Comparative analysis of the technical and environmental efficiency of the agricultural sector: The case of Southeast Asia countries

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Abstract

Elevating agricultural productivity most efficiently along with the protection of environment has been a desirable condition for policymakers worldwide. The introduction of technical and environmental efficiencies in farming could play a crucial role for achieving this motive. This paper measures the technical and environmental efficiency of the agricultural sector in Southeast Asia countries using balanced panel data over the period of 2002-2016. Translog stochastic production frontier analysis (SFA) with a composite error term has been used for the computation of relevant efficiencies. Results of the study reveal that estimated average technical efficiency scores of agricultural sectors in the Southeast Asia countries were 0.76, implying that output can be increased by 24%, by reallocating resources. The estimated average environmental efficiency score was 0.67, suggesting that Southeast Asia region could decrease environmentally detrimental input about 33% at the current level of conventional inputs and output. It was concluded that Vietnam is the most technically and environmentally efficient country in the Southeast Asia region with technical efficiency (TE) scores of 0.98 and environmental efficiency (EE) scores of 0.97 followed by Singapore (TE 0.97, EE 0.92), Myanmar (TE 0.96, EE 0.91), Malaysia (TE 0.80, EE 0.70), Philippines (TE 0.77, EE 0.62), Thailand (TE 0.72, EE 0.59), Cambodia (TE 0.65, EE 0.49), Brunei (TE 0.58, EE 0.47) and Indonesia (TE 0.43, EE 0.0.38). Further, results show that there is still significant room for improvement in both technical and environmental efficiency in Southeast Asia countries. Findings of this paper further illustrate empirical evidence for the need to decrease consumption of chemical fertilizer without decreasing agricultural production in the Southeast Asia region.

Keywords: Efficiency. Environment. Agriculture. SFA. Southeast Asia.

1. Introduction

The increasing world population is alarming and a real threat to food security. It is projected that in the year 2050 this population might reach a figure of nine billion. To mitigate global food insecurity through sustainable food production would be a serious challenge (FAO, 2009). The most affected regions would be developing countries because it is understood that approximately entire these nations face the issues of a growing population (PRB, 2015). To feed the population, nearly all developing countries depend on agriculture. An about 75% of these peoples dwell in rural areas. This means that growth in agricultural production helps the poor farmers to earn income (IFAD, 2011; World Bank, 2008). This growth can help to achieve the objectives of sustainable development goals for the eradication of hunger and poverty in the year 2030 (UN, 2015).

Southeast Asia encompasses a diverse range of countries (Brunei, Cambodia, Indonesia, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam and Laos) at varying levels of development and endowments. Recently, significant development has been undergone by this region through a variety of mix in manufacturing global value chains and structural changes. Due to these developments in Southeast Asia, most of the economies have gained robust Gross Domestic Product (GDP) growth (FAO, 2017). Nonetheless, in this region, the fast-growing population trend was observed over the last couple of decades. Presumably, these countries have achieved a milestone to overcome the problems of food security. Since the 1990s the world undernourishment rates were 31% but by 2014-16 drastic decreased occurred when these rates were declined to only 10%. Despite the fact that many developments occurred in these countries but still 8% of the world population is undernourished in this region (FAO, 2017a). In order to alleviate this issue, it is essential that the agricultural sector of these countries needs more improvement and development.

Currently, the agricultural sector of the Southeast Asia countries plays a vital role in economic development. It has engaged 60% of the rural population as a workforce. With the development of this sector, it has greatly contributed to food security. Therefore, it is an important sector to play its role to eradicate poverty in these countries. With the increasing population in these regions, the agricultural sector has used over-exploitation of natural resources. This means that natural resources are diminishing day by day due to these over exploitations of natural resources. Therefore, efficient usage of resources is required in the agricultural sector of Southeast Asia countries (Teng and McConville, 2016). More specifically, increasing agricultural productivity is important in Southeast Asia to meet the growing demand for food. Generally, biological, chemical and agricultural equipment and facilities are used as inputs in the process of agricultural production. More specifically, a chemical used as inputs in agricultural production, for instance, biological and natural pesticides, chemical, synthetic and natural fertilizers. Moreover, the usage of chemical fertilizers is often exceeded to achieve higher economic performance, for example, cost minimization of inputs and improving the productivity of production (Udeigwe et al., 2015). Consequently, increasing agricultural productivity always been accompanied by usage of higher fertilizer dosage, causing environmental degradation. Nevertheless, the present emphasis on environmental issues has led the farmers to target improvements in both agricultural productivity and environmental performance. One of the challenges of sustainable agriculture centres on using fertilizer efficiently to grow crops without polluting the environment. In addition, unsustainable agricultural practices have substantial, negative environmental impacts (FAO, 2016). Gross agricultural production measured in million US dollar is depicted in Figure 1 for the Southeast Asia countries. Since 2002 to 2016, if one compares the gross agricultural production of Southeast Asia countries, the first leading countries is Indonesia followed by Thailand, Vietnam, Philippines, Myanmar, Malaysia, Singapore and Cambodia. However, Brunei and Singapore have almost the lowest similar gross agricultural production.

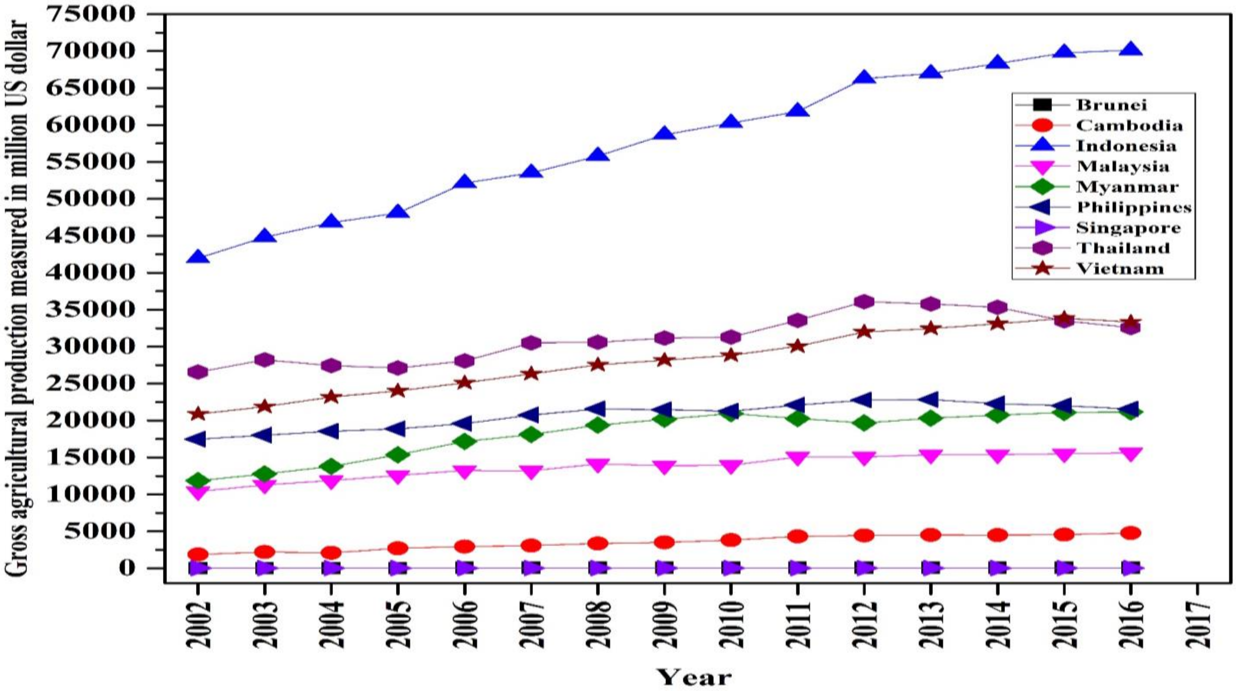

Figure 1: Gross agricultural production of Southeast Asia countries.

