 denotes farmer locate in Long An province and 0 denotes otherwise
Region (Ben Tre)	Farm location — dummy variable, 1 denotes farmer locate in Ben Tre province and 0 denotes otherwise

Table 3 Descriptive statistics of exogenous variables in the technical inefficiency effects model

Variables	Mean	Standard deviation	Min	Max
Adaptation	0.7074	0.4556	0	1
CSA	0.0625	0.2424	0	1
Extension services	0.5568	0.4975	0	1
Education	5.8977	3.4716	0	16
Experience	26.9716	11.0066	5	60
Belief in climate change	3.7528	0.9777	1	5
Farm area	1.2688	1.3798	0.1	10
Region_Long An	0.3352	0.4727	0	1
Region_Ben Tre	0.3295	0.4707	0	1
Access to water_Near	0.4545	0.4986	0	1
Access to water_Medium	0.4659	0.4995	0	1

organic fertilizer quantity use per hectare. Chemical input is measured as the total cost per hectare of pesticide for insects and herbicide for grass while irrigation input is measured as the total cost per hectare of irrigation water use for rice crop. These three input variables are also expected to have positive relationship with output of rice yield.

Variables for the inefficiency effects model

To explain for the level of technical inefficiency, exogenous variables involving farmer and farm characteristics in the inefficiency effects model are statistically described in Table

2 and Table 3.

According to farmer's characteristics, the level of education is expected to have a negative effect on technical inefficiency of rice farming (Stefanou and Saxena, 1988; Battese *et al.,* 1996, Dey *et al.,* 2005). This means that more educated farmers are less technical inefficient due to their better skills and capability to access to information and new technology. The average level of education among the delta's farmers is approximately 6 years of formal schooling.

Regarding experience, more experienced farmers may be better in farming rice and therefore becomes less inefficient (Stefanou and Saxena, 1988). Approximately 60% of residents in the Mekong Delta traditionally live on agriculture (MARD, 2011). Therefore, their experience in rice farming is, on average, nearly 27 years.

In terms of shocks related to climate change, the belief in climate change is expected to be negative with inefficiency, possibly due to their awareness of climate change and its impacts.

Likewise, the participation in agricultural extension services, which provide information associated with climate change and climate change adaptation practices and farming technique, is expected to be better in accessing information and enhancing farmers' awareness and action, and therefore to yield less inefficiency. Majority of rice farmers (55%) participated in agricultural extension services and technical trainings from either local government and institutions or agricultural materials companies.

In addition, the performance of adaptation response is expected to be able to control or mitigate the adverse impacts of climate change, and therefore produces a less inefficiency in rice production. In the study site, there are 70.7% farmers decided to perform their adaptation responses associated with crop improvement, water management, crop and income diversification, and conservation practices to mitigate the adverse impacts of climate change. Meanwhile, 29.3% the others did not perform their adaptation response.

Farmers who decided to join in CSA pilot programs (e.g. reduction of amount of seed as well as fertilizer and chemical use, application of IPM and new rice variety) are expected to produce less inefficiency than farmers who did not. In the study sites, only twenty-two rice farmers are participating in the CSA pilot programs which are implemented by institutions and agricultural companies.

In terms of farm characteristics, geographical locations are expected to have significant effects on technical inefficiency (Ngoc *et al.,* 2018). More specifically, technical inefficiency is expected to vary across provinces. Regarding location at micro-level such as access to water source which was defines as in Ho and Ubukata (2018), farmers located at a near distance is expected to yield less inefficient due to an important input of irrigation water for rice production. The surveyed data reported that 45% of respondents are located near to water sources and 46% are located at medium distance while 9% of respondents are located at a far distance to water source.

Furthermore, farmers with more land area are expected to be better in managing input resources and, therefore, could produce less inefficient rice yield. The average land area was approximately 1.3 hectares.

4. Empirical results and discussion

4.1. Technical efficiency of rice farming

Table 4 shows parameter estimates of the stochastic production frontier model by SFA approach. These estimated coefficients are the direct elasticities due to the production function of Cobb-Douglass. As expected, all input variables are positively significant at the significant level of 0.01 where fertilizer input has the largest contribution to output level of rice production. In details, an increase in fertilizer use by 1% contributes to an increase of 0.1% rice yield. Furthermore, irrigation is also important resource for rice farming. Increasing the cost for irrigation water use by 1% could lead to increase in rice yield by 0.09%. Similarly, an increase of the total amount of seeds by 1% could increase rice yield by 0.07% while an increase of the total cost of chemical use by 1% could make an increase of rice yield by 0.04%.

