The Impact of Climate Change on Agriculture Sector in ASEAN

Chonrada Nunti[1], and Kewalin Somboon[2]

[1] Faculty of Economics, Chiang Mai University, Chiang Mai, 50200, Thailand

[2] Faculty of Economics, Maejo University, Chiang Mai, 50210, Thailand

[*]Corresponding author's e-mail: kewalin@mju.ac.th

Abstract. This study purposes to estimate climate change effect on agriculture sector in ASEAN by using the copula-based stochastic frontier approach to evaluate the technical efficiency and factors that affect agriculture production. Panel data of land, labour, fertilizer, and temperature in seven countries in ASEAN including Thailand, Vietnam, Myanmar, Philippines, Indonesia, Cambodia, and Malaysia. collected from 2002 - 2016 were used for estimating the model. The results presented that the land, labour, and fertilizer consumption according to the agriculture have positive and significant effects on agricultural production. The most interesting point from this study, found that there is a negative effect on agriculture production related by the climate change. Additionally, this study provides the most appropriate tools to analyse climate change impacts on ASEAN agriculture and the potential options for adaptation in the agriculture sector.

1.Introduction

Today, the most significant factor affecting the agricultural productivity is Climate. ASEAN agriculture has benefited from optimizing the adaptive areas of crops grown in diverse regions, soils, and climates. Climate and weather characteristics such as rainfall, water resource, temperature, and carbon dioxide (CO_2) directly affect the health and well-being of plants. Regarding the effects of climate change on agricultural production, the climate change caused after the greenhouse gases released within the atmosphere, as the result of global warming. In terms of climate change, one of the most important sectors is the agriculture sector. The empirical focus of this study is agriculture. Numerous weights with updated evidence from a recent analysis of ASEAN agriculture are affected by climate change.

The SFM model which applied for TE estimation presented by Aigner et al. [1] and Meeusen et al. [2]. Nonetheless, Since the independence of the error components is the crucial in SFM assumptions. Pal and Sengupta [3] explained that if let weather be the random factor, it might influence the managerial decisions. Also, ignoring the significant variable is another argument when there is a misspecification of the model which bring about the dependence between the error components. Smith [4] presented the copula model to examine a relation between them. Additionally, Wiboonpongse et al [5] presented that the dependence should take into consideration since the standard SFM given the overestimated TE which mean there is dependence between the error. Hence, these are reasons why this study employ copula based SFM to investigate the technical efficiency.

2. Methodology

2.1 Stochastic frontier model (*SFM*)

The initial model of the SFM measure the productive efficiency of firm when produced at the lowest cost while the stage when firm cannot provide the lowest cost is defined by the productive inefficiency. The technology upgrading and process improvement are ways to improve productivity. For instance, the improvement of labour education, apply optimal technical efficiency labour. Firm will operate closer to the existing frontier if they have a good performance. Thus, the efficiency improvement might be attributed by the increasing in the productivity. The SFM can be formulated as below,

$$\log Y = x^{'}\beta - U + V, \tag{1}$$

The number of output defined by $Y = y \in \mathbb{R}_{+}$, a vector $k \times 1$ of inputs defined by x, and β indicates a vector of uninformed parameters. $V = v \in \mathbb{R}$ identify a zero-mean in the error component, the symmetric error which independent and continuous in x defined by $G(v) = \Pr(V \le v)$. Nevertheless, the unknown parameters which collected from vector δ_v are determined by the error component. Another error belongs to $U = u \in \mathbb{R}_{+}$ where a random variable is $\mathbb{R}_{+} = \mathbb{R}_{+} \cup \{0\}$ with $F(u) = \Pr(U \le u)$ which is a cumulative distribution function. The positive error is the major characteristic of this error. However, in the SFM, the unobserved inefficiency is defined by U. The maximal frontier output where given a set of input x showed the full efficiency in the production. Contrarily, U will decrease output which represent as the frontier departure when there are inefficiencies in production.

