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# Measuring technical efficiency of Thai rubber production using the three-stage data envelopment analysis

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**Abstract**: The study investigated the technical efficiency of rubber production in Thailand. Secondary data were collected from the Thai rubber plantations in four regions from 2005 to 2014 by using a three-stage data envelopment analysis (DEA) model. The DEA was used to evaluate the technical efficiency levels and to remove undesirable environmental impacts. Furthermore, the Malmquist productivity index was used to measure the changes in the rubber production efficiency and estimate the rubber productivity trend. The findings indicate that the efficiency scores obtained using adjusted inputs in stage 3 of the DEA approach were higher than the efficiency scores in stage 1 of the DEA approach. Moreover, the results also showed that the Northern region has the worst scores of technical efficiency and declination of productivity among the four regions. However, the technical performance of the Thai rubber production has shown a good performance, an upward productivity trend, and has demonstrated the advantages of the method used. Findings from the study could provide crucial information to farmers, the Thai government, and agricultural planners for formulating effective strategies or plans to improve their technology and efficiency levels.

**Keywords**: Malmquist productivity index, technical efficiency, Thai rubber production, three-stage DEA

Rubber is one of the most crucial crops in tropical regions worldwide, particularly in the Southeast Asia. In Thailand, natural rubber has been a crucial agricultural product for the Thai economy since 1991. The country is the world's largest natural rubber producer, and the expansion of rubber cultivation in different regions is on the rise in accordance with the demand, especially for the automotive industry. According to the Rubber Research Institute of Thailand (2016), the Thailand natural rubber production was 4.47 million tons in 2015, of which 0.60 million tons (13.42%) were domestically consumed, 0.12 million tons (2.69%) were the stock and 3.75 million tons (83.89%) were exported. Consequently, the export revenue of 260,482 million Baht (7502.64 million USD) (1 USD = 34.7187 Baht as of August 2016) was generated. In 2015, the rubber production involved 1.85 million families of farmers, which accounts for more than 6 million people across the country and includes entrepreneurs, labourers, and government officials (National Statistical Office 2016). The major export markets for the Thai rubber are China (2.32 million tons, 61.87%), followed by Malaysia (0.63 million tons, 16.80%), Japan (0.27 million tons, 7.20%), the United States (0.16 million tons, 4.27%), and others (0.37 million tons, 9.86%) (RRIT 2005). The Thai government has released several strong policies to improve the rubber production throughout the country. According to (RRIT 2005), the area for the rubber plantations was already high in 2000, occupying 1.96 million ha. In 2013, Thailand's area for rubber plantations was 18.76 million ha, located mainly in Southern Thailand (65%); however, the plantation area in this area has reached its limit. Since the last decade, rubber plantations have expanded to new areas including Northeast (20%), Central and Eastern (10%),

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and Northern Thailand (5%), and are likely to expand further. The increasing trend of rubber planting is a strategy associated with sustainability (Longpichai et al. 2012). Land, capital and labour have been considered as the assessment parameters of sustainable development by the economists (Van Passel et al. 2009; Longpichai et al. 2012), and measuring efficiency led to the advancement of sustainability. Measurement of efficiency is based on physical factors, inputs and outputs; which is consistent with several studies (De Koeijer et al. 2002; Longpichai et al. 2012). Nowak et al. (2015) noted that to evaluate the effectiveness of agriculture is quite complicated, not only due to the uncertainty of weather conditions, but also because of the wide variety of households in different areas and the production profile. Efficiency measurements are derived according to the differences in available stocks of fertilizer, rainfall rate, labour force, quantity of rubber, and other characteristics of the social and economic environment where rubber production occurs (Mustapha 2011; Areetrakul and Wongchai 2015). It is necessary, when estimating the production frontier, to assess efficiency among different areas. In addition, Thailand has had an inexpensive land and labour, a little agricultural research, and no shortage of food for many years. Because of these factors, this study investigates the technical efficiency (TE) of rubber production among the four regions of Thailand.

In studies devoted to rubber productivity, the non-parametric methods have been used in parallel with the related indicators. The non-parametric method is widely used to measure the TE of agricultural productivity; that is the data envelopment analysis (DEA). The DEA is a methodology based on the applications of linear programming and the most appropriate method for measuring the relative efficiency of decision-making units (DMUs). The power of the DEA is in its ability to deal with multiple inputs and outputs and, to calculate the TE of each DMU. The DEA model allows the comparison of a firm to a benchmark (best producer) and measures the efficiency relative to the best producer in that group of firms. The main advantage of the DEA is in its ability to avoid the parametric specification of technology such as the distributional assumption for the inefficiency term. Further, the DEA approach has the advantage of considering the multiple input and multiple output simultaneously (Waduge et al. 2015). Reig-Martınez and Picazo-Tadeo (2004) proposed that the advantage of the DEA over the stochastic frontier analysis (SFA) is that the technological frontier is constructed without imposing a parametric functional form. On the contrary, the major limitation of the DEA is that it is complex, because the single-stage DEA is unable to separate the effects of uncontrollable environmental variables from the effect of differences in the farm management (Silva et al. 2013). Despite the above shortcoming, there is a large number of applications to evaluate the performance of DMUs in different issues (Lygnerud and Peltola-Ojala 2010; Assaf et al. 2011; Chung 2011). TE and its components at the regional level in the Thai agriculture will provide strategic constant returns to scale (CRS) for addressing the increasing competitiveness in rubber production; thus, this study focused on the TE assessment of different DMUs. Such an assessment can provide a detailed understanding of the nature of the TE in Thai agriculture particularly in the Thai rubber-producing regions. Therefore, in this study, a new analysis using a three-stage DEA model is used to eliminate the environmental variables of the Thai rubber production from 2005 to 2014. The advantage of the three-stage DEA models is the elimination of the disturbance produced by environmental factors in the measurement of the efficiency score to improve the objective and accuracy of the measurement results. Moreover, the Malmquist productivity index (MPI) was used to measure the changes in the rubber production efficiency and to estimate the rubber productivity trend. Few empirical studies have measured the performance of the operation or management of rubber production, because of the data limitations and difficulty in defining the inputs and outputs of production.