The result from table 4 also shows the Likelihood-ratio test (chibar2(01)=72.77) with a p-value of 0.000 for the exponential model. This confirms that the null hypothesis of no technical inefficiency component in the model can be rejected at the significant level of 0.01. It means that rice farms households are operating their rice production with a

Table 4 Parameter estimates of the production frontier model

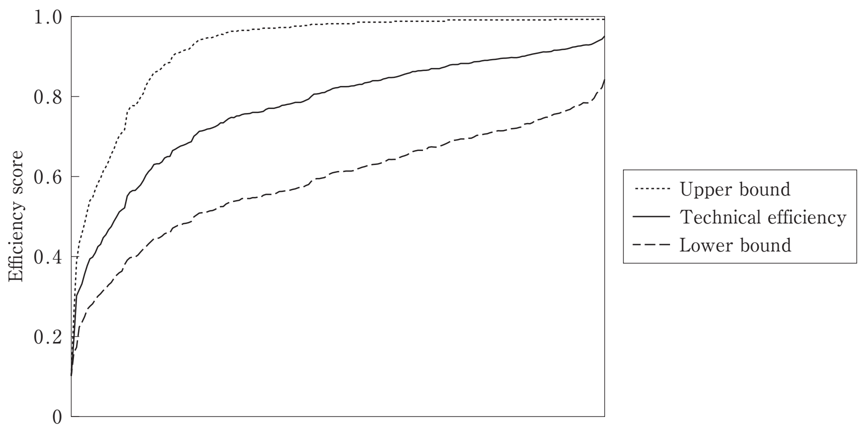
	Coefficient	Standard error	p-value
lnSEED	0.0745**	0.0298	0.0120
lnFERTILIZER	0.1067***	0.0254	0.0000
lnCHEMICAL	0.0374**	0.0186	0.0450
lnIRRIGATION	0.0895***	0.0217	0.0000
Constant	1.0336***	0.2030	0.0000
/lnsig2v	−3.5411	0.1852	
/lnsig2u	−2.4408	0.1727	
sigma_v	0.1702	0.0158	
sigma_u	0.2951	0.0255	
sigma2	0.1161	0.0132	
lambda	1.7335	0.0361	
Number of observations	352		
Wald chi2(4)	45.12		
Probability＞chi2	0.0000		

Likelihood-ratio test of sigma_u=0: chibar2(01)=72.77, Probability＞=chibar2=0.000
Note: *, **, and *** means significance with confidence interval at 90%, 95%, and 99%

Table 5 Frequency distribution of the efficiency score from the production frontier model

Technical efficiency	Number of households	Frequency (%)
Less than 0.4	15	4.26
From 0.4 to less than 0.6	34	9.66
From 0.6 to less than 0.8	108	30.68
From 0.8 to 1.0	195	55.40
Mean technical efficiency	0.7725	
Standard deviation	0.1564	
Minimum	0.1497	
Maximum	0.9543	

Figure 1 Distribution of SFA estimates of technical efficiency



certain level of inefficiency.

In addition, the estimated return-to-scale computed as the sum of coefficients from the Cobb-Douglass production frontier model is 0.3801 implying that rice farms in the Mekong delta are operating at decreasing returns to scale (DRS). This means that an increase in one unit of the quantity of inputs would lead to less than proportionate increase to the output, ceteris paribus.

Furthermore, Table 5 presents that the overall mean score of technical efficiency relative to the frontier was 0.77, which indicated that rice farmers produced 77% of rice at best at the current level of inputs and technology. Since this technical efficiency score was estimated by the output-oriented production frontier model, it can be explained as 23% by which output these farm households have the potential to increase given the same level of inputs and technology.

In detail, a large majority of rice farm households are operating at a high efficiency level of 60-80% (108 households) and greater than 80% (195 households) while only fifteen rice farm households are operating below 40%. The distribution of SFA estimates with lower and upper bound is shown in Figure 1.

Table 6 The technical inefficiency effects model

	Coefficient	Standard error	p-value
Adaptation	−0.2089***	0.0281	0.0000
CSA	−0.0411	0.0532	0.4400
Education	−0.0046	0.0038	0.2260
Experience	0.0004	0.0011	0.7000
Extension	−0.0470*	0.0265	0.0770
Belief in climate change	0.0213	0.0129	0.1010
Farm area	−0.0344***	0.0099	0.0010
Region_Long An	0.0666**	0.0305	0.0300
Region_Ben Tre	0.0967***	0.0314	0.0020
Access to water source_Near	−0.0905*	0.0479	0.0600
Access to water source_Medium	−0.0381	0.0477	0.4240
Constant	0.4551***	0.0833	0.0000

Note: *, **, and *** means significance with confidence interval at 90%, 95%, and 99%

4.2. Determinants of technical inefficiency

The determinants of rice production's driving technical inefficiency are presented in Table 6. It is obvious that adaptation response, participation in agricultural extension services, the area of rice farm, and geographical location at provincial level and micro-level such as access to water source had negative relationship with inefficiency of rice production at either significant level of 0.01 or 0.05. This implies positive relationships of these influencing factors and technical efficiency of rice production in the Mekong Delta.

