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Evaluation of total factor productivity and environmental efficiency of agriculture in nine East Asian countries

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Abstract: This study assessed the change in productivity and environmental efficiency of agriculture for nine East Asian countries for the time period from 2002 to 2010. Data were collected and then analysed by data envelopment analysis (DEA) approaches, including Malmquist total factor productivity (TFP) index and slacks-based measure (SBM) with the consideration of undesirable outputs. The results showed that there existed relatively large differences in productivity growth and environmental performance in the agricultural sector between countries in the sample. Overall, the countries examined in the present study experienced a decline in TFP due to decreases in technical efficiency. Taiwan, Japan, and Korea were found to show growths in productivity and fully efficient environmental performances throughout the study period, while Thailand was identified as having the lowest environmental efficiency score. Therefore, agriculture production and operation models in Taiwan, Japan, and Korea could serve as good references for the other six countries.

Keywords: environmental efficiency; Malmquist total factor productivity index; slacks-based measure DEA (data envelopment analysis); total factor productivity growth

Agriculture plays the most crucial role in feeding the world's population, and it also serves as a major driver for economic development of many countries. Across developing countries, agriculture supports the rural livelihood. In case of East Asian countries, there is a large difference in the contribution of agricultural sector to total Gross Domestic Product (GDP) between individual countries, ranging from only 1–2% for Japan and Korea, through approximately 10% for China, Malaysia, and Thailand, to over 20% for Vietnam (The World Bank 2018). Improvement in agricultural total factor productivity (TFP) is one of the ultimate goals of all agriculture-based countries. Therefore, there is a great number of empirical studies that have examined agricultural performance in terms of technical and environmental efficiency at farm level as well as at national level. For example, as regards cross-country analyses of agricultural technical efficiency, Blazejczyk-Majka et al. (2011) analysed eighty-five European Union regions from 1989 to 2007; Zamanian et al. (2013) investigated twenty-seven MENA countries for the time period of 2007–2008; Nowak et al. (2015) examined twenty-seven countries of the European Union for 2010; specifically for agricultural TFP, Suhariyanto and Thirtle (2001) explored eighteen Asian countries over the period 1965–1996; Nkamleu (2004) measured its changes for sixteen African countries from 1970 to 2001; Coelli and Rao (2005) assessed its changes as well as technical efficiency for ninety-three countries situated in six continents from 1980 to 2000; and Anik et al. (2017) evaluated four countries situated in South Asia, i.e. Pakistan, India, Bangladesh, and Nepal, for the time period of 1980–2013. In addition, Luh et al.

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(2008) analysed the efficiency change and the growth of agriculture sector for eight East Asian countries from 1961 to 2001.

In recent years, environmental efficiency analyses in agriculture have been taken into consideration carefully. Most of them were conducted at farm and regional levels such as dairy farms in the Netherlands (Reinhard et al. 2002), pig-finishing farms in Belgium (Coelli et al. 2007), rice farms in Pakistan (Abedullah et al. 2010), South Korea (Thanh Nguyen et al. 2012), China (Marchand and Guo 2014), and Vietnam (Tu et al. 2015), and farming villages in Taiwan (Kuo et al. 2014). On the other hand, there are studies addressing cross-country analysis of agricultural and environmental efficiency, e.g. Hoang and Coelli (2011) evaluated it along with TFP growth for thirty member countries of OECD for the time period of 1990–2003, and Moreno-Moreno et al. (2017) measured it and the operational efficiency of eighteen countries in Latin America and the Caribbean for 2012. The main initiative for this kind of studies is due to negative impacts of agriculture on the environment. Agriculture is also recognized as the major source of GHG emissions which attribute to climate change. The estimates of FAO (2014) indicated that, between 2001 and 2011, total agricultural emissions had increased by approximately 14%, or from 4.7 tons to over 5.3 billion tons CO_2-eq, and that developing countries are the main sources of this increase owing to expansion of their agricultural output.

In 2010, the agriculture of Asian countries accounted for over 54% of the world's total value of agricultural production; however, it was accompanied by 2 259 million tons of CO_2-eq generated, representing about 44.5% of global agricultural GHG emissions (FAOSTAT 2017). This may be due to the fact that Asia is the most populated continent with approximately 60% of the world population, and that it is home to many important agriculture-based countries. Reducing GHG emissions while keeping up with the demand for food by boosting agricultural production is a globally emergent challenge to the agricultural producers and policymakers. Hence, there is indeed a need to conduct in-depth investigations so that efficiency of both agricultural production and protection of environment can be improved.