The overexploitation of natural resources and usage of excessive chemical fertilizer have puts tremendous pressure on the environment. The increasing usage of a high level of environmental detrimental inputs should be decreased to a considerable level. This decrease would not only reduce the costs of production to the farmers but would be considered less harmful for the environment (Ullah et al., 2018). In this scenario, not only farmers should improve production efficiency through efficient utilization of input but also produce environmentally friendly products. What is the existing state to estimate technical and environmental efficiency of Southeast Asia' agriculture sector? Is there any difference between regions in terms of technical and environmental efficiency? To answer these two questions, we quantitatively calculate the technical and environmental efficiency of the Southeast Asia agriculture sector.

Based on the above number of studies it is now possible to calculate environmental efficiency, but none of the researchers has used the balance panel data approach to measure the technical and environmental efficiency of the agricultural sector of Southeast Asia countries. To fill this gap, we have made an attempt and we predict that this study would be highly significant. Because, in addition to the producers' ability estimation this study will check the environmental effect in the agricultural sector which is a global environmental issue. Moreover, the findings of this study would provide insights into possible improvements in agricultural production towards sustainable development in agriculture and clearing the way for green production in this strategic sector of the Southeast Asia region. Rest of the paper is outlined as follows: next section is all about the methodology of the study. Section 3 presents the results and discussions. Finally, based on the findings of the study, conclusions were settled and possible policy recommendations were made.

The stochastic frontier and data envelopment analysis are the two major approaches to measuring efficiency. These approaches are based on parametric and non-parametric techniques. Mathematical linear programming is used for the estimation of data envelopment analysis while stochastic frontier estimation commonly based on econometric procedures. The selection of the functional form of the model is highly sensitive while conduction stochastic frontier analysis. This suggests that this approach can be effectively and openly applied to the data with measurement error. However, in the case of data envelopment analysis, these assumptions are violated and having no functional form of the model (Tsionas, 2003). Therefore, compared to data envelopment analysis stochastic frontier approach is more appropriate for this research study. This argument is supported by Coelli (1995) and recommended that the stochastic frontier approach is the best applications in the field of the agricultural sector. This approach has the additional advantage to perform tests of hypotheses about the production structure and the degree of inefficiency.

The estimation of efficiency or inefficiency scores for every variable is the other advantages of stochastic frontier analysis (Aigner et al. 1977; Meeusen & Broeck, 1977). In addition, this work was extended towards panel data while measuring efficiency. This pioneering was performed by Hjalmarsson et al. (1996). They argued that using panel data, this approach is the most appropriate method. Because it allows testing statistical hypotheses in the model. The concept of efficiency can be traced back to the work of Farrell (1957) where the farm's efficiency was directly measured from observed data based on a single output and multiple inputs. Technical efficiency is the farm's ability to optimize output from a given set of inputs. Environmental efficiency has got the importance due to the recognition of agriculture effect on the environment. Inputs used in the process of production can have an effect on the environment, either positive or negative. This is an input-oriented single input measure of technical efficiency of the environmentally detrimental input. According to Reinhard et al. (1999) the ratio of minimum feasible to observed use of an environmentally detrimental input, conditional on observed levels of the desired output and the conventional inputs. It is an aspect of technical efficiency, focuses on environmentally detrimental input which has negative environmental effects. A decrease in the level of environmentally detrimental input affects both technical and environmental efficiency.

2. Literature Review

The stochastic frontier analysis has been widely used for measuring the technical and environmental efficiency of the agricultural sector around the world. First, to estimate and measure technical efficiency various approaches have been used. In this line of earlier studies, we have reviewed, Rauf (1991) used a Cobb-Douglas production model to calculate the technical efficiency of irrigated area of Pakistan. Kalirajan (1991) used a translog frontier production function to estimate the technical efficiency of rice farmers in India. Battese (1992) used the stochastic frontier approach to measure the technical efficiency of paddy farmers in India using panel data. Moreover, Chen and Song (2008) applied the stochastic frontier approach to measure technical efficiency and the technology gap in agriculture of China. Rahman et al. (2012) used the same approach to examine the technical efficiency of rice growers in Bangladesh. Kim et al. (2016) and Yang et al. (2016) determined technical efficiency for Korea and China in their respective studies. The authors in both studies have employed a stochastic production frontier model. Liu et al. (2017) applied a zero-inefficiency stochastic frontier approach for measuring efficiency and productivity of Thai rice farmers. All of the researchers in these past studies did not take the case of undesirable outputs. Thus, it is essential when analyzing producer behaviour, we should take care of all outputs such as various gases and wastewater (Shephard and Färe 1974). To assess environmental performance Pittman (1983) designed the multi-output productivity index of Tornqvist. However, it was essential to price undesirable outputs. This pricing issue was removed by Pittman (1983) involving the shadow price of the undesirable output. Nonetheless, this approach was unable to differentiate in shadow prices among individual. Likewise, to estimate environmental efficiency, the hyperbolic productive efficiency model was designed by Färe et al. (1989) using the multi-output technical efficiency concept of Farrell (1957). Hyperbolic productive efficiency may vary according to the disposal cost of the undesirable output. This happened when an undesirable output treated as the output variable. Therefore, the shadow should be ignored when employing the DEA approach. This method is also called nonparametric mathematical programming technique. However, for most of the producers, this approach estimates the same performance of the environment. Moreover, Färe et al. (1993) estimated the environmental efficiency of pulp and paper in Wisconsin and Michigan using a parametric mathematical programming method. Nevertheless, this work was, later on, was denied by Yang et al. (2008) and Yang (2009) in their respective research work. They argued that this technique was suffering from serious issues.