Banker and Morey (1986) adapted the mathematical programming treatment of the DEA models to enable the partial analysis of efficiency on the basis of concepts that they initially termed exogenously and non-exogenously fixed inputs and outputs. Adjusting for the environmental variables is another extension of the basic DEA model that enables the evaluation of some factors influencing the efficiency of a firm, where such factors are not conventional inputs and are assumed to be not under the control of the manager. Environmental variables can be considered using several approaches such as the three-stage method developed by Charnes et al. (1981). Ferrier and Lovell (1990) assumed that another feasible method is the inclusion of environmental variables directly into the linear programming formulation. The latest expansion of these methods is the three-stage DEA model proposed by Fried et al. (2002). Chen et al. (2007)

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proposed a three-stage approach for improving the measurement of the productivity growth for 263 farmers in Taiwan. In this approach, the Malmquist productivity indices were used to adjust the impacts of undesirable outputs, environmental variables, and the statistical noise. They showed that productivity deteriorated during 1998–2000 owing to the regression of technology. Lee (2008) measured the efficiency of 89 global forest and paper companies in 2001 using the three-stage DEA method and showed that the environmental factors and the statistical noise influenced the efficiency scores. Furthermore, the final adjusted efficiency scores were lower than those measured using the conventional first-stage DEA. Gorman and Ruggiero (2008) surveyed the performance of state police services in 49 continental states of the United States by using the three-stage DEA method, and the results showed that most states exhibited technically efficient scores, but nearly half were operating at less than the optimal scale size. Shang et al. (2008) assessed the performance of 57 hotels in Taiwan and found that the efficiency score measured using the three-stage DEA method was 0.917, and that service outsourcing was not the main determinant for the international tourist hotels. Tsay et al. (2009) studied environmental effects and statistical noise by using the third-stage DEA-SFA approach to survey the farmers' credit unions in Taiwan. Their results showed that the three-stage DEA efficiency scores were lower than the SFA scores.

Mustapha (2011) measured the performance of rubber smallholders in Malaysia. The DEA model had one output (rubber quantity) and two inputs (cultivated area and tapping area). A total of 35 rubber smallholders were investigated and their performance varied significantly. Mustapha revealed that the 23% of the total cultivators achieved 0.950–1.000 of the TE score. However, the variations in tangible and intangible factors such as the quantity of fertilizer application, soil fertility, the species of the rubber trees, weather conditions might have contributed to this difference. Kumarasinghe et al. (2012) analysed the TE of rubber smallholders in the Gampaha district in Sri Lanka by using the DEA and Tobit model and the results showed that the mean TE of rubber smallholding sector was 49.8%, which indicates that the output could be increased by 50.2% if all farmers achieved the full TE. Waduge et al. (2015) investigated the risks related to labour and weather of smallholder rubber producers in Kalutara district of Sri Lanka. The results showed that the variability of rainfall and labour usage are risk increasing while price is risk reducing and the relationship between the variability of labour and rubber price showed statistical significance. Longpichai et al. (2012) found positive relationship between the access level of the livelihood capital and the levels of diversification for smallholder rubber producers in Southern Thailand. However, the diversification and integration of rubber-based farming systems resulted in the higher production and farm income. Therefore, the diversification and crop integration should be supported as a pathway for sustaining the farmers' livelihood.

Several studies have suggested that the DEA methods based on the concept of the MPI have been developed for evaluating the total factor productivity change (TFP), the efficiency change (EC), and the technical change (TC) (Asmild et al. 2004; Estache et al. 2004; Coelli and Rao 2005; Xue et al. 2008; Liu et al. 2015). In addition, Wei et al. (2007) and He et al. (2013) proposed an MPI based on the DEA for measuring the productivity change over time. Nomikos and Pouliasis (2011) attempted to assess the utilization efficiency of capacity of the Indian rubber industry in terms of the econometric framework for the period 1979–1980 to 2008–2009. The result suggested that there has been a declining growth rate of the capacity utilization in the rubber industry of India during the post reforms period accompanied by the declining output growth as well as the capacity growth. Odeck (2009) combined the DEA and the Malmquist index to assess the performance of 19 specialized grain farm operators in Eastern Norway between 1987 and 1997. The results demonstrated an average productivity progress of 38% over the study period. The excellent productivity progress is mainly attributable to the TC. Moreover, environmental factors affect productivity and efficiency. This literature review of the MPI demonstrates that this distinctive technique is an appropriate and useful research method for measuring the productivity change over time.

