CLIMATE CHANGE AND ASEAN RICE PRODUCTION

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Abstract:

There has been a growing concern over the escalating signs of climate change that could adversely affect the production of rice in ASEAN region. This study attempts to assess the impact of climate change on food security measured in terms of rice yield, with the focus being on ASEAN member countries. Panel data are collected on nine ASEAN countries and static panel data equations are estimated. In addition, the dynamic panel ARDL technique is also adopted to investigate the long-term and short-term cointegration between the variables. The findings show mixed results of impact of CO_2 on rice yield among majority of ASEAN member countries in short-run which signify the positive CO_2 fertilization effect in the region over the adverse impact of temperature increase on rice yield. In long-run, however, the negative effects are projected which might reduce rice yield in this tropical area. Thus, serious collaboration between developing and least-developed countries in the region to address the issues in agriculture and rice production is very crucial to solve food insecurity within the region in the long-term.

Keywords:

food security; ASEAN; panel ARDL; climate change

Introduction

Rice has long been hailed as the staple in many parts of the world. And this comes as no exception to the cluster of countries located in the Southeast Asian region – more formally known as the Association of Southeast Asian Nations (ASEAN). Over the decades, as diets

become more diversified, the share of rice in total caloric intake for the average consumer has declined in the majority of ASEAN countries, while rice consumption per capita has also decreased in some. As illustrated in Figure 1 and 2, Malaysia and Thailand have been displaying the biggest reductions since the 1970s in both per capita consumption of rice as well as the share of rice in total caloric intake. The rest of the countries are also exhibiting a downward trend when it comes to the share of rice in the average household diet, except for the Philippines, and Brunei – since the 1980s. In terms of per capita consumption, the trends are more varied with Malaysia and Thailand showing obvious decreases while the Philippines and Myanmar are displaying the opposite. Despite what may seem as the weakening role of rice in the dietary consumption of the population in ASEAN, this important staple nonetheless, still maintains its dominant position and is not easily replaced or substituted by other food sources. Even in Malaysia where per capita consumption has fallen greatly, rice still contributes the biggest portion of total caloric supply to the country's population (Khazanah Research Institute, 2019).
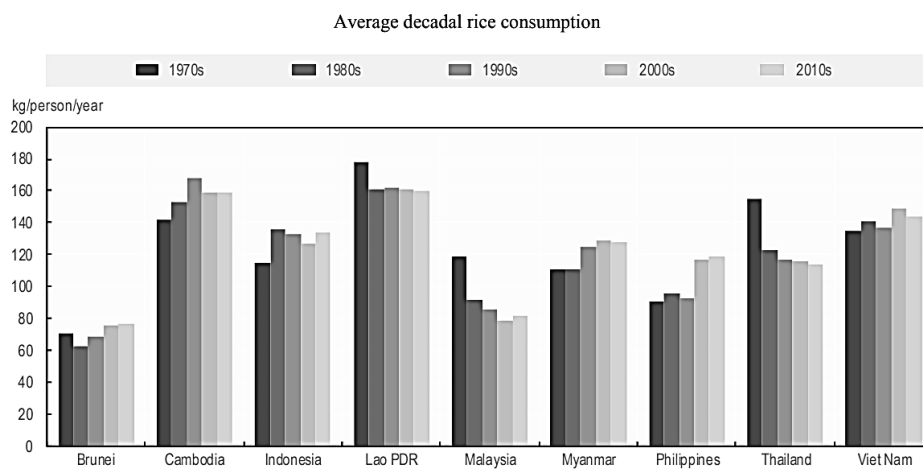
Figure 1: Per Capita Consumption of Rice across ASEAN Member Countries