The present study aims to assess the TFP growth and environmental efficiency of the agricultural sector in East Asian countries where cross-country studies related to environmental efficiency have, to the authors' knowledge, not been conducted yet. This study estimates the relative extent of differences for both technical and environmental performance between the selected countries and identifies leading countries with respect to agricultural TFP growth and environmental efficiency. The agricultural production practices, technologies, and policies of the leading country could be used as a benchmark for the follower countries in the region.

MATERIAL AND METHODS

Empirical strategy

For technical efficiency measurement, this study adopted the traditional output-oriented data envelopment analysis (DEA) under the assumption of constant returns to scale (CRS) developed by Charnes et al. (1978), and also used Malmquist Productivity Index approach to evaluate the growth of agricultural productivity over time. Moreover, SBM-DEA model (SBM stands for slacks-based measure model) with undesirable output was used to estimate the environmental efficiency of the agriculture sector for nine East Asian countries in question.

Malmquist TFP index approach

The Malmquist TFP index method can be applied to assess the productivity variations over time of a decision-making unit (DMU) when the panel data are available. It is a distance function using only the quantity of input and output data. The index can be used to compare the efficiency of DMU at the observed time to a previous time, and it can also show the efficiency frontier changes over time (Cooper et al. 2007). In essence, it is applied to measure productivity change comprising two components, i.e. technical or technology change and technical efficiency change. An advantage of the Malmquist TFP index method is that it does not require price data for the analysis. This approach has been applied for measuring agricultural productivity change in several studies, e.g. Suhariyanto and Thirtle (2001), Nkamleu (2004), Coelli and Rao (2005), Ludena et al. (2007), and Alene (2010).

The distance function of output-orientated Malmquist productivity change index outlined by Fare et al. (1994) can be expressed as follows:

$$M_0\left(y_s,x_s,y_t,x_t\right)=\frac{d_0^t\left(y_t,x_t\right)}{d_0^s\left(y_s,x_s\right)}\times\left[\frac{d_0^s\left(y_t,x_t\right)}{d_0^t\left(y_t,x_t\right)}\times\frac{d_0^s\left(y_s,x_s\right)}{d_0^t\left(y_s,x_s\right)}\right]^{\frac{1}{2}} \quad (1)$$

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or

$$M_0\left(y_s, x_s, y_t, x_t\right) = \textit{Efficiency change} \times \textit{Technical change}$$

where y and x denote the vector of outputs and inputs of the DMUs in the two periods, s and t; and M_0 is the index of TFP. If M_0 is greater than one, it indicates a progressive growth in TFP during the observed period s to t. In contrast, if it is less than one, it indicates a decline in TFP index.

Regarding the two components of the Malmquist TFP index, efficiency change is evaluated by the ratio of the output-oriented technical efficiency in period t to that in period s; while the technical change displays the geometric average of the variation in technology between the two evaluated periods, t and s. In both cases, if the value is greater than one, it indicates that there has been an improvement over time in production efficiency or in technology, respectively. This study adopted constant return to scale for the assessment of Malmquist TFP index because this is a common choice in distance function measurement (Coelli et al. 1998).

SBM-DEA approach dealing with undesirable output

Song et al. (2012) reviewed studies related to environmental efficiency evaluations using DEA techniques and concluded that there were many advantages of using DEA with the presence of unexpected output to estimate environmental efficiency and many achievements can be accomplished in this regard. Out of various DEA approaches, the SBM-DEA method proposed by Tone (2001) is commonly adopted. This is a non-radial and non-oriented approach in which slacks of input and output are used to generate an efficiency estimate directly. Tone (2004) later modified this method in order to take into account the existence of unexpected outputs, and in this modified method the estimated results identify excess inputs and bad outputs that need to be reduced if the DMU wants to increase its environmental efficiency. The SBM-DEA model with undesirable outputs has been widely applied in many empirical studies in recent years (Song et al. 2013; Song et al. 2015; Chang 2013; Kuo et al. 2014; Zhang et al. 2017). Assume that n decision-making units (DMUs) employ x inputs ($x \in R^m$) to produce y outputs comprising good or desirable outputs ($y^g \in R^{s_1}$) along with bad or un-expected outputs ($y^b \in R^{s_2}$). Here, m denotes the numbers of inputs, s_1 and s_2 are the numbers of good output and bad output variables, respectively. The model is specified as follows.