## MATERIAL AND METHODS

### DEA model

The DEA is the most commonly applied technique in agricultural economics (Aigner et al. 1977; Meeusen and Van den Broeck 1977). It is a popular tool used to analyse the efficiency in various fields (Barros and Leach 2006; Liu et al. 2013). Many studies have shown

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that the DEA applications involve a wide range of contexts such as banking (Tsolas and Charles 2015; Sahin et al. 2016; Stewart et al. 2016), transportation (Chang et al. 2013; Cui and Li 2014; Ji et al. 2015), health care (Torres-Jiménez et al. 2015; Shwartz et al. 2016), education (Fuentes et al. 2016; Lee and Worthington 2016), and agriculture (Kocisova 2015; Shrestha et al. 2016) and such previous DEA studies provide useful managerial information on improving the productivity. The DEA is a non-parametric approach to evaluate the performance that was originally developed by Charnes et al. (1978) and is based on the technological assumptions of CRS and later was extended to accommodate the technologies that exhibit variable returns to scale (VRS) by Banker et al. (1984). The most important point for analysis using the DEA is its management tool; it is designed to construct specific benchmarks for evaluating the performance of the individual DMUs (Coelli et al. 2005). The DEA is an excellent empirical model that compares a decision unit with an efficient frontier using the performance indicators. It further enables the extension of the single-input/single-output technical efficiency measure to the multiple-input/multiple-output case to evaluate the relative efficiency of peer units with respect to multiple performance measures (Charnes et al. 2013). Unlike the parametric methods, which require a detailed knowledge of the processes under investigation, the DEA does not require an explicit functional form relating inputs and outputs (Cooper et al. 2006; Cook and Seiford 2009) for the evaluation of the theoretical foundations and development in the DEA approach. Although the DEA can evaluate the relative efficiency of a set of the individual DMUs, it cannot identify the source of inefficiency in each DMU because the conventional DEA models view each DMU as a black box that consumes a set of inputs to produce a set of outputs (Avkiran 2009; Tavana and Khalili-Damghani 2014). Fried et al. (2002) proposed multistage input-oriented DEA models to differentiate the possibly uncontrollable effects of the environment on the firm performance. The models can be used to distinguish the pure management inefficiency from the inefficiencies resulting from external variables in forms of data, area characteristics, labour relativity, and government regulations (Fried et al. 1999). In addition, Rho and An (2007) showed that the use of the single-stage DEA might result in the inaccurate efficiency evaluation. Thus, there is a need for a further development of simulation methods to extend the variety of DEA developments and the scope of its applications. Fried et al. (2002) provided a three-stage DEA model for distinguishing environmental effects and the statistical noise into the producer performance evaluation based on the DEA.

In this study, we investigated the TE of Thai rubber production using the three-stage DEA model and the MPI model. This new DEA model involves a three-stage analysis. The first stage involves estimating the efficiency frontier by using a simple DEA model without environmental variables. The DEA models can be input or output oriented. The input-oriented model minimizes inputs to produce a given level of output. Conversely, the output-oriented model maximizes outputs while using no more than the observed amount of inputs. In this study, the input-oriented model was used to investigate the efficiency levels of the Thai rubber production. In the second stage, the ordinary least squares (OLS) is used to control the influence of exogenous factors by integrating environmental factors into one combined non-discretionary input. Efficiency is measured once again, but in a model in which the input variables are adjusted according to the effects of the environmental variables and exclusion of input slacks. Finally, the third-stage factors are effectively adjusted for in the production frontier. Compared with the first stage, the output variable remains unchanged in the DEA model, but in this stage, the input variables are adjusted from the second stage. In summary, the second stage involves decomposing the influence of the environmental factors, and the third stage entails measuring the inefficiency under the desirable circumstances. Efficiency scores measured using the rational three-stage DEA are ranked from 0, the lowest to 1, the highest. Our modified model is briefly explained below.

## Modified three-stage DEA model

### *Stage 1: Conventional DEA model*

We used the CCR (Charnes, Cooper and Rhodes) model created by Charnes et al. (1978) (also referred to as the CRS model). Models with a CRS envelopment surface assume that an increase in input results in a proportional increase in outputs (Amini et al. 2015). The CCR model can be categorized into input-oriented and output-oriented versions, and this study applied input-oriented versions to evaluate the performance of management; this model in the relevant form can be written as follows (Charnes et al. 1978):

https://doi.org/10.17221/19/2016-AGRICECON

$$min\,\theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \quad (1)$$

Subject to

$$\sum_{j=1}^{n} x_{ij}\,\lambda_j + s_i^- = \theta x_{ijo} \quad i = 1, 2, ..., m$$

$$\sum_{j=1}^{n} y_{rj}\,\lambda_j - s_r^+ = y_{rjo} \quad r = 1, 2, ..., s$$

$$\lambda_j\,, s_i^-, s_r^+ \geq 0 \quad j = 1, 2, ..., n$$

In equation (1), $s_i^-$ and $s_r^+$ are the slack variables; $m$ and $s$ represent the input and output indexes, respectively. $x_{ijo}$ and $y_{rjo}$ are the observed input and output values, respectively, of $DMU_o$. ε is the non-Archimedes infinitesimal, which represents the infinitesimal in the calculations. θ represents efficiency value of each DMU, and $0 \leq \theta \leq 1$, i.e., $\theta = 1$ shows a TE of each DMU; $\theta < 1$ shows the technically inefficiency of each DMU. Equation (1) implicitly assumes CRS, which means that the firm increases production by the same percentage for the given investment as input; in other words, the scale of the investment does not affect efficiency. Because this stage cannot discriminate the impacts of external environmental factors, random errors, and internal management factors on production efficiency,the efficiency value does not reflect the real cause of inefficiency. Therefore, to assess the efficiency of DMUs, the external factors should be peeled and the second stage is required.