Note: Consumption drawn from FAO food balance sheets and represents rice used for food. Decade averages taken as the simple average over each decade, with 2010s covering only up to 2013.
Source: ASEAN (2021) and FAO (2018), FAOSTAT, http://faostat.fao.org/.
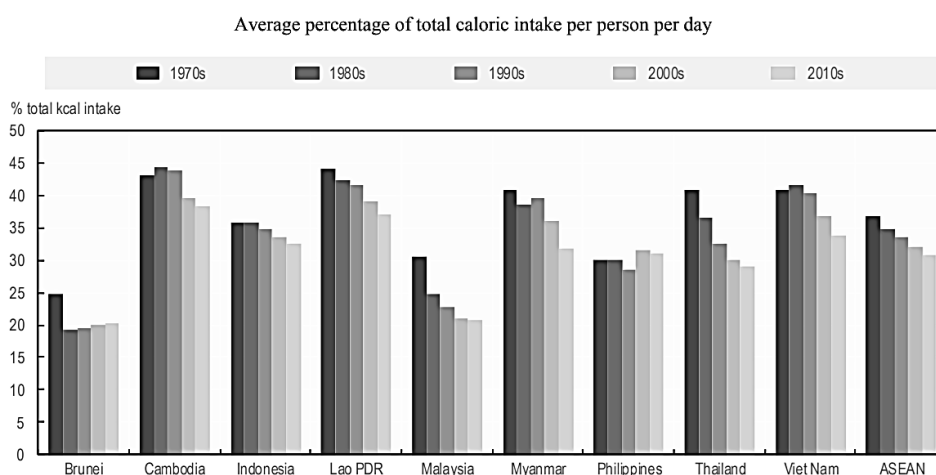

Figure 2: Share of Rice in Total Caloric Consumption across ASEAN Member Countries

Note: kcal consumption drawn from FAO food balance sheets and represents kcal from milled rice as a share of total kcal. Decade averages taken as the simple average over each decade, with 2010s covering only up to 2013.
Source: ASEAN (2021) and FAO (2018), FAOSTAT, http://faostat.fao.org/.

Due to the primary importance of rice as the staple food in every ASEAN country, ensuring adequate amount of rice is produced and available for household consumption is therefore, imperative. In order to meet the consumption needs and demand of each of the countries' growing population, the rice yield of all ASEAN member countries – with the exclusion of Singapore which does not grow and produce its own rice, has been displaying progress as demonstrated in Figure 3. Vietnam seems to be leading the pact as being the most progressive and having the highest yield in 2019. This would be unsurprising since Vietnam alongside Thailand are known for being the major producers and exporters of rice. Both of these countries are also expected to exhibit the highest growth in rice production just behind India and China by 2030 (OECD/FAO, 2021). Indonesia as the third biggest producer of rice in the world is just behind Vietnam in terms of rice yield. As half of the countries in the ASEAN region are in fact among the top 10 leading producers of rice globally, the whole region boasts itself as a net exporter of rice. This is indeed expected from the region due to fact that several of its members occupy the highest share of global demand for rice. In Figure 4, Indonesia, Vietnam and the Philippines are seen as amongst the top five countries where the global rice demand will be heavily concentrated based on projections for the year 2030 (OECD/FAO, 2021).
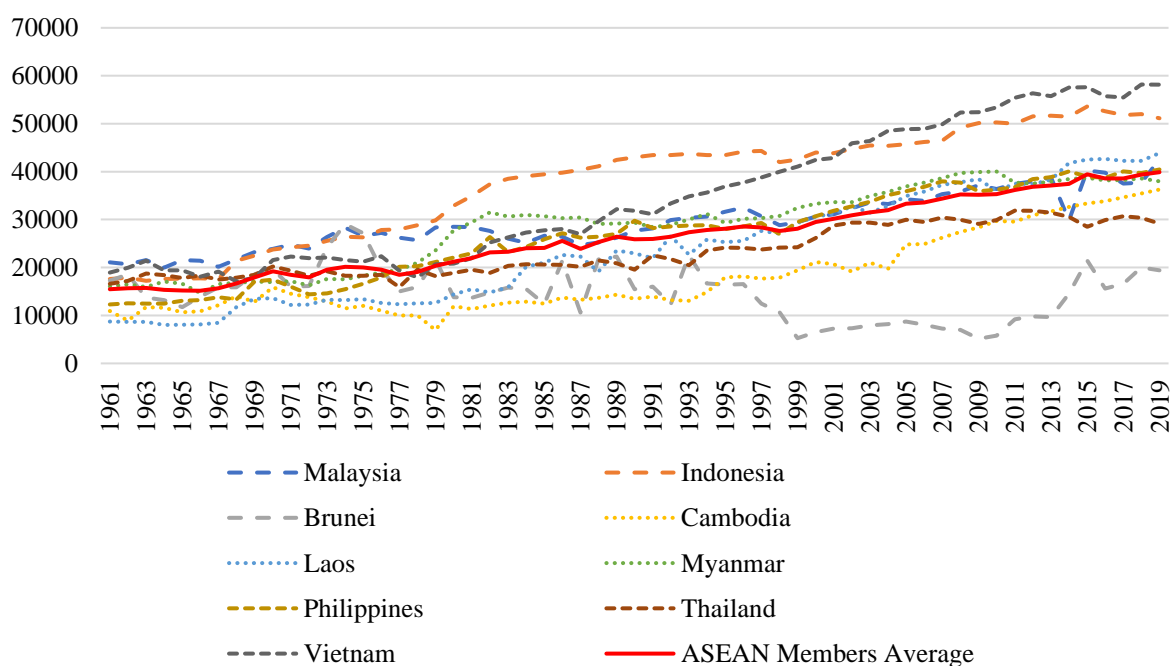
Figure 3: Rice Yield across ASEAN Member Countries from 1961 to 2019