$$X = \left[x_1, \ldots, x_n\right] \in R^{m \times n},$$

$$Y^g = \left[y_1^g, \ldots, y_n^g\right] \in R^{s_1 \times n},$$

$$Y^b = \left[y_1^b, \ldots, y_n^b\right] \in R^{s_2 \times n},$$

$$X, Y^g, \text{ and } Y^b > 0.$$

The constant returns to scale of the production possibility set (P) can be defined as follows:

$$P = \left\{\left(x, y^g, y^b\right) | x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\right\} \quad (2)$$

Tone (2001, 2004) offered the SBM model with incorporation of undesirable outputs, specified as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}\right)} \quad (3)$$

Subject to $x_0 = X\lambda + s^-$; $y_0^g = Y^g\lambda - s^g$; $y_0^b = Y^b\lambda + s^b$; $s^- \geq 0$, $s^g \geq 0$, $s^b \geq 0$, $\lambda \geq 0$.

where s^- represents slacks of inputs, s^g is slack of good outputs, s^b is slacks of bad outputs, and λ represents weight vector. The vector $s^- \in R^m$ illustrates the excesses of inputs use, $s^b \in R^{s_2}$ represents the excesses of undesirable outputs, while $s^g \in R^{s_1}$ shows the shortage in good outputs. The DMU with $r^* = 1$ is considered to be efficient even though there is the existence of bad outputs, implying that all s^-, s^g and s^b are equal to zero. In contrast, if $r^* < 1$, indicating that the DMU is inefficient, it is necessary to adjust the inputs, good outputs, and reduce bad outputs if the DMU wants to become environmentally efficient.

Data sources and variable selection

This study focuses on estimating environmental efficiency and the changes in TFP of the agricultural sector in nine Asian countries, i.e. mainland China (China), Taiwan, Indonesia, Japan, Malaysia, Philippines, Republic of Korea (Korea), Thailand, and Vietnam for the time period from 2002 to 2010. These countries are chosen due to the significance of agricultural sectors in these countries' economies

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and in supporting livelihood of millions of farmers in rural areas, especially in case of the less developed countries. The main source of data used in the analysis is the FAOSTAT Database provided by the Food and Agriculture Organization of the United Nations (FAOSTAT 2017).

Four inputs and two outputs, which were also typically used in many previous studies, were adopted for efficiency analysis models. The average values of these variables are shown in Table 1 and the definitions are specified as follows.

Inputs. Four conventional inputs were adopted in this study, i.e. *labour*, *capital stock*, *agricultural land*, and *agricultural consumption of fertilisers*.

Labour. This is the total labour force of the country that participates in agricultural activities based on the source of labour force survey, expressed in thousands of people. Because the data of this variable for Vietnam are not fully available from the FAOSTAT Database (FAOSTAT 2017), they were instead retrieved from the Statistical Yearbook of Vietnam (GSO 2008, 2011).

Capital stock. This is the value of gross fixed capital formation of agriculture, forestry, and fishing. In other words, this is the physical investment of the country in its agriculture, expressed in million USD.

Agricultural land. This is the total area of the country used in agricultural activities, expressed in thousands of hectares.

Fertiliser application. This variable represents the total quantity of the three major nutrients, i.e. nitrogen (N), phosphate (P_2O_5), and potash (K_2O), expressed in thousand tons. Most of the data for this variable were obtained from the FAOSTAT Database (FAOSTAT 2017), except for the total potash use in Indonesia for 2010 which was retrieved from Heffer (2013). It is found that fertiliser application takes part in releasing GHG emissions in agriculture, thus this variable has been commonly adopted in assessing environmental efficiency as total usage (Coelli et al. 2007; Abedullah et al. 2010; Tu et al. 2015; Moreno-Moreno et al. 2017) or nutrient surplus (Reinhard et al. 2000; Kiatpathomchai 2008).

Outputs. This study selected two outputs, one *desirable* and one *undesirable*.