***Stage 2: OLS model***

The efficiency scores estimated in stage 1 are affected by three sources: managerial inefficiency, environmental influence, and statistical noise. Therefore, we used the OLS regression to analyze the factors of slack variables on each factor input and to decompose the effects on efficiency scores. According to Aigner et al. (1977), the presented model takes the form of a linear programming model as follows:

$$\min \sum_{j=1}^{n} \varepsilon_j \quad (2)$$

Subject to

$$In\beta_0 + \sum_{i=1}^{m} \beta_i\, Inx_{ij} - Iny_i = \varepsilon_j \quad j = 1, 2, ..., n$$

$$\varepsilon_j\,, \beta_i \geq 0 \quad \forall i, j$$

In equation (2), $j = 1, 2,..., n$ refers to the observations. The OLS method minimizes the sum of squared residuals and leads to a closed-form expression for the estimated value of the unknown parameter $\hat{\beta}$ (Aigner et al. 1977):

$$\hat{\beta} = (\acute{x}x)^{-1}\acute{x}y \quad (3)$$

and

$$\hat{\beta} = \left(\frac{1}{n}\sum x_i\, x_i'\right)^{-1}\left(\frac{1}{n}\sum x_i\, y_i\right) \quad (4)$$

Estimates are unbiased and consistent if the error variance is limited and uncorrelated to regressors: $E[x_i, \varepsilon_i] = 0$. Estimates are also effective under the assumption that the error variance is limited and homoscedastic, meaning that $E[\varepsilon_i^2|x_i]$ does not depend on $i$. The condition that errors are uncorrelated to regressors is generally satisfied in an experiment, but in the case of the observational data, it is difficult to exclude the possibility that an omitted covariate related to both the observed covariates and the response variable exists. The existence of such a covariate generally leads to a correlation between the regressors and the response variable, and hence, an inconsistent estimator of $\hat{\beta}$. The condition of homoscedasticity can fail with either experimental or observational data. When the target is either inference or predictive modeling, the performance of OLS estimates can be poor if multicollinearity is present, unless the sample size is large.

In the simple linear regression, where there is only one repressor (with a constant), the OLS coefficient estimates have a simple form that is closely related to the correlation coefficient between the covariate and the response. Using the method for adjusting input variables suggested by Fried et al. (2002), each DMU can be placed under identical operating environments and receive identical opportunities by uplifting the data of input variables. The adjusted equation is shown as follows (Fried et al. 2002):

$$x'_{ij} = x_{ij} + [max_i(z_i\hat{\beta}) - z_i\hat{\beta}\,] + [max_i(\hat{v}_{ij}) - \hat{v}_{ij}] \quad (5)$$
$$i = 1, 2, ..., m;\ j = 1, 2, ..., n$$

In equation (5), $x_{ij}$ is the original input, $\acute{x}_{ij}$ is the adjusted input, $max_i(z_i\hat{\beta}) - z_i\hat{\beta}$ is used to preclude influences of the environment and place all DMUs under the same external environmental conditions, and $max_i(\hat{v}_{ij}) - \hat{v}_{ij}$ is adjusted random errors of all DMUs in the same context so that each DMU faces the same operating environment and has the same luck. Therefore, final differences in the production efficiency are attributed to the internal management factors.

https://doi.org/10.17221/19/2016-AGRICECON

***Stage 3: DEA model with adjusted inputs***

In the final stage, we used the original output from stage 1 and adjusted input variables from stage 2 to measure the performance of all DMUs. The efficiency scores in this stage decomposed the effects on environmental variables and statistical noise; therefore, we obtained the real efficiency of each DMU. Notably, Fried et al. (2002) recognized that a firm's TE is influenced by the external environment. They suggested that the effect of environmental variables on the change in the input slack variable be evaluated.

**Malmquist productivity index (MPI)**

Caves et al. (1982) invented the MPI as a theoretical index, and Fare et al. (1994) stated that the MPI was commonly employed as an empirical index. In the present analysis, the input factors of production were adjusted completely during 2005–2014, and subsequently, this was evaluated using the MPI based on the adjusted input ($x'_{ij}$) from stage 2 and the original output variables from stage 1. The MPI, which is based on the DEA model, uses panel data to calculate the indices of the TFP change,TC, and EC. In theory, an index score of more than 1 indicates a productivity growth, an index score of 1 indicates a constant productivity, and a score less than 1 implies a productivity decline between time $t$ and time $t$ + 1. The MPI can be decomposed into two components. The first component is a measure of the TC in production technology and the second component is a measure of the EC in a gap between the maximum feasible production and the observed production function. The two component indices can effectively identify the causes of the productivity change. The MPI can be written as shown in equation 6 (Fare et al. 1994):

$$M(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\left(\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}}) \times \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} = \mathrm{TC} \times \mathrm{EC} \quad (6)$$

After the calculation, $M$ can take three different values. $M$ > 1 denotes the productivity growth; $M$ < 1 indicates productivity decline; M = 1 means no change in productivity from period $t$ to $t$ + 1. EC > 1 shows the increase of rubber production efficiency from the time period $t$ to the time period $t$ + 1; EC < 1 indicates the decrease of rubber production efficiency; EC = 1 means the rubber production efficiency remains stable during the period $t$ to the time period $t$ + 1. TC > 1 shows there is an advance in technology; TC < 1 indicates a deteriorating technology; TC = 1 means that there is unchanged technology (Fare et al. 1994).