More specifically, the result from the inefficiency effects model reports that adaptation response has a significantly negative influence on technical inefficiency of rice production. It means that adapting farmers are better in managing their inputs and therefore enhance better economic performance of rice production (i. e. technical efficiency) than non-adapting farmers.

Furthermore, agricultural extension services regarding crop technique and management trainings have had beneficial for reducing inefficiency of rice farming. This means that farmers who have participated in agricultural extension services at local level have higher technical efficiency than those who have not participated.

The coefficient of CSA appears to be insignificant in terms of technical inefficiency. This means that there is no significant difference in technical inefficiency between CSA participating and non-participating farmers. Possible reason why CSA is not effective in promoting rice production efficiency is that non-participating farmers might either participate in agricultural extension services or perform adaptation practices which are strongly positive to technical efficiency. Therefore, CSA does not drive effect on technical inefficiency in this model.

The area of rice farming also appears to be negatively associated with technical inefficiency. This means that the larger farm farmers own, the better in allocating their input resources and therefore the higher technical efficiency they have.

Regarding geographical location at provincial level, farmers in Long An province have higher level of inefficiency by 6.7% than others while farmers in Ben Tre province have a higher level of inefficiency by 9.7% than others. This implies that technical inefficiency is significantly different among three provinces. In details, Ben Tre rice farmers have higher level of inefficiency compared to Long An rice farmers. Possible reason why they have lower technical efficiencies is that Ben Tre province has moderate vulnerability to climate change and is located near the coastal region where water is often intruded by saline water while Long An province has low vulnerability to climate change and is located in further inland where water sources are slightly affected by salinity intrusion. Moreover, Ben Tre farmers prefer to diversify their income sources by changing from rice production into farming grass for livestock or farming shrimp. Although Tra Vinh province has high vulnerability to climate change and is located at the coastal region where water source is dramatically affected by salinity intrusion, it has the least technical inefficiency. This can be explained that Tra Vinh farmers had previously experienced salinity intrusion and had previously taken actions to protect their rice farming (e.g. diversifying crop, water management), and therefore they are more likely to have less inefficiency compared to the others.

The negative relationship between geographical location at micro-level such as access to water source and technical inefficiency suggests that farmers with farms located in a near distance to water sources are less inefficient because they have near access to irrigation water sources, an important input for rice farming.

5. Conclusion

The main objective of this study was to measure the technical efficiency of rice production in the Mekong delta of Vietnam and determine key factors driving the level of technical inefficiency.

Results indicated that the overall mean technical efficiency is 0.77 which implies that rice farm households in the delta have the potential to increase their output by 23% given the same level of inputs and technology. Furthermore, they are operating at decreasing returns to scale with the sum of elasticities of 0.3801. The study also found that technical inefficiency could be improved by the participation in agricultural extension services, as well as the performance of adaptation response through the inefficiency effects model. More specifically, farmers with adaptation response and participation in agricultural extension services are generally better in managing inputs and producing rice yield. Geographical location also has significant influence on technical efficiency of rice farming. In details, Ben Tre has the least efficiency compared to the others. Better allocating input resources and less inefficiency were found for farmers in near access to water sources compared to farmers in medium and far access to water source. Farming in larger area is also found to be associated with less technical inefficiency in the production of rice.

Authors hope that these results could provide useful information for farmers and policy makers in designing measures to improve the performance of rice farming in the Mekong Delta. For instance, adaptation practices which are typically implemented by rural farmers can be emphasized as policy options for increasing technical efficiency of rice production and enhancing sustainable agriculture and resilience to mitigate the adverse impacts of climate change related to salinity intrusion and drought. The main reason why the study recommends policy implication on the introduction of climate change adaptation practices in terms of rice production efficiency improvement rather than a climate smart agriculture program is that adaptation practices implemented by rural farmers and CSA program introduced by institutions seem to be overlap. More specifically, adaptation practices consist of a variety of measures such as adjustment in fertilizer and chemical use, change in irrigation water scheme, soil conservation, as well as diversification of crop while the current CSA pilot program only involve adjustment in amount of seed and fertilizer and chemical use. Furthermore, policy makers can assist farmers to improve their farm management by targeting farmers with small scale of farm or no participation in agricultural extension services at local level. Specifically, the importance of providing information associated with climate change adaptation practices and better farming techniques suitable for specific locations through agricultural extension services should be strengthened.

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