Desirable (good) output. This is the total value of agricultural production comprising the aggregate production of various food and agriculture commodities expressed in million USD at the constant prices of 2004–2006. This is the gross agricultural production value expressed as physical gross production

Table 1. Average input and output variables of the agricultural sector by country, 2002–2010

Country	Agricultural area (1000 ha)	Labour (1 000 people)	Fertilisers (1 000 tons nutrients)	Capital stock (million USD)	Agricultural production (million USD)	Agricultural emission (1 000 tons CO_2-eq)
China	515 653.89	322 813.33	49 131.53	45 419.45	383 298.78	661 657.76
Taiwan	829.56	595.74	446.87	421.44	6 243.69	4 461.07
Indonesia	52 677.67	42 673.90	3 596.26	6 395.53	35 748.88	143 898.08
Japan	4 672.89	2 758.89	1 368.05	15 897.54	64 999.95	22 572.75
Malaysia	7 179.63	1 494.49	1 507.95	2 532.01	10 018.64	14 618.79
Philippines	11 642.22	11 650.00	751.18	1 526.92	10 190.16	49 276.69
Korea	1 853.11	1 791.49	741.84	4 265.97	27 674.04	12 682.04
Thailand	19 988.56	15 337.59	1 981.00	3 183.72	16 073.90	62 327.36
Vietnam	10 030.58	24 296.01	2 160.03	746.53	11 703.31	59 970.79

Source: FAOSTAT (2017), NDC (2016), GSO (2008, 2011), and Heffer (2013)

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multiplied by corresponding prices at the farm-gate level. This data variable for Taiwan was obtained from the Taiwan Statistical Data Book (NDC 2016).

Undesirable (bad) output. This variable represents agricultural emissions, expressed in thousand tons of CO_2-eq. This value represents total GHG emissions produced by agriculture-related activities. The variable of GHG emissions is a popular indicator that has been used as a bad output for evaluating environmental efficiency in many previous studies (Färe et al. 1996; Zhou et al. 2006, 2008; Sueyoshi and Goto 2011, 2012; Song et al. 2013; Song et al. 2015; Moreno-Moreno et al. 2017).

Therefore, this study chose four conventionally used inputs and one good output for technical efficiency and TFP analysis. To assess environmental efficiency, a pollution variable was chosen as an undesirable output and added into the SBM-DEA model. The technical and environmental efficiencies of agriculture in the nine countries were evaluated using the DEA-Solver Pro 5.0 software, and the Malmquist TFP indices were computed using the DEAP computer program version 2.1 (Coelli 1996).

RESULTS AND DISCUSSION

Total factor productivity changes

Table 2 illustrates the average technical efficiency change, technical change, and TFP change for the time period of 2002–2010. Taiwan, Japan, and Korea were found to have had positive changes in TFP. Taiwan had the highest TFP change (1.033), followed by Japan and Korea with the same index number of 1.013, meaning that the corresponding average growths in agricultural TFP were 3.3% for Taiwan, and 1.3% for Japan and Korea, where all these productivity improvements came from growth in technical changes while the efficiency changes were sustained. The other countries exhibited TFP levels lower than one, indicating declines in their agricultural productivity despite the fact that there were certain growths in their technical changes. In contrast, Vietnam was shown to have a stable production efficiency but a deteriorating technology over the studied period.

Table 3 displays the annual average of changes in agriculture of the studied countries for the period of 2002–2010. The annual means of efficiency, technical, and TFP changes over time across these countries were 0.969, 1.025, and 0.993, respectively. These figures indicate a decline in agricultural productivity despite improvements in technology. Furthermore, the calculated results also revealed that the annual agricultural productivity of the studied countries experienced fluctuation over time. There was an improvement in agricultural productivity for 2004, 2005, 2006, 2008, and 2009, and the major factors of the improvement were due to technical growth. On the contrary, Coelli and Rao (2005) reported that the growth in agricultural productivity in Asia in the period 1980–2000 mainly came from the improvements of efficiency changes. The main reason for this difference may be seen in a change in the goals of agriculture over time. In the past, most countries used to aim to in-

Table 2. Malmquist index summary of country means, 2002–2010

Country	Efficiency change	Technical change	TFP change
China	0.919	1.045	0.960
Taiwan	1.000	1.033	1.033
Indonesia	0.964	1.032	0.995
Japan	1.000	1.013	1.013
Malaysia	0.960	1.038	0.997
Philippines	0.956	1.031	0.985
Korea	1.000	1.013	1.013
Thailand	0.925	1.030	0.953
Vietnam	1.000	0.987	0.987