Note: Rice yield measured in hectogram per hectare (hg/hectare).

Source: FAOSTAT, http://faostat.fao.org/.
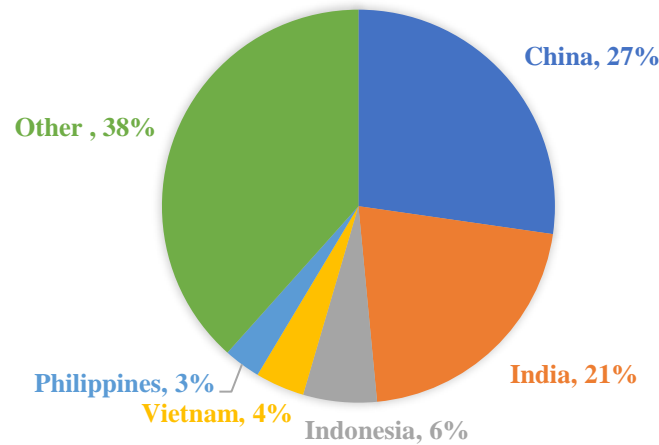
Figure 4: Global Rice Demand Concentration in 2030

Source: OECD/FAO (2021)

Although rice production in the ASEAN region has been showing progress with further growth expected in the future, there has been a growing concern over the escalating signs of climate change that could adversely affect the production of rice. As the key contributor to climate change, CO_2 emissions have been rising relentlessly in all of the ASEAN member countries. From Figure 5, the increase in CO_2 emissions in most countries has been primarily led by electricity and heat production or more specifically, the power sector. The manufacturing industries and construction sector as well as the transport sector, are also major contributors of CO_2 emissions in the majority of countries. The share of emissions coming from the different sectors of the ASEAN countries on average is in fact very similar to the global average. Hence, with the increasing emissions of CO_2 further enhancing climate change, the serious threat which climate change could pose on the production of the region's staple must therefore be assessed closely in order to better address the subject matter.
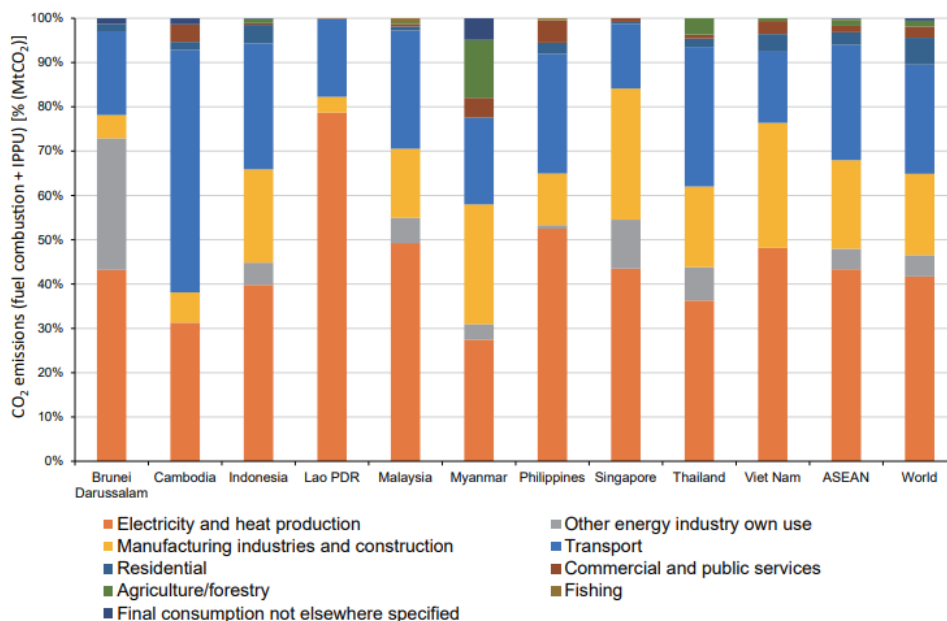
Figure 5: Sectoral Share of CO2 Emissions Across ASEAN Member Countries in 2018

Note: IPPU represents industrial processes and product use and $MtCO_2$ denotes metric tons of carbon dioxide.
Source: ASEAN (2021) and IEA (2020)

Literature Review