Environmental efficiency has also been a desirable topic for many researchers in the past for the purpose to enhance the environmental efficiency and to minimize undesirable outputs. Most of the researchers have treated the undesirable output as environmental detrimental variables in their respective studies. In this context, the most similar study was done by Reinhard et al. (1999) who employed the stochastic frontier analysis to measure the environmental efficiency of Dutch dairy farms. He defined that environmental efficiency is the ratio between the possible minimum undesirable output and the observed output. One year later, Reinhard et al. (2000) comparison of environmental efficiencies was estimated employing both techniques SFA and DEA. The environmental efficiency estimates were based on nitrogen surplus, phosphate and total energy consumed in Dutch dairy farms. Both econometric techniques were shoeing different results as SFA estimated the efficiency score of 80%, while DEA computed 52% efficiency scores in the region. Recently, Hong et al. (2016) adopted SFA approach to measure the environmental efficiency and economic losses of tea producers in Vietnam. Chemical fertilizers and pesticides were utilized to estimate the efficiency. The efficiency scores were computed in order to enhance the total agricultural productivity as well as to combat challenges associated with pests and diseases. The research found that environmentally detrimental inputs were overused in the farms and there is a considerable scope for decreasing their application with the existing technology. Zhang and Xue (2005) initially computed technical efficiency in case of China's vegetable production by using SFA approach, then by taking under consideration the Reinhard et al. (1999) technique, they computed the environmental efficiency by using pesticides and chemical fertilizer as environment detrimental inputs in Chinese farming. The mean environmental efficiency score of pesticides was 69.7%, indicating a great potential for reducing the use of pesticides in vegetable production in Chinese farming.

3. Methodology

In this article, we applied the stochastic frontier analysis approach, based on the neoclassical theory of production to measure technical and environmental efficiency of Southeast Asia agricultural sector using the balanced panel data over the period of 2002-2016. The detail data of the Laos country was not available, based on this reason it was excluded from the study. The data used in this study was collected from the database of the Food and Agriculture Organization of the United Nations (FAO, 2018). Figure 2 presents a map of the

Southeast Asia countries.

Figure 2: Map of the Southeast Asia countries (De Koninck & Rousseau, 2013).

This study is based on one output denoted by Y (gross agricultural production), three conventional or normal inputs denoted by X (land, labour & capital) and environmentally detrimental input denoted by Z (fertilizer surplus). The value of the gross agricultural production was used as output measured in million US dollar, based on the constant price of 2010 and treated as a dependent variable in the stochastic frontier model. The land, labour and capital are conventional inputs of production. These variables were included in the model based on a similar previous study by Moreno-Moreno et al. (2018). The agricultural land of Southeast Asia was measured in thousand hectares. The labour of Southeast Asia was calculated as the total economically active population in agriculture measured in thousands of people. While the capital of this region was taken as gross fixed capital stock measured in agriculture orientation index based on the constant price of 2010 US dollar. The total consumption of fertilizer data was calculated by adding the Nitrogen N, Potash K_2O, and Phosphate P_2O_5 and measured in thousands of tons. However, this is our environmental detrimental variable. Based on fertilizer surplus variable environmental efficiency scores were determined. The application of surplus fertilizer is environmentally detrimental input and is responsible variable for environmental pollution and degradation (Solazzo et al., 2016). The description of all variables and their measurement units are given Table 1.

Table 1: Description of the variables used in this study

Variables	Description of the variables
Output	Value of the gross agricultural production measured in million US dollar, based on the constant price of 2010.
Land	Agricultural land measured in thousand hectares.
Labor	Total economically active population in agriculture measured in thousands of people.
Capital	Gross fixed capital stock measured in agriculture orientation index based on constant price of 2010 US dollar.
Fertilizer	Consumption of fertilizer (Nitrogen N, Potash K_2O, and Phosphate P_2O_5) measured in thousands of tons.

Source: FAO (2018)

We used the stochastic frontier model to examine the technical efficiency. Previous studies show that this technique was designed by Aigner et al. (1977) and, Meeusen and Broeck (1977). However, after the provision of basic concept this work was continued by Pitt and Lee (1981); Battese and Coelli (1988, 1992) and Hjalmarsson et al. (1996). These mentioned studies have extended the stochastic frontier production model for panel data approach. Besides, calculating the technical efficiency it was realized that the overexploitation of inputs is deteriorating the environment contentiously. Thus, environmental efficiency can be defined as the least possible application of environmentally detrimental input to the observed input. Therefore, prior to calculate environmental efficiency it is imperative to estimate technical efficiency. In this approach often some inputs of production are treated as environmental detrimental variables. Reinhard et al. (1999) did this pioneering work and later on, it was applied by Reinhard et al. (2000), Tu et al. (2015), Tu (2015) and Tu (2017) in their respective research studies. Moreover, the ratio of observed output to the possible maximum output refers to the technical efficiency keeping the factor of production and technology remain constant. Figure 3 presents the Farrell (1957) concept of measuring the technical efficiency of a firm. Farrell (1957) considered that when a firm uses two factors of production X and Y for the production of an output N under constant returns to scale (RTS). The isoquant QQ´ shows different combinations of two inputs and provides the same level of output. N shows the combination of two inputs for the firm that can be utilized to produce per unit of output. Isoquant QQ´ presents a lower bound of a scatter and provides the same level of output. P and N are on the same isoquant and P gives an efficient combination of two factors of production that the firm employs in the same ratio as N. Fraction OP/ON of each input produces the same quantity of output as P. ON/OP times more output can be obtained using the same level of inputs. Technical efficiency of the firm is equal to ON/OP and it is shown by PN. The budget line in the figure represents SS´ and its slope is equal to the ratio of two inputs prices. Point Q´ shows the optimum combination of two factors of production where the isoquant QQ´ is tangent to the budget line S$\acute{S}$ and the firm is technically efficient at point Q´.

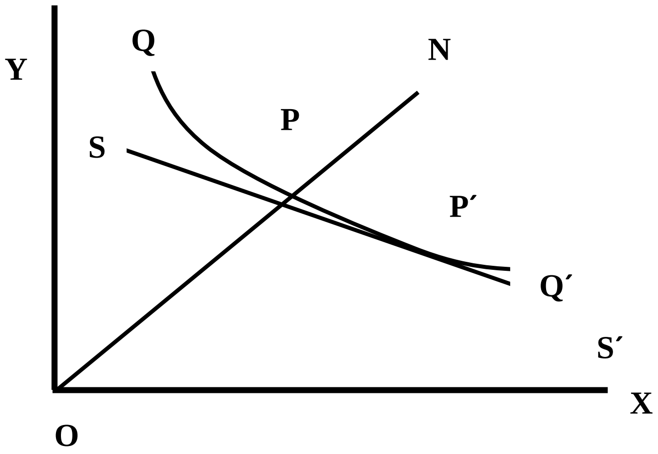

Figure 3: Farrell (1957) concept of technical efficiency.

The production frontier using conventional input X and environmentally detrimental input Z if, citrus peribus are presented in Figure 4. Further, Z_F is the least possible environmental detrimental input provides the production function. QQ ´ is the output and X_R refer to observed values of conventional input. Thus, environmental efficiency having non-radial input-oriented variables can be considered as EE = | OZ_F | / |OZ_R|. Whereas, estimating environmental efficiency both the necessary and sufficient condition of technical efficiency should be examined. However, the compatibility between a high degree of technical and low degree environmental efficiency depend on the difference of the detrimental input usage (Reinhard et al. (1999).