**Data and variables**

The study examined four regions; Northern, North-Eastern, Central, and Southern Thailand, covering 77 cities. We analysed the Thai rubber production during 2005–2014 and assessed the TE of rubber productivity by using a sample of 77 DMUs in the four regions. This study used secondary data collected from surveys through various Thai governmental agencies: the Rubber Research Institute, the Office of the Rubber Replanting Aid Fund, the Office of Agricultural Economics, the Thai Meteorological Department, the Ministry of Agriculture and Cooperatives and the Ministry of Labour. In this study, a feasible input-output combination was identified by accounting for the characteristics of rubber production and environmental conditions.

We analysed a total of five inputs, namely plantation area ($X_1$), tapping area ($X_2$), fertilizer ($X_3$), number of tractors ($X_4$), and labour force ($X_5$), and two outputs, rubber quantity ($Y_1$) and price of quantity ($Y_2$). Moreover, we analysed two environmental factors, temperature ($B_1$) and rainfall volume ($B_2$), which cannot be controlled by farmers. The variables used in this study were considered using the input-output combination described in DEA model. The data descriptions are listed in Table 1. Data analyses were conducted using the DEAP Version 2.1, EViews program Version 8.0, and the SPSS Version 23.0.

The summary descriptive statistics of each variable used in this study are presented in Table 2. The average plantation area was quite big (587 332 ha) and the tapping area (398 666 ha), which indicated that more than half of the plantation area can produce rubber. The results showed that on average, fertilizer used 28 630 tons, the number of tractors was 8550 per area per number of tractor, and 683 602 persons per hour of labour force in the rubber production sector. In terms of output, the average rubber quantity was 68 586 tons. Moreover, the mean price was 39 Baht/kg. The major environmental variables were the temperature (27.50°C) and rainfall volume (231.60 mm), which where consistent with the previous studies (Sdoodee and Rongsawat 2012; Mesike and Esekhade 2014; Nguyen and Dang 2016).

https://doi.org/10.17221/19/2016-AGRICECON

Table 1. Data descriptions of variables items and source

| Variables | Symbol | Unit | Definition | Source |
|---|---|---|---|---|
| **Input variables** | | | | |
| Plantation area | ($X_1$) | hectare | total area for rubber production | Mustapha (2011); Zamanian et al. (2013) |
| Tapping area | ($X_2$) | hectare | area to harvest the latex for rubber production | Mustapha (2011); Kumarasinghe et al. (2012) |
| Fertilizer | ($X_3$) | tons | inorganic and organic fertilizers for rubber production | Kumarasinghe et al. (2012); Zamanian et al. (2013); Waduge et al. (2015) |
| Number of tractors | ($X_4$) | per area per number of tractors | total tractors for area in rubber production | Zamanian et al. (2013) |
| Labour force | ($X_5$) | persons/hour | workers in a firm of rubber production | Zamanian et al. (2013); Waduge et al. (2015) |
| **Output variables** | | | | |
| Rubber quantity | ($Y_1$) | tons | total rubber quantity | Mustapha (2011); Kumarasinghe et al. (2012) |
| Price of quantity | ($Y_2$) | Baht/kg | price of rubber quantity per 1 kg for rubber production | Waduge et al. (2015) |
| **Environmental factors** | | | | |
| Temperature | ($B_1$) | degree Celsius | the degree of hotness or coldness for rubber production | Mesike and Esekhade (2014); Yu et al. (2014); Nguyen and Dang (2016) |
| Rainfall volume | ($B_2$) | millimeter | the intensity of rainfall is a measure of the amount of rain that falls in the period | Sdoodee and Rongsawat (2012); Mesike and Esekhade (2014); Waduge et al. (2015) |

Source: Author's composition

Table 2. Descriptive statistics of the input, output and environmental factors in Thailand

| Variable | Un | Mean | Standard deviation | Maximum | Minimum |
|---|---|---|---|---|---|
| **Input variables** | | | | | |
| Plantation area ($X_1$) | hectare | 587 332 | 142 524 | 4 395 849 | 26 |
| Tapping area ($X_2$) | hectare | 398 666 | 457 056 | 1 729 790 | 78 650 |
| Fertilizer ($X_3$) | tons | 28 630 | 19 925 | 146 726 | 3 |
| Number of tractors($X_4$) | per area per number of tractors | 8 550 | 13 535 | 131 190 | 1 |
| Labour force ($X_5$) | persons/hour | 683 602 | 490 534 | 23 760 | 3 772 |
| **Output variables** | | | | | |
| Rubber quantity ($Y_1$) | tons | 68 586.2 | 79 035 | 541 003 | 320 885 |
| Price of quantity ($Y_2$) | Baht/kg | 39 | 3.09 | 46.35 | 35.70 |
| **Environmental factors** | | | | | |
| Temperature ($B_1$) | degree Celsius | 27.50 | 0.334 | 31.00 | 24.50 |
| Rainfall volume ($B_2$) | millimetre | 231.60 | 89.43 | 463.28 | 129.91 |

Source: Author's calculations

## RESULTS AND DISCUSSION

### Outcome of stage 1: using the conventional DEA model

The DEAP 2.1 software (Coelli 1996) was used to analyse the efficiency level and returns to scale of rubber production in the 77 cities of four regions on the basis of their geographic location. As indicated in Table 3, without considering the external environmental variables, we observed that the calculated average TE of the Thai rubber production from 2005 to 2014 was 0.681, the standard deviation (SD) was 0.196, the maximum TE was 0.962, and the minimum TE was 0.515 by using the conventional DEA. It can be seen that the average TE remained moderate, so