The interest in assessing the impact of climate change on crop yield is not new. Nonetheless, the topic has received greater attention in recent years as the devastations from climate change are becoming more apparent by the day. Since increase in CO_2 levels is one of the major signs of climate change, many studies have taken a closer examination on how rising atmospheric CO_2 concentration would affect crop yield, especially that of major food grains. The latest study by Zhang, Niu and Yu (2021) revealed that, variations in crop yield were primarily driven by elevations in CO_2 concentration; and together with precipitation levels, both positively affect crop yield of rice, wheat and maize in China. Another research conducted in China reported that, elevated CO_2 level increased grain yield of rice by 5.9 percent, but at the expense of decreased grain quality in terms of protein content by 7 percent (Wang et al., 2019).

From a simulation done by Kinose et al. (2020) to analyse the effects of climate change on the yield of Ciherang – the main rice cultivar in Indonesia, findings displayed that every year from 2039 to 2042, the rice yield increased up to 8 percent with changes in the concentration of CO_2. Likewise, Poulton et al. (2016) found a 22.6 percent increase in rice yield on average in Cambodia, resulting from a 118 percent elevation in CO_2 level. The reason for the positive correlation between CO_2 concentration rate and rice yield is attributed to the CO_2 fertilization effect (Zhang, Niu & Yu, 2021), since CO_2 is essential for plant crops to carry out photosynthesis. The increase in CO_2 concentration have also been found to result in other beneficial gains such as more efficient use of agricultural water consumption, as well as bigger leaf area, increase in crop biomass and higher photosynthetic rate (Deryng et al, 2016; Kimball, 2011). Thus, the production of important food crops like rice could possibly benefit considerably from higher CO_2 concentration in the atmosphere.