In addition, the two-error assumption where one-side and two-side error terms are assumed to be independence since it is suitable to calculate these two errors joint distribution, but in some case studies are impractical.

2.2 Copula models

Sklar [6] expressed that a usual copula function captures amongst the random variables in the dependence structure which familiar as a marginal distribution functions and copula function. Hence, the two random variables (X_1, X_2) in any CDF $F(x_1, x_2)$ can be described as

$$F(x_1, x_2) = C\left(F_1(x_1), F_2(x_2)\right), \tag{2}$$

Where $F_1(x_1)$ and $F_2(x_2)$ indicated the marginal CDFs of X_1 and X_2, and C defined a bivariate function of copula.

2.3 Copula-based SFM panel data

There are independent in the error component between u and v which is the main classical SFM assumption. Furthermore, Smith [7] represented the used of copula model was allowed for the dependence between the errors. The copula approach can extend the classical SFM. Let $f(v, \varepsilon)$ be the joint density which can be shown as below,

$$f(u, \varepsilon) = f(u, u + \varepsilon) = f_U(u) f_V(u + \varepsilon) c_\theta\left(F_U(u), F_V(u + \varepsilon)\right). \tag{3}$$

Thus, the $f_\theta(\varepsilon)$ can be obtained by U to marginalize out as follows,

$$f_\theta(\varepsilon) = E_U\left(f_V(U + \varepsilon) c_\theta\left(F_U(U), F_V(u + \varepsilon)\right)\right), \tag{4}$$

Let the function of copula and the marginals' parameters vector denoted by the incapability U and θ which indicated by $E_U(\cdot)$.

Wiboonpongse et al. [5] estimated the copula based SFM by using MLE. This research applied panel data and provided the Hausman test for choosing between random effects and fixed effects. The suggestion from the result states that the most appropriate test for this data belongs to the fixed effects. The equation of likelihood can be presented by

$$L(\beta,\sigma_u,\sigma_v,\theta)=\prod_{i=1}^{n} f_\theta(\log y_{it}-x_{it}^{'}\beta), \tag{5}$$

where y_{it} indicates the output of firm i, $t=1,...,T$. The regressors vector is x_{it}. The scale of marginal parameters U and V indicated by σ_u and σ_v. As Smith [7] proved that a close-form expression can be found from a few density functions of ε. Let assume a half-normal distribution by U and V be a normal distribution. The PDF for ε presented as,

$$\begin{aligned}
f(\varepsilon) &= \int_0^\infty f_U(u)\times f_v(u+\varepsilon)\times c_\theta(F_U(u),F_V(u+\varepsilon))du \\
&= \int_0^\infty \frac{2\exp\left(-\frac{u}{2\sigma_u^2}^2\right)}{\sqrt{2\pi\sigma_u}}\times f_V(u+\varepsilon)\times c_\theta(F_U(u),F_V(u+\varepsilon))du \\
&= \int_0^\infty \frac{2\exp\left(-\frac{(\sigma_u u_0)^2}{2\sigma_u^2}\right)}{\sqrt{2\pi\sigma_u}}\times f_V(\sigma_u u_0+\varepsilon)\times c_\theta(F_U(\sigma_u u_0),F_V(\sigma_u u_0+\varepsilon))d\sigma_u u_0 \\
&= \int_0^\infty \frac{2\exp\left(-\frac{u_0^2}{2}\right)}{\sqrt{2\pi}}\times f_V(\sigma_u u_0+\varepsilon)\times c_\theta(F_U(\sigma_u u_0),F_V(\sigma_u u_0+\varepsilon))du_0 \\
\hat{f}(\varepsilon) &= \frac{1}{N}\sum_{r=1}^{N} f_V(\sigma_u u_{0,itr}+\varepsilon)\times c_\theta(F_u(\sigma_u u_{0,r}),F_V(\sigma_u u_{0,itr}+\varepsilon)),
\end{aligned} \tag{6}$$