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Table 3. Efficiency scores in the first stage

| Region | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Northern | 0.419 | 0.440 | 0.484 | 0.472 | 0.494 | 0.552 | 0.566 | 0.612 | 0.629 | 0.641 | 0.531 |
| North-Eastern | 0.650 | 0.607 | 0.630 | 0.587 | 0.616 | 0.640 | 0.639 | 0.652 | 0.666 | 0.648 | 0.634 |
| Central | 0.635 | 0.621 | 0.637 | 0.576 | 0.612 | 0.579 | 0.584 | 0.548 | 0.595 | 0.575 | 0.596 |
| Southern | 0.979 | 0.965 | 0.967 | 0.967 | 0.961 | 0.960 | 0.957 | 0.955 | 0.954 | 0.950 | 0.962 |
| Total average | 0.671 | 0.658 | 0.679 | 0.651 | 0.671 | 0.683 | 0.686 | 0.692 | 0.711 | 0.704 | 0.681 |
| SD | 0.231 | 0.220 | 0.204 | 0.217 | 0.202 | 0.189 | 0.183 | 0.181 | 0.165 | 0.168 | 0.196 |
| Maximum | 0.979 | 0.965 | 0.967 | 0.967 | 0.961 | 0.960 | 0.957 | 0.955 | 0.954 | 0.950 | 0.962 |
| Minimum | 0.419 | 0.440 | 0.484 | 0.472 | 0.494 | 0.552 | 0.566 | 0.548 | 0.595 | 0.575 | 0.515 |

Source: Author's calculations

it may be necessary to optimize the technique for rubber production. Regarding the TE in each year, we found that the TE in 2005–2014 was 0.671, 0.658, 0.679, 0.651, 0.671, 0.683, 0.686, 0.692, 0.711, and 0.704, respectively. The results further show that in 2008, the TE is the lowest when compared to other years due to the global economic downturn that affected the global demand for rubber. However, in the following year after the global economy improved, the rubber demand and productivity improved as well. The technical performance for the Northern region was clearly low in 2005 (0.419) compared with that of other years. Moreover, the technical performance for the Southern region was high in 2005 (0.979) compared with that of other years. The inputs and outputs variable suitable for the rubber production in the Southern part were high, resulting in high technical performance. The conventional DEA cannot distinguish the higher efficiency from the lower efficiency.

**Outcome of stage 2: OLS model**

As indicated in Table 4, in the second stage, the OLS model was used to obtain estimates of the deterministic frontiers for five input slacks during 2005–2014. We used the ratios of the input slacks to the input quantities as the dependent variables for input slack regressions. The input slack variables were the plantation area, tapping area, fertilizer, the number of tractors, and labour force. In this stage, the environmental variables were temperature and rainfall volume, which were used as independent variables in the OLS estimations. The coefficients and *t* values of each independent variable and dependent variable are presented in Table 4. The rainfall volume and temperature had positive and negative impacts, respectively, on the efficiency score of the rubber plantation area in the model, with statistically significant coefficient estimates of 4.721 and −1.810, respectively, at the 5% level. Furthermore, the temperature and rainfall volume had positive and negative impacts, respectively, on the efficiency score of the tapping area, with statistically significant coefficient estimates of 7.923 and −1.520, respectively, at the 5% level. Similar observations were made on the fertilizer amount in the model, with the temperature having a non-significant coefficient estimate of 2.900 and the rainfall volume having a significant estimate of −1.771 at the 1% level. The temperature and rainfall volume had positive and negative impacts, respectively, on the efficiency score of the number of tractors with statistically significant coefficient estimates of 6.890 and −3.190 at the 10% and 1% levels, respectively. Finally, similar observations were made on the efficiency score of the labour force in the model, with statistically significant coefficient estimates of 2.157 and −4.559 at the 10% and 1% level, respectively.

The OLS regression showed that environmental factors have a significant influence on the rubber production efficiency. It is thus necessary to strip out and analyse the environmental factors of the model. Therefore, before discussing the results, it should be confirmed that the coefficients listed in Table 4 are determined by the regressing environment variables on the input slack variables. If the estimating correlation coefficient is negative, there is a negative correlation relationship between the environmental variables and input variables. If the environmental variables are increased, the input variable of waste or negative output will be reduced, indicating an improvement efficiency of rubber production. On the other hand, if the estimating correlation coefficient is positive, an increase in the environmental variables will increase the input variables, and the efficiency performance of the rubber production will be reduced. The estimating

https://doi.org/10.17221/19/2016-AGRICECON

correlation coefficients of temperature had positive significant impacts on the tapping area, the number of tractors and the labour force in the model, and the temperature having a non-significant coefficient with the fertilizer of rubber production; thus, the temperature is not conducive to improving the efficiency of the rubber production in Thailand. The temperature that indicates increases in the input variables in a region will reduce the efficiency of production. In contrast, the estimating correlation coefficients of the temperature level for the one type of input variables are negative, indicating that an increase in temperature level will reduce the input and improve the efficiency of the rubber production. The estimating correlation coefficients of the rainfall volume for four types of input variables are negative, indicating that when the rainfall volume increased, the efficiency of the tapping area, fertilizer, the number of tractors and labour force were reduced. If the region has effects of a high rainfall, it means that the technical performance and development of the rubber production is higher than other regions; which reflects an improvement in the efficiency of the rubber production for that region. Waduge et al. (2015) proposed that the rainfall is used because it is the primary weather factor that affects the rubber production. Once farmers need water, they seek a higher level in their pursuits. These needs will effectively promote the development of production, which will help the farmers to improve their efficiency. Moreover, the estimating correlation coefficients for the index of one input variables are positive, indicating that an increase in the rainfall volume will lead to an increase in the input of the rubber production; hence, will not improve the efficiency. The results suggest the saturated plantation areas, which makes the management a hard task; hence, the lowered production efficiency.