With more advanced simulation techniques and methodology as compared to in the past, the results from the recent studies mentioned before are actually consistent with and supportive of findings from older research works. As an attempt to understand the impact of changing climate on agriculture, research experiments conducted prior to the 21st century were largely conducted either in gas chambers or greenhouses as opposed to newer experiments conducted in open-air settings (Kimball, 1983; Horie, Matsui, Nakagawa & Omasa, 1996). In fact, one of (if not) the earliest studies which delve into the topic of enhanced CO_2 levels on plant crops goes back to as early as 1804 by de Saussure, who observed better growth in pea plants which are exposed to high levels of CO_2 in comparison to those growing in ambient condition (Kimball, 1983). From an experiment conducted by Horie et al. (1996), a 7 to 8 percent increase in Japan's rice yield was predicted when CO_2 level rises by 100 µmol mol-1. Findings by Kimball (1983) also showed that there would be an overwhelming 33 percent increase in agricultural yields as atmospheric CO_2 level doubles.

The positive effect of atmospheric CO_2 concentration on crop yield is considerably viewed as an opportunity which can be taken advantage of, in order to mitigate the adverse effects resulting from other signs of climate change - such as rising temperature and increasing ozone. Since the increase in temperature has been considered by many as the main culprit which could potentially cause significant reductions in crop yield (Wang et al., 2021; Kinose et al., 2020; Liu et al., 2020; Wang et al., 2019; Poulton et al., 2016), this negative impact could be negated by the positive gains from higher CO_2 concentration (Zhang, Niu & Yu, 2021; Faisal & Parveen, 2004). The overall effect nevertheless, is still in debate - whether the positive effects from CO_2 elevations can outweigh and cancel out the adverse impact of warming. Based on an empirical study by Faisal and Parveen (2004), it was projected that Bangladesh would not

suffer much from the effects of climate change in the year 2030 because the adverse impacts of rising temperature and sea levels would be compensated by the positive CO2 fertilization effect; but then again, the negative effects might intensify in 2050 which consequently translates into an 8 percent decline in rice yield. As for Liu et al. (2020), it was discovered that despite the positive CO2 fertilization effect on rice yield, the impact was unable to offset the negative consequences of higher temperature as rice yield in China still declined on average, when a 1.5- and 2.0-degree Celsius warming scenarios were considered, respectively.

Similarly, Wang et al. (2021) found the effect from CO2 fertilization could not fully compensate the adverse impact of temperature increase on rice yield. On the contrary to this, Gerardeaux, Giner, Ramanantsoanirina and Dusserre (2012) identified a positive overall effect on rice yield in Madagascar even under the worst climate change scenario, that is largely due to the positive impact from temperature and higher CO2 on the growth of rice. There seems to be some trade-offs associated with the opposing effects of higher CO2 and temperature levels – where greater CO2 concentration would raise yield but reduce grain protein, while temperature rise would induce higher protein content at the cost of lower yield (Wang et al., 2019). In that matter, it is also worth noting what Long, Ainsworth, Leakey and Morgan (2005) observed from the projections of global food security being overly optimistic when considering the effects of higher CO2 level on crop yield, as substantial loss in yield resulting from increase in ozone was not taken into account in the experiments done previously.

In light of the previous findings, it would be the primary interest of this study to assess the impact of CO2 emission as a factor of climate change on food security measured in terms of rice yield, with the focus being on ASEAN member countries. If increase in CO2 has a positive and significant relationship with rice yield in the countries studied, then such finding will be invaluable in the contribution towards the planning of suitable adaptive strategies - that is for the countries to better address the effects of climate change on the production of their staple food crop. Aside from employing CO2 emission as the key climatic factor, other non-climatic factors which affect rice yield are also considered and thus, included as part of the analysis. Fertilizer consumption has been often identified previously, as one of the main significant drivers of agricultural production and growth (Kea et al., 2016; Haji-Rahimi, 2012; Hussain & Ishfaq, 1997). Area harvested is another important factor incorporated in the current study due to the significant role the factor plays in rice production as observed from past research works (Tanko et al., 2016; Kea et al., 2016).