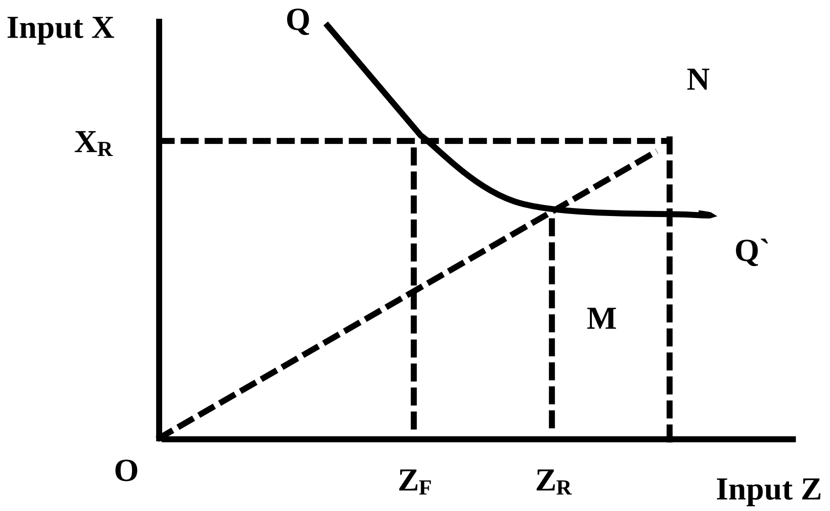

Figure 4: Reinhard (1999) concept of environmental efficiency.

The mathematical expression of production frontier model without stochastic components are presented in Equation 1 which is as follow:

$$Y_{it} = f(x_{it}, z_{it}; \alpha, \beta, \gamma) * TE_{it} \tag{1}$$

Where the subscript *i* and t signifies all countries and all years respectively. The output is shown with Y_{it}. Here in this study, we have taken the output variable for all countries in term of value of the gross agricultural production. The vector of conventional inputs (land, labour and capital) used by the countries are denoted with x_{it}. Likewise, Z_{it} is a vector of environmentally detrimental input (consumption of fertilizer calculated by adding Nitrogen N, Potash K_2O, and Phosphate P_2O_5)); α , β , γ are parameters of the model to be estimated; TE_{it} presents the technical efficiency and is referred to as the ratio of observed output to maximum feasible output. The country gets the maximum feasible output when TE = 1; and TE < 1 shows a measure of the deficit of the observed output from the maximum feasible output. Random or exogenous shocks which are beyond the control of the producers also affect the production process and are captured by a stochastic component $v_{it;}$ this stochastic residual term is independent and identically distributed with zero mean and constant variance i.e. $N(0, \sigma_v^2)$. These shocks are denoted by $\exp\{v_{it}\}$. Each producer faces a different shock and it is expected that these shocks are random and have a common distribution. The stochastic production frontier model can be written as under:

$$Y_{it} = f(x_{it}, z_{it}; \alpha, \beta, \gamma) * TE_{it} * \exp\ \{v_{it}\} \tag{2}$$

It is assumed that TE_{it} is a random variable and has a common distribution function. It can be expressed as an exponential, $TE_{it} = \exp\{-u_{it}\}$ where $u_{it} \geq 0$ and $0 \leq \exp\{-u_{it}\} \leq 1$. The stochastic production frontier model can be expressed as under:

$$Y_{it} = f(x_{it}, z_{it}; \alpha, \beta, \gamma) * \exp\{-\upsilon_{it}\} * \exp\{u_{it}\}$$

(3)

Finally, the output-oriented technical efficiency is measured using the following expression:

$$TE_{it} = \exp\{-u_{it}\} = \frac{Y_{it}}{f(x_{it}, z_{it}; \alpha, \beta, \gamma) * \exp\{\upsilon_{it}\}}$$

(4)

The stochastic version of output-oriented technical efficiency determines the producer's ability to maximize output given a set of inputs (Aigner et al. 1977; Farrell 1957; Jondrow 1982). There are different forms of production function described in Equation (3). However, Cobb-Douglas and translog production functions are more commonly used. In order to find the best fitting functional form, which best fits the data of this research study, the attention was paid to translog stochastic production frontier function. This function is a member of de Janvry's generalized power production family and minimizes misspecification error. In the translog production function, the percentage change in the input ratio divided by the percentage change in the marginal rate of substitution (MRS) is not constant along the isoquant but changes from point to point. This function is generalized and includes any number of input categories. Each pair of inputs may have a different elasticity of substitution. The Cobb-Douglas is the restricted form of translog function. When coefficients of all interaction inputs are zero, translog function reduces to Cobb-Douglas form. Moreover, Likelihood ratio test (LR test) is used to select the most appropriate production form of the model (Coelli et al., 2005). The null hypothesis is determined as H_0 = Cobb-Douglas production function is the appropriate model against the alternative hypothesis as H_1 = Translog production function is the appropriate model. If chi-squared distribution statistical value is greater than the chi-squared critical value, then the alternative hypothesis is accepted against the null hypothesis. Thus, based on the LR test we would conclude that the translog frontier model form is the most appropriate production form.

Now assume that $f(X_{it}, Z_{it}; \alpha, \beta, \gamma)$ takes the log-linear translog stochastic production frontier function with a composite error term and Equation 3 can be written as:

$$\mathrm{LnY}_{it} = \alpha_o + \sum_{j=1}^{m} \alpha_j \mathrm{LnX}_j + \beta_k \mathrm{LnZ}_k + \frac{1}{2}\sum_{j=1}^{m}\sum_{l=1}^{m} \alpha_{jl}\mathrm{LnX}_j\mathrm{LnX}_l + \frac{1}{2}\beta_{kk}(\mathrm{LnZ}_k)^2 + \sum_{j=1}^{m}\gamma_{jk}\mathrm{LnX}_j\mathrm{LnZ}_k + \upsilon_{it} - u_{it}$$

(6)

Where $\alpha_{jl} = \alpha_{lj}$, LnY is logarithm of the output; LnX and LnZ are logarithms of normal and environmentally detrimental inputs, respectively; υ_{it} is the residual term and is normally distributed with zero mean and constant variance (σ_υ^2); u_{it} is the non-negative technical inefficiency component and υ_{it} - u_{it} is called compound error term. The logarithm of the output (Y_{it}) of a technically efficient producer is obtained by setting $u_{it} = 0$. The logarithm of the output of environmentally efficient producer is obtained by substituting Z with $EE_{it}.Z_{it}$ and setting u_{it} = 0 (Reinhard et al. 1999 & 2000). Now the equation for the environmentally efficient producer is as under:

$$\mathrm{LnY}_{it} = \alpha_o + \sum_{j=1}^{m} \alpha_j \mathrm{LnX}_j + \beta_k \mathrm{Ln}(\mathrm{EE}_{it}.\mathrm{Z}_k) + \frac{1}{2}\sum_{j=1}^{m}\sum_{l=1}^{n} \alpha_{jl}\mathrm{LnX}_j\mathrm{LnX}_l + \frac{1}{2}\beta_{kk}\{\mathrm{Ln}(\mathrm{EE}_{it}.\mathrm{Z}_k)\}^2 + \sum_{j=1}^{m}\gamma_{jk}\mathrm{LnX}_j\mathrm{Ln}(\mathrm{EE}_{it}.\mathrm{Z}_k) + \upsilon_{it}$$