where the distribution of U was drawing a sequence of random denoted by $u_{0,r}$, $r=1,...,N$. Thus, the simulated log-likelihood of the copula-based SFM is expressed as

$$\begin{aligned}
&L_s(\beta,\sigma_u,\sigma_v,\theta)\approx \\
&\sum_{i=1}^{N}\log\left\{\frac{1}{N}\sum_{r=1}^{N} f_V(\sigma_u u_{0,itr}+\varepsilon_{it})c_\theta\left(F_U(\sigma_u u_{0,itr}),F_V(\sigma_u u_{0,itr}+\varepsilon_{it})\right)\right\}
\end{aligned} \tag{7}$$

The parameters (σ_u,σ_v) studied by Battese and Coeli [8] can be converted into (λ,σ) with $\sigma=\sqrt{\sigma_u^2+\sigma_v^2}$ and $\lambda=\sigma_u/\sigma_v$. Greene [9] stated that the larger λ, the higher is the inefficiency component according to the model. Moreover, the inefficiency can also be measured by $\gamma=\sigma_u^2/(\sigma_u^2+\sigma_v^2)$, where λ and γ might disclose whenas the statistical error incapability is significant. Thus, the SFM of TE can be estimated by ε, as follows,

$$\begin{aligned}
TE_\theta &= E\left[\exp(-U)\middle|\varepsilon\right] \\
&= \frac{1}{f_\Theta(\varepsilon)}\int_0^{+\infty}\exp(-u)\,f(u,\varepsilon)du \\
&= \frac{E_u\left[\exp(-U)\,f_V(U+\varepsilon)c_\theta\left(F_u(U),F_V(U+\varepsilon)\right)\right]}{E_U\left[f_V(U+\varepsilon)c_\theta\left(F_u(U),F_V(U+\varepsilon)\right)\right]}
\end{aligned} \tag{8}$$

3. Data

Data are obtained from World Bank database and FAO statistics, based on a yearly basis ranging from 2002 - 2016 for seven countries in ASEAN including Thailand, Vietnam, Myanmar, Philippines, Indonesia, Cambodia, and Malaysia. Let an agriculture production (Y_{it}) be the dependent variable while the explanatory variables indicated by an employment in agriculture ($Labor_{it}$), an agriculture land ($Land_{it}$), temperature change ($Temperature_{it}$), and a fertilizer consumption ($Fertilizer_{it}$).

4. Empirical results

4.1 Panel Unit root test.

The used of Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Levin, Lin & Chu t (LLC) test, Im, Pesaran and Shin W-stat (IPS) test were employed for checking unit root test according to the procedure. Where the stationary in all variables with logarithm transformation were provided as the results.

4.2 The estimated results of SFM.

The SFM was analysed by regarded the corresponding of nine different copula families, the best model based on the lowest BIC was selected. The most appropriate model for this study is the SFM with Student-T, since the SFM with the Student-T copula has the lowest value in term of BIC. Hence, the estimated results show that there are positive and significant effect on the agriculture production land, labour, and the fertilizer consumption. The values of parameters β equal to 1.5092, 2.3296, and 0.3926, respectively. This indicates that the increasing of 1% in the agriculture land, labour, and the fertilizer consumption will increase agriculture production as 1.5092%, 2.3296% and 0.3926%, respectively. While there are negative and significant effect with the temperature change on the agriculture production where β is equal to -0.0089, which indicates that the increasing of 1% in the temperature change will decrease agriculture production by 0.0089% as exhibited in Table 1. The inefficiency in agriculture production indicated by the significant at 1% level of σ_u . The noise-inefficiency dependence can be confirmed by the significant at 1% level when the student-T copula of the estimated parameter is 0.8744. Thus, the errors correlation implies the standard SFM is less appropriate than the copula with SFM approach.