Methodology
Data
Panel data are collected for nine (out of ten ASEAN countries) consisted of Indonesia, Malaysia, Thailand, the Philippines, Lao PDR, Vietnam, Cambodia, Myanmar and Brunei. Singapore is drop from the current analysis as data on rice yield and area harvested for the country are not available from FAOSTAT databank. The data span from 1961 until 2015 (55 years) resulting to 442 observations in total. The recent years data (above 2015) for all variables of each country are mostly unavailable.

The selected variables employed in the model follows a standard production theory which is Cobb-Douglass Production function. The variables are rice yield (RY) as a dependent variable (production or output) and area harvested (a proxy for land as fixed input), fertilizer consumption (as variable input) and CO2 emission (another determinant). Details on the variables are displayed on Table 1.

All data are transformed into natural logarithm. The reason is that some variables might be in terms of scale and unit which are not standardized. The regression based on unstandardized variables gives extraordinarily big coefficient for particular variable. Besides, panel data that contains both cross section and time series data are heteroskedastic. Thus, the form of logarithm can improve the fit of the linear regression as they are more normally distributed. Another reason of transforming data into log in the model is for interpretation or convenience reason. By taking log for both dependent and independent variables, the regression coefficients (β) will be interpreted as elasticities. There is also a theoretical reason for doing so. Since we would like to estimate a multiplicative and therefore nonlinear Cobb-Douglas production function, taking logarithms allows this model to be estimated by linear regression.

Data are obtained from several sources including the FAO, World Rice Statistics (WRR) and World Bank as displayed in Table 1 below.

Table 1: Variables and Sources of Data

Variable	Measurement	Sources of data
Rice Yield (RY)	Hg/Hectare	FAO
Carbon Dioxide Emissions (CO2)	Metric Tonne Per Capita	World Bank
Area Harvested (AH)	Hectare	FAO
Fertilizer Consumption (FC)	Tonne	WRR

Method

This study is undertaken in the context of panel data sets. Commonly, panel data equations are estimated using either random (REM) or fixed effects (FEM) which allow for country heterogeneity, in contrast to the Pooled Ordinary Least Square (POLS) model which assumes all countries as homogenous. The difference between RE and FE lies in their treatment towards the random error term, εit. The εit consists of individual specific-effect λi and the remainder error term, μit. The REM assumes the individual specific effect independently drawn from probability distribution while FEM assumes the individual specific effect as a constant. Iterative stepwise regression (IOLS) is also estimated in addition to POLS which adds or removes one independent variable at a time to or from the multiple linear regression equation.

Four methods are adopted: common effects (Pooled OLS), iterative OLS (IOLS), fixed effects (FE) and random effects (RE) method. The model for panel regression is generally as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \beta_n X_{nit} + u_{it} \tag{1}$$

In specific, the model above model can be written as:

$$lnRY_{it} = \beta_0 + \beta_1 \, lnAH_{it} + \beta_2 \, lnFC_{it} + \beta_3 \, lnCO2_{it} + u_{it} \tag{2}$$

where *ln* is the natural log and *u* is the error term. *Hausman* test will be conducted to decide which model is preferred for the dataset. The test is run to check whether the random error term is correlated with other explanatory variables. The null hypothesis is that the preferred model is random effects (RE) and the alternative is fixed effects (FE). If they are not correlated, the RE method is preferred.

However, if they are correlated, the FE method is preferred. According to Martinez-Zarzoso and Nowak-Lehmann (2003), REM is more suitable when the sample countries are taken to be the representative of a larger population. For the pre-determined selection of sample countries, the FEM is more appropriate (Egger, 2000). The F test (*Breusch-Pagan* LM) is applied to choose between POLS and FEM.