Before the implementation of stage 3, the inputs variables were adjusted for the effect of the unfavourable external environment on the Thai rubber production by estimating the correlation coefficients. In this stage, we increasingly reduced the adverse effects of producers with a relatively undesirable external environment and poor appearance through the adjustment. It is likely that some producers with a significant competitive advantage may have undesirable results that are low to the extent that they become negative. Therefore, the method proposed by Portela et al. (2004) was adopted to handle the problem of negative data before advancing to stage 3.

**Outcome of stage 3: DEA model with adjusted input variables**

In the second stage, the parameters were estimated according to the principles proposed by Fried et al. (2002), to exclude the influence of environmental factors on input factors. However, the performance of the DEA relies on adjusted inputs and outputs from the first stage. The DEAP2.1 software was used to measure the efficiency after adjusting the input variables, and the results for the third stage are shown in Table 5. The results of the first and third stages are easy to find after excluding the impact of environmental factors and the efficiency scores of all data.

As indicated in Table 5, without consideration of the external environment variables, the average technical efficiency of the Thai rubber production from 2005 to 2014 was 0.708, having the SD and the maximum TE of 0.182, and 0.970, respectively. The minimum TE was 0.560 according to the third-stage DEA. Comparison between stage 1 and 3 showed that stage 3 had an average TE more than stage 1, rising

Table 4. Outcome of the secondary stage

| Independent variable | Dependent variable | | | | |
|---|---|---|---|---|---|
| | plantation area ($X_1$) | tapping area ($X_2$) | fertilizer ($X_3$) | number of tractors ($X_4$) | labour force ($X_5$) |
| Constant term ($B_0$) | $-1.572^{ns,a}$ $(-0.387)^{e}$ | $1.119^{ns}$ (0.718) | $1.298^{ns}$ (1.131) | $1.025^{***,b}$ (4.550) | $-2.371^{ns}$ (−0.839) |
| Temperature ($B_1$) | $-1.810^{**,c}$ (−2.742) | $7.923^{**}$ (3.126) | $2.900^{ns}$ (1.554) | $6.890^{*,d}$ (1.927) | $2.157^{*}$ (2.235) |
| Rainfall volume ($B_2$) | $4.721^{**}$ (2.529) | $-1.520^{**}$ (−2.122) | $-1.771^{***}$ (−3.357) | $-3.190^{***}$ (−3.158) | $-4.559^{***}$ (−3.507) |

[a]Correlation is not-statistically significant in all levels; [b], [c], [d], ***, **, *correlation is significant at levels 1, 5 and 10%, respectively; [e]the number shown in parentheses is *t*-value;

Source: Author's calculations

https://doi.org/10.17221/19/2016-AGRICECON

Table 5. Efficiency scores in the third stage

| Region | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Northern | 0.467 | 0.476 | 0.529 | 0.518 | 0.544 | 0.567 | 0.558 | 0.626 | 0.624 | 0.688 | 0.560 |
| North-Eastern | 0.623 | 0.628 | 0.656 | 0.661 | 0.658 | 0.678 | 0.702 | 0.727 | 0.740 | 0.771 | 0.684 |
| Central | 0.504 | 0.545 | 0.565 | 0.571 | 0.609 | 0.629 | 0.652 | 0.675 | 0.699 | 0.724 | 0.617 |
| Southern | 0.961 | 0.951 | 0.963 | 0.968 | 0.967 | 0.969 | 0.982 | 0.980 | 0.981 | 0.979 | 0.970 |
| Total average | 0.639 | 0.650 | 0.678 | 0.679 | 0.695 | 0.711 | 0.723 | 0.752 | 0.761 | 0.791 | 0.708 |
| SD | 0.225 | 0.210 | 0.197 | 0.201 | 0.188 | 0.178 | 0.183 | 0.158 | 0.154 | 0.130 | 0.182 |
| Maximum | 0.961 | 0.951 | 0.963 | 0.968 | 0.967 | 0.969 | 0.982 | 0.980 | 0.981 | 0.979 | 0.970 |
| Minimum | 0.467 | 0.476 | 0.529 | 0.518 | 0.544 | 0.567 | 0.558 | 0.626 | 0.624 | 0.688 | 0.560 |

Source: Author's calculations

from 0.681 to 0.708. We can deduce that the rubber production is shifting from decreasing returns to scale (DRS) to increasing returns to scale (IRS) through the adjustment of the effects on the environment and rand effort in the three-stage DEA model. This implies that the production scale of the DMUs were adjusted and are close to the optimum scale. Besides, the highest TE in 2014 was 0.791, and in 2005, the lowest TE was 0.639. We adjusted for the environmental variables, since they influence the efficiency of the Thai rubber production. The Southern region has higher efficiency scores when compared with other regions, followed by the North-Eastern, Central, and Northern regions. It should be noted, however, that the Southern region has the most plantation area, the economic growth is relatively fast, and farmers have great skills of producing rubber. Further, the geography and weather conditions are favourable to the rubber production, which often resulted in rubber of a good quality.