(7)

Since environmental efficiency is the capacity to reduce environmentally detrimental input while holding constant the current output and the normal inputs; Setting equation (6) equal to equation (7); the environmental efficiency is measured using the following equation:

$$\beta_k \mathrm{Ln}(\mathrm{EE}_{it}.\mathrm{Z}_k) - \beta_k \mathrm{LnZ}_k + \frac{1}{2}\beta_{kk}\{\mathrm{Ln}(\mathrm{EE}_{it}.\mathrm{Z}_k)\}^2 - \frac{1}{2}\beta_{kk}(\mathrm{LnZ}_k)^2 + \sum_{k=1}^{n}\gamma_{jk}\mathrm{LnX}_j\mathrm{Ln}(\mathrm{EE}_{it}.\mathrm{Z}_k) - \sum_{k=1}^{n}\gamma_{jk}\mathrm{LnX}_j\mathrm{LnZ}_k + u_{it} = 0$$

(8)

We further simplified and re-arranged equation (8) and got the following equations:

$$\frac{1}{2}\beta_{kk}(\mathrm{LnEE}_{it})^2 + \left[\beta_k + \beta_{kk}\mathrm{LnZ}_k + \sum_{k=1}^{n}\gamma_{jk}\mathrm{LnX}_j\right]\mathrm{LnEE}_{it} + u_{it} = 0$$

(9)

$$a_{it}(\mathrm{LnEE}_{it})^2 + b_{it}(\mathrm{LnEE}_{it}) + c_{it} = 0$$

(10)

Where;

$a_{it} = \frac{1}{2}\beta_{kk,}$ $b_{it} = \beta_k + \beta_{kk}\mathrm{LnZ}_k + \sum_{k=1}^{n}\gamma_{jk}\mathrm{LnX}_j$ and $c_{it} = u_{it}$; the root-formula was used and got the value for Ln EE$_{it}$:

$$\mathrm{LnEE}_{it} = \left[-\left(\beta_k + \beta_{kk}\mathrm{LnZ}_k + \sum_{k=1}^{n}\gamma_{jk}\mathrm{LnX}_j\right) \pm \left\{\left(\beta_k + \beta_{kk}\mathrm{LnZ}_k + \sum_{k=1}^{n}\gamma_{jk}\mathrm{LnX}_j\right)^2 - 2\beta_{kk}u_{it}\right\}^{0.5}\right] / \beta_{kk}$$

(11)

According to Reinhard et al. (1999 & 2000), environmental efficiency is measured with the "+√" formula in equation (11) because the technically efficient country is essentially environmentally efficient. Finally, the environmental efficiency was measured using the following equation (12):

$$E_{it} = \exp\left[-\left(\beta_k + \beta_{kk}\mathrm{LnZ}_k + \sum_{k=1}^{n}\gamma_{jk}\mathrm{LnX}_j\right) + \left\{\left(\beta_k + \beta_{kk}\mathrm{LnZ}_k + \sum_{k=1}^{n}\gamma_{jk}\mathrm{LnX}_j\right)^2 - 2\beta_{kk}u_{it}\right\}^{0.5}\right] / \beta_{kk}$$

(12)

To estimate the translog stochastic production frontier model and to calculate the technical and environmental efficiency scores of Southeast Asia countries, we have used Microsoft excel worksheet and econometric software STATA version 13 in this study.

4. Results and Discussion

Table 2 summarizes the descriptive statistics of all the variables used in the efficiency analysis. The descriptive statistics of Southeast Asia countries show some fantastic and interesting results. The table illustrates that in Southeast Asia the highest average value of the gross agricultural production was estimated 57692.78 million US dollar belongs to Indonesia. The average output value was followed by Thailand, Vietnam and the Philippines and their respective mean gross agricultural production is 31185.14, 28050.41 and 20743.35 million US dollar. This pattern has been observed while using agricultural land in Southeast Asia. Because Indonesia has used on average highest agricultural land 54339.93 thousand hectares. However, among all Southeast Asia region, the only country Vietnam shows tremendous average agricultural output compared to their mean agricultural land utilization. This means Vietnam is using efficient usage of land utilization. Further, we did not find any constant trend while using the labour workforce, capital utilization and fertilizer application. As Vietnam has used on average a greater number of labour workforce and fertilizer application compared to Thailand. Similarly, the Philippines has used a greater number of capitals stock compared to Thailand. Based on descriptive statistics, Table 2 we assume that the country having high technical efficiency is not necessary that their environmental efficiency would be the same. Next, based on descriptive statistics we predict that Southeast Asia' agriculture is not technically efficient. Furthermore, our analysis proceeds further, to choose the best fit model between Cobb–Douglas production function and translog production function.

Table 2: Descriptive statistics of the variables used in the efficiency analysis

Variables	Brunei	Cambodia	Indonesia	Malaysia	Myanmar	Philippines	Singapore	Thailand	Vietnam
Output									
Mean	42.06	3512.56	57692.78	13771.37	18188.90	20743.35	28.76	31185.14	28050.41
Max	52.43	4779.50	70125.23	15618.04	21165.41	22848.21	33.58	36089.55	33841.52
Min	24.34	1868.25	41973.23	10397.47	11856.89	17480.83	26.21	26558.89	20877.33
St. Dev.	8.46	997.45	9538.44	1655.67	3220.89	1776.57	2.05	3235.92	4373.47
Land									
Mean	12.55	5352.73	54339.93	7537.80	12060.80	11948.67	0.76	20750.47	10612.53
Max	14.40	5455.00	57000.00	8627.00	12760.00	12440.00	1.20	22110.00	12178.00
Min	10.30	5000.00	48181.00	7037.50	10925.00	11135.00	0.66	19554.00	9455.00
St. Dev.	1.56	140.56	2764.61	556.82	693.25	481.87	0.13	1089.50	913.46
Labor									
Mean	1.33	4001.10	41991.80	1611.00	14701.60	12033.67	2598.00	15292.40	25061.00
Max	2.00	5491.00	45313.00	1792.00	16782.00	12694.00	3214.00	16801.00	26952.00
Min	1.00	2499.00	38254.00	1421.00	12743.00	11228.00	1980.00	12478.00	23316.00
St. Dev.	0.49	1060.74	1876.89	110.49	1388.17	491.35	410.70	1377.91	947.22
Capital									
Mean	0.40	0.25	0.58	0.68	0.35	0.58	0.91	0.29	0.29
Max	0.97	0.33	0.65	0.89	0.64	0.71	1.08	0.36	0.42
Min	0.16	0.17	0.51	0.52	0.22	0.44	0.80	0.22	0.21
St. Dev.	0.69	0.06	0.04	0.10	0.13	0.09	0.09	0.05	0.08
Fertilizer									
Mean	0.59	48.50	4217.98	1515.92	143.01	773.90	8.00	2299.58	2379.97
Max	1.73	95.94	5448.91	1866.57	263.27	880.00	18.52	3092.06	3146.82
Min	0.13	14.27	2489.22	1085.33	42.31	572.10	0.59	1700.83	1858.22
St. Dev.	0.41	27.16	973.38	216.33	73.05	91.19	5.35	470.67	451.36