TFP – total factor productivity

Source: author's calculations

Table 3. Malmquist index summary of annual means, 2002–2010

Year	Efficiency change	Technical change	TFP change
2002–2003	0.979	0.975	0.955
2003–2004	0.914	1.130	1.032
2004–2005	1.057	0.953	1.008
2005–2006	0.968	1.053	1.019
2006–2007	0.879	1.120	0.984
2007–2008	0.939	1.081	1.015
2008–2009	1.017	1.016	1.033
2009–2010	1.010	0.894	0.903
Mean	0.969	1.025	0.993

TFP – total factor productivity

Source: author's calculations

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crease agricultural production, while in recent years, more and more advanced technologies have been applied in agriculture and its goal is to produce efficiently while not sacrificing the well-being of the society. Suhariyanto and Thirtle (2001) explained that the differences in agricultural productivity levels from country to country and from time to time were due to financial resources, conditions, and stage of economic development of each respective country. Evenson and Fuglie (2010) pointed out that technology capital had significant impacts on the growth of TFP. High and sustained improvement in agricultural TFP was mostly found for industrialized countries, and this may be attributed to their higher formation of technology capital.

Technical and environmental efficiency

The assessed results of technical and environmental efficiency in agriculture of nine countries are presented in Table 4. Technical efficiency scores were measured by using the Charnes, Cooper, and Rhodes (CCR) model with four inputs and one good output, i.e. no explicit environmental factor was considered in this model; the environmental efficiency values were calculated by the SBM model with the presence of a bad output.

The average technical efficiency score measured by the CCR model for the nine countries for the time period of 2002–2010 was 0.73, while the estimated environmental efficiency measured by the SBM model was 0.55. The results revealed that the measured efficiency values tend to be lower when an undesirable output is added in the efficiency analysis. Song et al. (2015) claimed that the relatively lower value assessed by the SBM model compared to that of the CCR model was due to its consideration of environmental pollution which causes efficiency loss. Therefore, it is argued that in this study, in order to more accurately measure the efficiency of agricultural production, environmental consideration must not be overlooked.

Table 4 shows efficiency estimates for the nine countries in this study. Taiwan, Japan, and Korea were found to be fully technically and environmentally efficient

Table 4. Technical and environmental efficiency scores of agricultural sector in nine sampled countries, 2002–2010

Year		China	Taiwan	Indonesia	Japan	Malaysia	Philippines	Korea	Thailand	Vietnam	Average
2002	CCR	0.36	1.00	0.22	1.00	0.27	0.33	1.00	0.27	1.00	0.61
	SBM	0.36	1.00	0.22	1.00	0.27	0.33	1.00	0.27	1.00	0.61
2003	CCR	0.90	1.00	0.64	1.00	0.61	0.78	1.00	0.55	1.00	0.83
	SBM	0.39	1.00	0.23	1.00	0.29	0.31	1.00	0.24	1.00	0.61
2004	CCR	0.71	1.00	0.57	1.00	0.50	0.69	1.00	0.49	1.00	0.77
	SBM	0.30	1.00	0.20	1.00	0.24	0.25	1.00	0.19	1.00	0.57
2005	CCR	0.77	1.00	0.62	1.00	0.55	0.77	1.00	0.56	1.00	0.81
	SBM	0.31	1.00	0.23	1.00	0.28	0.28	1.00	0.21	1.00	0.59
2006	CCR	0.62	1.00	0.63	1.00	0.53	0.77	1.00	0.51	1.00	0.79
	SBM	0.27	1.00	0.25	1.00	0.28	0.29	1.00	0.20	1.00	0.59
2007	CCR	0.52	1.00	0.53	1.00	0.45	0.66	1.00	0.47	0.67	0.70
	SBM	0.23	1.00	0.20	1.00	0.23	0.25	1.00	0.19	0.23	0.48
2008	CCR	0.47	1.00	0.44	1.00	0.45	0.67	1.00	0.39	0.60	0.67
	SBM	0.22	1.00	0.18	1.00	0.21	0.24	1.00	0.16	0.22	0.47
2009	CCR	0.44	1.00	0.45	1.00	0.47	0.62	1.00	0.40	0.75	0.68
	SBM	0.20	1.00	0.18	1.00	0.23	0.22	1.00	0.16	0.22	0.47
2010	CCR	0.46	1.00	0.48	1.00	0.41	0.59	1.00	0.35	1.00	0.70
	SBM	0.21	1.00	0.19	1.00	0.21	0.22	1.00	0.15	1.00	0.55
Average	CCR	0.58	1.00	0.51	1.00	0.47	0.65	1.00	0.44	0.89	0.73
	SBM	0.28	1.00	0.21	1.00	0.25	0.26	1.00	0.20	0.74	0.55