## Outcome of the MPI

This study measured the change in the productivity trend of the Thai rubber production during 2005–2014 by using the MPI for empirical estimation. The inputs used were adjusted for external environmental effects and estimated changes. The CCR version of input orientation in the MPI studies was used to decompose the TFP into the EC and the TC. Table 6 summarizes the results of the MPI for the years 2005–2014. The average TC was 1.034, the average EC was 0.977, and the average TFP was 1.010. We find that, during that period, the Malmquist TFP of rubber production increased, which implies that the productivity of rubber production has improved in the years 2005 and 2014. Furthermore, for the decomposition effects of the MPI, rubber production has shown efficiency improvements and the technical progress when the years 2005 and 2014 are compared, except during 2006–2007, 2007–2008, and 2010–2011, which seemed to have decreased in the production efficiency and technological progress. As indicated in Table 7, an analysis of change in efficiency (Malmquist indices) showed that the rubber productivity increased by region from 2005 to 2014. Through the MPI decomposing, it is possible to determine the sources of the productivity growth. An upward trend was found for the TFP (> 1) in the North-Eastern, Central, and Southern regions,

Table 6. MPI summary of annual means

| Year | TC | EC | TFP | Estimates of the productivity trend |
|---|---|---|---|---|
| 2005–2006 | 1.010 | 0.992 | 1.002 | increasing |
| 2006–2007 | 0.995 | 0.944 | 0.939 | decreasing |
| 2007–2008 | 0.977 | 0.966 | 0.944 | decreasing |
| 2008–2009 | 1.042 | 0.984 | 1.025 | increasing |
| 2009–2010 | 1.000 | 1.015 | 1.015 | increasing |
| 2010–2011 | 1.013 | 0.951 | 0.963 | decreasing |
| 2011–2012 | 1.115 | 0.937 | 1.045 | increasing |
| 2012–2013 | 1.117 | 1.004 | 1.122 | increasing |
| 2013–2014 | 1.034 | 0.996 | 1.030 | increasing |
| Mean | 1.034 | 0.977 | 1.010 | increasing |

Source: Author's calculations

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Table 7. Malmquist index summary of firm means

| Region | TC | EC | TFP | Estimates of the productivity trend |
|---|---|---|---|---|
| Northern | 0.908 | 0.989 | 0.898 | decreasing |
| North-Eastern | 1.109 | 0.956 | 1.060 | increasing |
| Central | 1.078 | 0.986 | 1.063 | increasing |
| Southern | 1.041 | 0.978 | 1.018 | increasing |
| Mean | 1.034 | 0.977 | 1.010 | increasing |

Source: Author's calculations

which implies an improvement in the efficiency as well as technology. On the other hand, a downward trend (< 1) was found in the northern region, which implies a need to improve performance and technology. In addition, the analysis of the MPI showed improvements over 2005–2014. It does not only suitably describe the physical relationship between the whole process and the component sub-processes, but also produces reliable results for the efficiency measurement. In general, we conclude that the rubber production in Thailand has enjoyed the efficiency improvement, the technical progress and the productivity growth between 2005–2014.

## CONCLUSIONS AND IMPLICATIONS

Thailand is known as an agricultural country; with its famous agricultural product, rubber. The Thai government implemented rubber-related policies and schemes, including small and mega projects since 1961. For this reason, the production of rubber in Thailand has been varying among the four different regions. Therefore, in this study we investigated the TE of the Thai rubber production from 2005 to 2014 by using the three-stage DEA model. Moreover, we used the MPI to measure the changes in the rubber production efficiency and to estimate the rubber productivity trend. A data set comprising 77 DMUs in four regions of Thailand during the period from 2005 to 2014 was used to illustrate the benefits of this approach.

The empirical results showed that the efficiency scores obtained using the adjusted inputs in stage 3 of the DEA approach were higher than the efficiency scores in stage 1 of the DEA approach. The TE score of the Thai rubber production revealed favourable results, but it still needs to be improved since the TE score is not close to 1. Generally, the overall efficiency of the rubber production in Thailand is quite high, implying that production is in a high standardized technology production function. However, Thailand still needs to improve its efficiency in order to maintain the high rubber production standard. Moreover, the results also showed that the Northern region has the worst scores of TE and declination of productivity among the four different regions in 2005–2014. This implies that the Northern region of the country has faced a critical problem of the rubber technology production. The main reason lies on an input-output combination. This region has somehow related to an overuse of plantation area, tapping area, fertilizer, number of tractors, and labour force with the same level of the rubber quantity. Therefore, the focus has been on the Northern region, intensively improving the TE throughout the region, followed by the Central, North-Eastern, and Southern, respectively.

Findings in the study further indicated the importance of considering the external environment when measuring the true efficiency and productivity performance of the rubber production. The approach employed here involved adjusting inputs in stage 2 and decomposing the influence of the environmental factors. The results suggest that the productivity and efficiency improvement of the Thai rubber production during 2005–2014 may be due to the environmental factors. The factors affecting the inefficiency of the rubber production are the temperature and rainfall volume.

Trend of the TFP for the rubber production has unveiled an advantage of the technology productivity, which was hidden over a ten-year period. Therefore, the productivity index showed an upward trend, implying that the country has improved in productivity for the Thai rubber production. The demand for rubber is likely to increase. Thailand, as a producer and exporter of the agricultural products worldwide, has recognized the importance of this commodity and strives to increase its production. As the global economy grows, the demand for rubber has increased, and many people have turned to the rubber plantation without controlling the plantation area, and this

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could be suggesting deficiencies in the production skills. The empirical results generated in this research could provide crucial information to the managers of rubber farms, agricultural planners, and the Thai government for formulating the effective strategies or plans to improve their technology and efficiency levels. It may help push the people involved in the rubber production to issue some beneficial and useful policies to help increasing the trend of the rubber productivity index in certain areas.

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