Source: Estimation from the FAO Statistics (2018)

In order to identify a true production function model between Cobb–Douglas production function and translog production function which best fits the data of this research study, we employed likelihood ratio test known as LR test (Coelli et al., 2005). The null hypothesis was tested that the Cobb-Douglas production form is the most appropriate model against the alternative hypothesis assuming that the translog production function form is the appropriate model. As the statistical value of the LR test is 595.43 which is greater than chi-squared distribution having value 23.21 at 1% level of significance. Therefore, the outcomes of the LR test suggests that the null hypothesis was rejected in favour of the alternative hypothesis. Therefore, we straightforward preferred translog production function model over the Cobb–Douglas production function. Our results are in line with the previous studies done by Carrer et al. (2015) and Ullah et al. (2017). Hereafter, we proceed with analysis in this study and performed a translog production model.

Results of the translog stochastic production frontier model are reported in Table 3. To investigate technical inefficiency presence or absence we performed the Log-likelihood test known as LL test (Coelli et.al 2005). The LL test statistic value was figured out 170.1. This value exceeds 1% from the critical value. Consequently, we reject the null hypothesis at 1% level of significance. This suggests that Southeast Asia countries' agriculture is not technically efficient. Further, this shows that the Southeast Asia' agriculture sector is technically inefficient. The parameters (σ_u^2, σ_v^2) can be transformed to (σ^2, γ) with $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2/\sigma 2$ (Battese and Coelli, 1992). The value of γ (variance parameter) plays a significant role in the composite error term (Greene, 2004) and captures the effect of technical inefficiency. The calculated value of γ denotes the percentage change in output due to inefficiency effect is significantly different from zero. This means that inefficiency effects does exist as the level of output shows variation in the model (Coelli and Battese, 1996). The larger the value of the variance parameter the greater would be inefficiency component in the model. The value of the variance parameter at the bottom of Table 3 was calculated having value 0.99. This value of the variance parameter indicates that inefficiency is highly significant to clarify the deviation of the firms in relation to the production frontier. This variance parameter value denotes that technical inefficiency is the major component of the composite error term and contributes 99% to the total variability of output produced. The estimated coefficients of the stochastic frontier production function are reported in Table 3. This presents that labour force has non-significant impact while capital has positive and significant impact on agricultural sector of Southeast Asia. The coefficient of land shows the highest positive and significant effect on output. This finding is in line with the result of Liu et al., (2019). However, fertilizer application has negatively significant impact on agricultural sector of Southeast Asia region.

Table 3: Estimates of the translog stochastic production frontier model

Variables	Parameter	Coefficient estimate	Standard error	Prob.
Constant	α_0	2.61*	0.63	< 0.01
lnLand	α_D	0.77*	0.23	< 0.01
lnLabor	α_L	-0.11	0.09	0.21
lnCapiatl	α_K	0.28***	0.15	0.06
lnFertilizer	β_F	-0.24*	0.08	< 0.01
½(lnLand)^2	α_{DD}	0.00	0.03	0.99
½(lnLabor)^2	α_{LL}	0.05*	0.02	< 0.01
½(lnCapiatl)^2	α_{KK}	-0.14*	0.03	< 0.01
½(lnFertilizer)^2	β_{FF}	0.04**	0.02	< 0.05
lnLand × lnLabor	α_{DL}	-0.05*	0.02	< 0.01
lnLand × lnCapiatl	α_{DK}	0.07**	0.03	< 0.05
lnLand × lnFertilizer	γ_{DF}	-0.01**	0.01	0.05
lnLabor × lnCapiatl	α_{LK}	0.04***	0.02	0.06
lnLabor × lnFertilizer	γ_{LF}	-0.00	0.01	0.57
lnCapiatl × lnFertilizer	γ_{KF}	-0.01	0.04	0.75
Model diagnostics				
Sigma squared	σ^2	0.28		
Gamma	Γ	0.99		
Sigma u^2	σ_u^2	0.27		
Sigma v^2	σ_v^2	0.00		
Eta	Η	0.02		
Mu	μ	-0.62		
Log-likelihood	LL	170.10		
Wald χ^2 value (14)		27276.98		
Prob χ^2		< 0.01		

Author's calculation from the FAO Statistics (2018)
Note: *, **, *** show significant levels of 1%, 5% & 10% respectively

Since the coefficient of factors of production does not provide direct results for interpretation, therefore, elasticities of output with respect to each input were computed and are reported in Table 4. This table illustrates that elasticities of agricultural land, labour and fertilizer carry positive signs as expected prior to the results. This implies that holding all else constant, an increase in agricultural-cultivated land, labour and fertilizer would enhance agricultural productivity in the Southeast Asia countries. However, elasticity' sign of capital is negative; this may suggest that, on average, the use of capital input has already reached its optimal level. The land has achieved the highest elasticity of 0.65, implying that a 1% increase in agricultural land will increase production by 0.65%. The elasticities of labour and fertilizer are 0.57 and 0.49, respectively. These results are similar to the findings of Rahman et al. (2009); Sriboonchitta et al. (2017) and Liu (2017).

Table 4: Elasticity and returns to scale

Variables	Value
Land	0.65
Labor	0.57
Capital	-0.72
Fertilizer	0.49
Returns to scale	0.99 ≈ 1

Author's calculation from the FAO Statistics (2018)

The summation of output elasticities of all inputs at their mean values for the stochastic frontier model refers to returns to scale (RTS). The RTS value is provided in Table 4. The estimated value of the RTS parameter was figured out 0.99 which is quite equal to one (≈1). This figure signifies that Southeast Asia' agricultural sector is operating under constant returns to scale (CRTS). The CRTS can explain such that, the Southeast Asia' agricultural sector would neither an economy nor diseconomy of scale on the frontier. These results are quite interesting and present a robust analysis. Further, CRTS suggests and displays that Southeast Asia' agricultural sector is operating in the optimal scale region. These results intimate that the Southeast Asia region may increase their agricultural production by improving technical efficiency rather than by increasing production scales. These findings are similar to the results of Liu (2017) and Carrer et al. (2015).