CCR – Charnes, Cooper, and Rhodes model, SBM – slacks-based measure model

Source: author's calculations

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throughout the studied period, followed by Vietnam with average scores of 0.89 and 0.74 for technical and environmental efficiency, respectively. The other countries, i.e. China, Indonesia, Malaysia, Philippines, and Thailand, were found to be far below those average scores, Thailand was identified to have the lowest scores in both cases (0.44 and 0.20, respectively). The results indicated that the countries with efficiency scores lower than one should endeavour to improve agricultural production efficiency while keeping the environment intact so that agriculture can be operated and managed in a sustainable manner. Take Vietnam for example, it experienced decreases in both technical and environmental efficiency from 2007 to 2009, while being fully efficient in the other years (Table 4). This may be attributed to expansion of cultivation areas entailing an increase in fertiliser application and capital investment in agriculture in the period of 2007–2009. The resulting consequence was therefore an increase in GHG emission and higher environmental pollution. These findings also pointed out that farmers in Vietnam obviously did not fully optimize their operation scale for most of the studied period and they can further improve their efficiency by adjusting the use of inputs as well as the obtained outputs.

Potential reductions in carbon emissions reduction and fertiliser usage

The SBM-DEA model also calculates excesses of all inputs applied as well as excesses of bad outputs. As mentioned above, the less efficient countries can adjust by decreasing input use as well as bad outputs produced in order for their agriculture to become environmentally efficient. This study mainly focuses on the input of fertiliser usage and on the undesirable output of CO_2 emissions.

Table 5 shows the potential estimated decreases of CO_2 emissions from agriculture. It can be seen that China had a relatively low environment efficiency score of 0.28 (Table 4) with a huge amount of CO_2 emissions, nearly 5 955 million tons of CO_2-eq, and was found to have had the highest potential to reduce agricultural carbon emissions of over 3 439 million tons of CO_2-eq for the entire studied period. This implies that improvement in environmental efficiency could help to reduce GHG emissions from its agriculture significantly. Meanwhile, Malaysia was identified to have the lowest potential for CO_2 emissions reduction of about 90 million tons of CO_2-eq from 2002 to 2010. Taken together, the total CO_2 emission reductions from agriculture of six less efficient countries could be approximately 5 690 million tons of CO_2-eq for the studied period. This figure would certainly contribute to the global efforts to reduce GHG emissions.

In terms of reduction of fertiliser usage, Table 6 provides details of potential estimated savings for environmentally less efficient countries. It can be seen that for the six less efficient countries, the potential fertiliser reduction was over 243 million tons during the entire studied period. China was found to have had the highest potential fertiliser savings of over 194 million tons, accounting for 80% of the total potential fertiliser savings, although its environmental efficiency score was not the lowest. In contrast, the average environmental efficiency score

Table 5. Potential reduction in carbon emissions from the agricultural sector by countries (10^6 tons of CO_2-eq)

Country	Year									Total
	2002	2003	2004	2005	2006	2007	2008	2009	2010	
China	327.59	297.91	374.75	388.14	394.02	379.63	400.22	427.68	449.42	3 439.34
Taiwan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Indonesia	124.35	122.31	125.34	124.73	123.67	116.24	129.90	128.27	131.60	1 126.41
Japan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Malaysia	9.38	8.82	9.86	9.98	9.36	10.10	11.34	11.87	9.35	90.06
Philippines	41.05	42.03	45.17	43.75	43.28	41.85	45.38	46.18	45.17	393.86
Korea	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thailand	47.27	47.44	52.40	52.75	52.96	51.53	56.34	59.73	60.90	481.33
Vietnam	0.00	0.00	0.00	0.00	0.00	51.65	51.49	55.65	0.00	158.78