Table 1. The estimated parameters of copula-based SFM

Input variables	SFM based on Student-T copula		Bays factor
	Estimates	**S.E.**	
Constant	19.4997	1.4285	0.0000****
ln(Land$_{it}$)	1.5092	0.3220	0.0138***
ln(Labor$_{it}$)	2.3296	0.3055	0.0281***
ln(Fertilizer$_{it}$)	0.3926	0.0858	0.0000****
ln(Temperature$_{it}$)	-0.0089	0.1334	0.0212***
σ_v	0.8662	0.1404	0.0000****
σ_u	0.8744	0.0237	0.0000****
ρ	0.4275	0.2031	0.0353***

Note that: *,**,***,**** denote the weak, evidence, strong evidence, and very strong evidence, respectively

4.3 The technical efficiency (TE).

Regarding the TE based on the Student-T copula of agriculture production in different ASEAN countries. The empirical results present Indonesia is the best average TE score with 0.82, followed by Myanmar, Thailand, Vietnam, Malaysia, Cambodia, and Philippines with their TE values of 0.79, 0.77, 0.74, 0.73, 0.69, and 0.56, respectively.

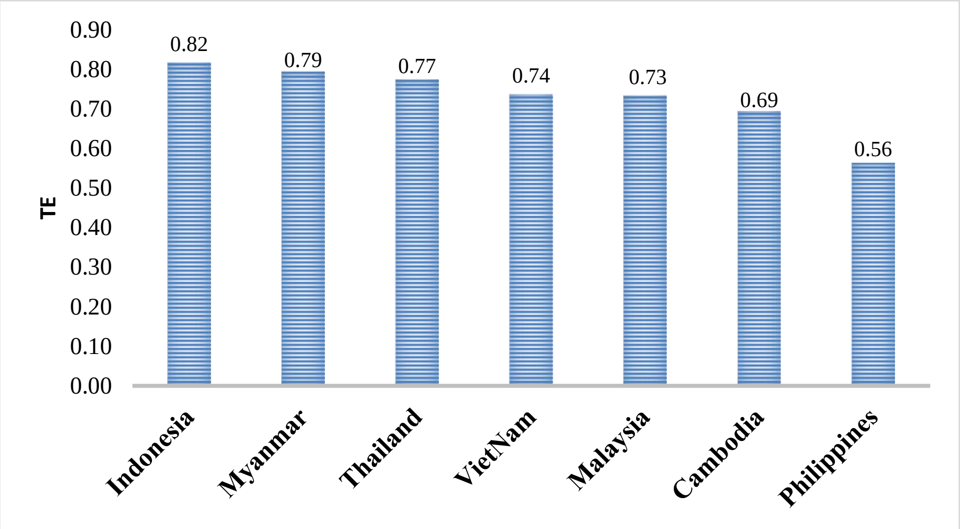

Figure 1. The Technical efficiency of the Countries in ASEAN

5. Conclusions

This study purposes to estimate climate change effect on agriculture sector in ASEAN by using the copula-based SFM approach to evaluate the TE and factors that affect agriculture production. Panel data of land, labor, fertilizer, and temperature in ASEAN collected from 2002 - 2016 were used for estimating the model. The empirical results present that Indonesia is the best average TE score with 0.82, followed by Myanmar, Thailand, Vietnam, Malaysia, Cambodia, and Philippines with their TE values of 0.79, 0.77, 0.74, 0.73, 0.69, and 0.56 respectively.

Indonesia is by far a rapidly developing country with a population of 225 million with ranked 4th in the world. Regarding the agricultural science in Indonesia, a large number of Indonesia's leading universities have expertise and strengths in applying agricultural technology, food sciences, agricultural engineering, and ecosystem which let Indonesian had basic skills in food and agriculture. Moreover, Indonesia also has strengths in the production of tools to support various agricultural operations, for instance, the faculty of agriculture engineering of Institute Pertanian Bogor (IPB) has integrated science in agricultural engineering including post-harvest technology will be able to support the development of the supply chain system in agricultural production in the future.

Additionally, this study provides the most appropriate tools to analyze climate change impacts on ASEAN agriculture and the potential options for adaptation in the agriculture sector.

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