Furthermore, output-oriented technical efficiency can be estimated based on two-panel data techniques. A first technique referred to time in-varying while the second one is known as time-varying decay model. We preferred in this study to adopt a time-varying decay model as the data is periodically long over the time span from 2002 to 2016. Therefore, time-varying decay model is reasonable which is best fit to estimate technical efficiency considering the time-period length. This means technical efficiency would be variate over a long period of time. During this time period, public policy can be updated and management could be up-graded (Zhou et al., 2015). The output-oriented technical efficiency scores of agricultural sectors in Southeast Asia countries were estimated using Equation 4 and are shown in Table 5. Based on time-varying decay model under stochastic frontier analysis, the results reveal that the average technical efficiency scores of agricultural sectors in the Southeast Asia countries were 0.76. These findings suggest that the Southeast Asia countries could increase output up to 24% by eliminating technical inefficiency effects. This finding is consistent with the result of Carrer et al. (2015); Liu et al. (2017) and Ullah et al. (2017). Technical efficiency scores largely varied among the Southeast Asia countries. On average technical efficiency in the Southeast Asia region varies from 0.49 to 0.98, implying that there is considerable room for improvement in the technical efficiency levels in these countries. Furthermore, the least technically efficient country could increase 51% of agricultural production with current inputs used. Nonetheless, the Vietnam is the most technically efficient country in Southeast Asia with technical efficiency scores of 0.98 followed by Singapore (0.97), Myanmar (0.96) which means that these countries are using a lowest scale of inputs and producing maximum agricultural output. Thus, these countries play a vital role in enhancing their agricultural competitiveness. Furthermore, these countries are followed by Malaysia (0.80), Philippines (0.77), Thailand (0.72), Cambodia (0.65), Brunei (0.58) and Indonesia (0.43). Year-wise technical efficiency scores are presented in Table 5. The table shows that in the year 2014 Vietnam has achieved maximum technical efficiency score of 99% and maintained this score over the next couple of years. Furthermore, the country has achieved an equal number of technical efficiency score during the time period from 2002 to 2013. Similar results were found in the case of Singapore, in the year 2014 having maximum technical efficiency score was 98%. Rest of the countries have a mixed sort of technical efficiency score except Myanmar. Myanmar has attained almost similar technical efficiency scores over the time span from 2006 to 2016. The average technical efficiency scores and ranks of Southeast Asia countries are presented in Figure 5 with the help of the radar chart.

Table 5: Technical efficiency scores in Southeast Asia countries

Year	Brunei	Cambodia	Indonesia	Malaysia	Myanmar	Philippins	Singapore	Thailand	Vietnam	Mean
2002	0.52	0.58	0.37	0.77	0.95	0.73	0.97	0.68	0.98	0.73
2003	0.53	0.61	0.37	0.78	0.95	0.74	0.97	0.69	0.98	0.74
2004	0.54	0.61	0.38	0.78	0.95	0.75	0.97	0.69	0.98	0.74
2005	0.55	0.62	0.39	0.78	0.95	0.75	0.97	0.70	0.98	0.74
2006	0.56	0.63	0.40	0.79	0.96	0.76	0.97	0.71	0.98	0.75
2007	0.56	0.63	0.41	0.79	0.96	0.76	0.97	0.71	0.98	0.75
2008	0.57	0.64	0.42	0.80	0.96	0.77	0.97	0.72	0.98	0.76
2009	0.58	0.65	0.43	0.80	0.96	0.77	0.97	0.72	0.98	0.76
2010	0.59	0.65	0.44	0.81	0.96	0.78	0.97	0.73	0.98	0.77
2011	0.59	0.66	0.44	0.81	0.96	0.78	0.97	0.73	0.98	0.77
2012	0.60	0.67	0.45	0.81	0.96	0.78	0.97	0.74	0.98	0.77
2013	0.61	0.67	0.46	0.82	0.96	0.79	0.97	0.74	0.98	0.78
2014	0.62	0.68	0.47	0.82	0.96	0.79	0.98	0.75	0.99	0.78
2015	0.62	0.69	0.48	0.83	0.96	0.80	0.98	0.76	0.99	0.79
2016	0.63	0.69	0.49	0.83	0.96	0.80	0.98	0.76	0.99	0.79
Mean	0.58	0.65	0.43	0.80	0.96	0.77	0.97	0.72	0.98	0.76
St.dev	0.03	0.03	0.04	0.08	0.01	0.02	0.01	0.03	0.01	0.02
Rank	8	7	9	4	3	5	2	6	1	

Author's calculation from the FAO Statistics (2018)

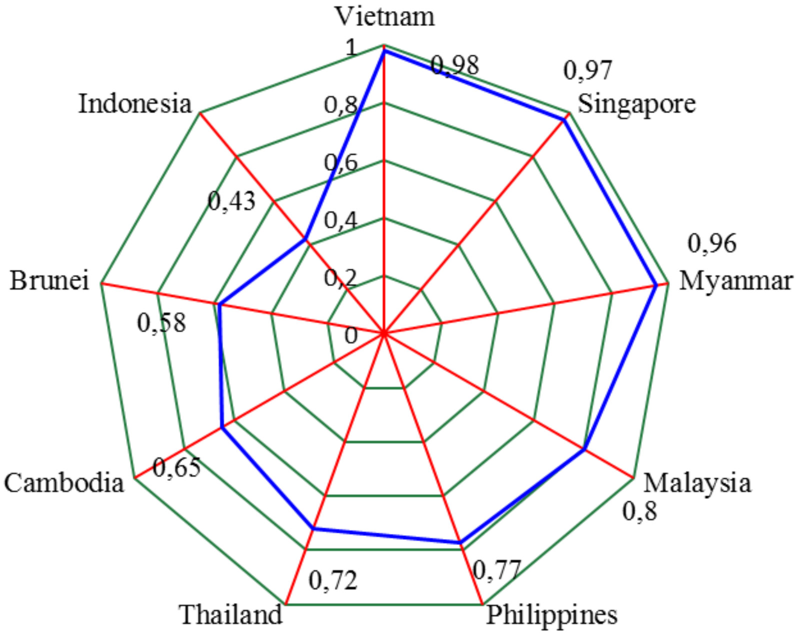

Figure 5: Comparison of the technical efficiency scores of Southeast Asia countries.

Data Resource: Calculated based on the data of FAO Statistics (2018) for Southeast Asia countries