Source: author's calculations

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Table 6. Potential fertiliser saving for agricultural sector in environmentally inefficient countries (million tons of nutrients)

Country	Year									Total
	2002	2003	2004	2005	2006	2007	2008	2009	2010	
China	16.34	16.26	18.11	21.07	20.88	20.87	24.48	27.79	28.80	194.60
Taiwan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Indonesia	1.79	2.04	2.26	2.07	2.30	1.16	3.24	1.79	1.99	18.65
Japan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Malaysia	0.89	0.93	1.21	1.03	1.25	1.41	1.60	1.22	1.65	11.18
Philippines	0.22	0.35	0.53	0.36	0.33	0.04	0.30	0.47	0.58	3.18
Korea	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Thailand	1.04	1.02	1.54	1.14	1.35	0.65	1.58	1.61	1.53	11.45
Vietnam	0.00	0.00	0.00	0.00	0.00	1.31	1.08	1.79	0.00	4.18

Source: author's calculations

for Thailand was the lowest (0.20), yet its potential fertiliser savings were ranked third after Indonesia. As pointed out by Song et al. (2015), this inconsistency may be due to the difference in the input usage practice. It is well-known that excessive application of fertilisers results not only in lower production and lower farmer profits, but also in severe environmental damage. Therefore, the findings in this study are inconsistent with the long-standing view that efforts to promote efficient use of fertilisers should progressively be made. The high potential fertiliser savings also imply that the country failed to use fertilisers at optimal levels, which may be the result of deterioration of soil quality, ineffective farming management, and poor fertiliser quality. As regards nutrient efficiency, nutrient imbalances are likely to be global agricultural challenges, and analyses related to route change within and across agricultural systems could be considered as solutions (Vitousek et al. 2009). According to EUROSTAT (2015), the reduction in nitrogen-based fertilisers application could help decrease GHG emissions in the agricultural sector. In addition to technical training, environmental education is also needed for the effective control of fertiliser use (Marchand and Guo 2014). Furthermore, these countries should actively seek to acquire advanced fertiliser-saving technology from other environmentally efficient countries.

The results showed that there were relatively large differences in TFP growth and technical and environmental performances in agriculture of Taiwan, Japan, and Korea on one hand and the other six studied countries on the other. This could be explained by two major reasons. First, the total areas used in agriculture in these countries are relatively smaller than in the other countries, thus their operation and management may be easier and require less efforts than the operations on larger scales due to the labour intensive nature of agriculture. The other reason could be the strong economic status and high living standards of these three countries that had enabled them to apply advanced technologies in agriculture for a long time, as well as to recognize environmental problems and address them by related policies. Song et al. (2015) assessed the environmental performance of Chinese transportation sector in different provinces and found that more economically active provinces tend to attain relatively higher environmental efficiency performance. Hoang and Coelli (2011) also stated that countries where environmental policies were well implemented were likely to achieve better environmental performance. Hence, the findings of this study are consistent with these previous studies that more environmentally conscious countries such as Taiwan, Japan, and Korea have better environmental efficiency related to agriculture production.

CONCLUSION

This study evaluated the change in agricultural TFP for nine countries in East Asia during the time period from 2002 to 2010 using Malmquist TFP approach. In addition, the environmental efficiencies of the agricultural sector were also assessed by the SBM-DEA model with the presence of an undesirable output.

The measured results of Malmquist productivity index cross-country analysis show that the growths in TFP were found only in case of Taiwan (3.3%),

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and Japan and Korea (both at 1.3%), and all the contributions came from technical changes. As for the annual changes, the nine studied countries experienced, on average, a decline in TFP of approximately 0.7% over the studied period, although there were improvements in agricultural productivity in the years 2004, 2005, 2006, 2008, and 2009.

As regards efficiency evaluations, there was a considerable difference in efficiency scores between the nine studied countries. Taiwan, Japan, and Korea were identified to be fully both technically and environmentally efficient with scores of 1 throughout the studied period, followed by Vietnam (0.89 and 0.74, respectively), and the lowest technical and environmental efficiency scores were found for Thailand (0.44 and 0.20, respectively). China had the highest potential for fertiliser savings as well as for carbon emissions reduction. Moreover, as regards the environmental impacts of agricultural production, the agriculture operation and management models of Taiwan, Japan, and Korea can serve as references for the other six, poorly performing, countries.

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