Chemical fertilizer is widely applied in the agricultural sector to enhance agricultural productivity. This enhancement brings minimization in total costs of production and maximizes per acre or hectare yield. Nevertheless, indiscriminate usage of chemical fertilizer creates numerous potential environmental effects (Hong et al., 2016). Therefore, careful management of fertilizer application is required to reduce losses to the environment. In this article, we have made an attempt to examine the environmental efficiency scores which are based on the nitrogen surplus, potash surplus and phosphate surplus. Table 6 shows that the input-oriented environmental efficiency scores of agricultural sectors in Southeast Asia countries using the time-varying decay model under translog stochastic frontier analysis. In order to determine the input-oriented environmental efficiency scores of Southeast Asia countries, Equation 12 was used. Results presented in the table show that the estimated average environmental efficiency scores of environmentally detrimental inputs in the Southeast Asia countries were 0.67 ranging from 0.32 to 0.98, implying that there is still considerable room for improvement in the environmental efficiency of Southeast Asia countries. This suggests that Southeast Asia countries have the ability to reduce environmental detrimental input fertilizer consumption 0.33 or 33% without compromising current agricultural production while holding conventional inputs constant. These findings are consistent with the studies of Tirado et al. (2017) and Tu et al. (2018). The authors of these studies reported that environmentally detrimental inputs are frequently overused in the agricultural sector of Southeast Asia countries. Similarly, the least environmentally efficient country could also reduce the use of detrimental input by 38%. These findings are consistent with the studies of Lamers et al. (2013) and Hong et al. (2016). Environmental efficiency scores are largely varied among the Southeast Asia countries. Results further show that Vietnam is the most environmentally efficient country in Southeast Asia region with average environmental efficiency scores of 0.97 followed by Singapore (EE 0.92), Myanmar (EE 0.91), Malaysia (EE 0.70), Philippines (EE 0.62), Thailand (EE 0.59), Cambodia (EE 0.49), Brunei (EE 0.47) and Indonesia (EE 0.38). The results indicate that most Southeast Asia countries are broadly environmentally inefficient, which primarily resulted from poor technical inefficiency. Year-wise environmental efficiency scores are presented in Table 6. Figure 6 portrays radar chart of average environmental efficiency scores and rank of Southeast Asia countries based on environmental efficiency scores.

Table 6: Environmental efficiency scores of Southeast Asia countries

Year	Brunei	Cambodia	Indonesia	Malaysia	Myanmar	Philippines	Singapore	Thailand	Vietnam	Mean
2002	0.39	0.43	0.32	0.64	0.87	0.55	0.88	0.52	0.97	0.62
2003	0.40	0.44	0.33	0.65	0.89	0.58	0.91	0.54	0.97	0.63
2004	0.42	0.45	0.34	0.67	0.90	0.59	0.92	0.55	0.97	0.65
2005	0.42	0.45	0.35	0.67	0.87	0.59	0.92	0.55	0.97	0.64
2006	0.43	0.46	0.36	0.68	0.90	0.60	0.93	0.56	0.97	0.65
2007	0.44	0.47	0.37	0.69	0.91	0.61	0.93	0.57	0.97	0.66
2008	0.46	0.48	0.37	0.70	0.90	0.60	0.93	0.58	0.97	0.67
2009	0.47	0.49	0.38	0.70	0.90	0.62	0.91	0.59	0.97	0.67
2010	0.48	0.50	0.39	0.71	0.90	0.63	0.90	0.60	0.97	0.68
2011	0.50	0.51	0.39	0.71	0.91	0.64	0.91	0.61	0.98	0.68
2012	0.51	0.51	0.40	0.72	0.92	0.64	0.93	0.62	0.98	0.69
2013	0.51	0.53	0.41	0.72	0.92	0.66	0.93	0.63	0.98	0.70
2014	0.52	0.54	0.42	0.73	0.93	0.66	0.87	0.64	0.98	0.70
2015	0.53	0.54	0.42	0.73	0.93	0.66	0.95	0.64	0.98	0.71
2016	0.53	0.55	0.43	0.74	0.93	0.68	0.95	0.65	0.98	0.72
Mean	0.47	0.49	0.38	0.70	0.91	0.62	0.92	0.59	0.97	0.67
St.dev.	0.05	0.04	0.03	0.03	0.02	0.04	0.02	0.04	0.01	0.04
Rank	8	7	9	4	3	5	2	6	1	

Author's calculation from the FAO Statistics (2018)

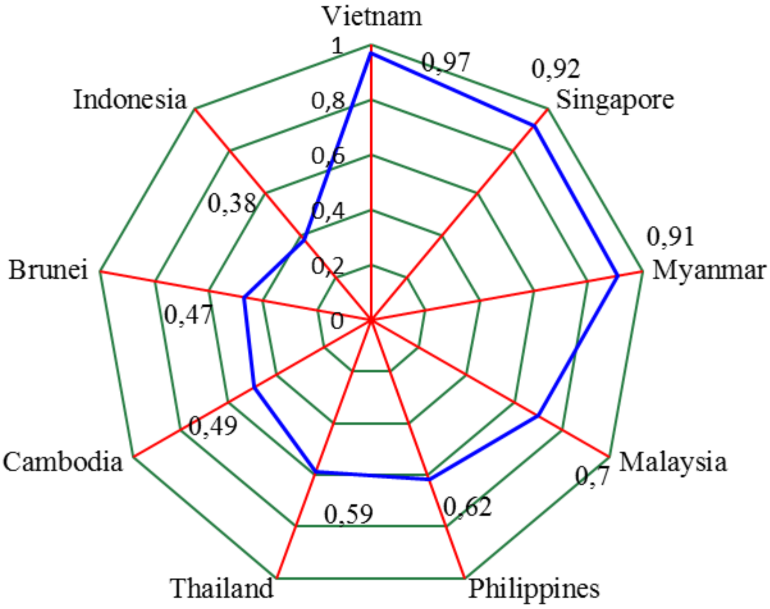

Figure 6: Comparison of the environmental efficiency scores of Southeast Asia Countries.

Data Resource: Calculated based on the data of FAO Statistics (2018) for Southeast Asia countries

5. Conclusions

Agriculture provides livelihoods to a large portion of the population and is an important driver for growth and poverty reduction in the Southeast Asia region but it has also provoked growing concerns about environmental pollution and ecological deterioration because of environmentally detrimental inputs, which threatens human health. Therefore, an attempt was made to examine the technical and environmental efficiency of the agricultural sector in the Southeast Asia region using translog stochastic frontier model. The average technical efficiency scores of agricultural sectors were 0.76, suggesting that the Southeast Asia countries could increase 24% of agricultural production with current technology and inputs used. Similarly, the mean environmental efficiency scores of detrimental inputs in the Southeast Asia countries is 0.67, suggesting that the Southeast Asia countries have the ability to reduce environmental detrimental inputs (fertilizer consumption) by 33% without compromising current agricultural production while holding conventional inputs constant. The findings in our study provide policy implication to the policymakers with useful information about the relative performance of chemical fertilizer and possible ways to improve their performance. Thus, public investment is needed in research and development (R&D) to ensure sustainable agricultural productivity growth. The farmers should improve the use of inputs which have a negative environmental effect so that to achieve the economic and environmental objectives simultaneously. The study further suggests that a substantial reduction of environmentally detrimental inputs can be attained through raising awareness among farmers about the negative influences of the overuse of chemical fertilizer. The legislation would be highly helpful to achieve good environmental performance by reducing the concentration of environmentally detrimental inputs.

Moreover, the findings of this research are also valuable for the future researchers as they would be able to acknowledge a guideline for their researches because this research contains a unique research area containing remarkable importance for its farming sector. Furthermore, this research also contains comparative analysis which is always a pathway for new researchers in order to select the most appropriate research topics. This particular research is also very crucial in the field of Agricultural Economics as currently food security and environmental degradation are the most alarming challenges worldwide. Based on the appropriate implementation of modern econometric techniques in this research, the students of pure subjects such as physics, chemistry, biology etc. will also be able to bring more efficiency and effectiveness in their future research works.

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