In recent econometric theory of panel data, there are several methods could be adopted to analyse panel data depending on the size of N (units) and T (time). In situations when T and N are large, or called "macro panels" and large N and small T or "micro panels", different methods are designed depending on T and N's sizes. This current study involves 9 countries (*i*) and 56 years (*t*). Since T > N in the current data of study, this study also opts to adopt a more appropriate estimation technique, that is panel ARDL. The panel ARDL technique is attempted to investigate the long-term and short-term cointegration correlations between the variables and extract the ECM (error correction model) of the panel characteristics to develop the short-term dynamic. This approach could be used regardless of whether variables were I(0), I(1), or both I(0) and I(1) (Sulaiman et al., 2018). Panel ARDL with various variables can include various lags, which are inapplicable using the standard cointegration test. Moreover, using panel ARDL, both long-term and short-term coefficients are provided at once (Sulaiman et al., 2015; Sheng et al., 2016). For this estimation technique, hence the unit root should be tested to check if the variables are stationary or not. For panel data, the Levin, Lin and Chu (2002), Breitung (2000), Maddala and Wu (1999) and Hadri (2000) panel unit root tests were recommended. Panel ARDL that ought to be analysed for the bounds test method is presented as the following:

$$\Delta lnRY_{it} = \beta_1 + \sum_{i=1}^{k} \alpha_{ij} \Delta lnRY_{j,t-i} + \sum_{i=1}^{k} \partial_{ij} \Delta lnAH_{j,t-i} + \sum_{i=1}^{k} \emptyset_{ij} \Delta lnFC_{j,t-i} + \sum_{i=1}^{k} \gamma_{ij} \Delta lnCO2_{j,t-i} + \theta_1 lnRY_{j,t-1} + \theta_2 lnAH_{j,t-1} + \theta_3 lnFC_{j,t-1} + \theta_4 lnCO2_{j,t-1} + \varepsilon_{jt}$$
(3)

where *t* is time, *i* refers to the studied country, Δ is the first difference, *k* is the ideal lag length and ε_{jt} is a random disturbance term. To investigate the long-term cointegration correlation between the determinants, the below assumptions are formed on equation (3):

H_0: $\theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$ (There is no cointegration).

H_a: $\theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq 0$ (There is cointegration).

This cointegration test is conducted by applying the *F* test. The test uses panel autoregressive distributed lag bounds, which relies on whether the variables are purely I(0), purely I(1), or a combination of I(0) and I(1). Two critical values are computed; I(0) identified with lower restriction (lower bound), and I(1) identified with higher restriction (upper bound). If the F statistics surpass the upper bound, it can be concluded that there is a cointegration among variables. If the F statistics below the lower bound, the null hypothesis cannot be rejected, and if the F statistics is between the I(0) and I(1), a derivation cannot be made.

A proof of cointegration among variables will lead to below long term and short-term equations, respectively:

$$lnRY_{it} = \beta_2 + \sum_{i=0}^{k} \alpha_{i2} lnRY_{j,t-i} + \sum_{i=0}^{k} \partial_{i2} lnAH_{j,t-i} + \sum_{i=0}^{k} \emptyset_{i2} lnFC_{j,t-i} + \sum_{i=0}^{k} \gamma_{i2} lnCO2_{j,t-i} + \varepsilon_{it2}$$ (4)

$$\Delta lnRY_{it} = \beta_3 + \sum_{i=1}^{k} \alpha_{i3} \Delta lnRY_{j,t-i} + \sum_{i=0}^{k} \partial_{i3} \Delta lnAH_{j,t-i} + \sum_{i=0}^{k} \emptyset_{i3} \Delta lnFC_{j,t-i} + \sum_{i=0}^{k} \gamma_{i3} \Delta lnCO2_{j,t-i} + \mu ECT_{j,t-1} + \varepsilon_{jt3}$$ (5)

The error correction term (ECT) is formed as in Equation (5) where the coefficient of the lag ECT, μ, can validate the quickness of the dependent variable's movement towards the equilibrium. Moreover, the coefficient gives input regarding the long-term correlation between variables in Equation (4). In equation (4), $lnRY_{it-1}$ implies the lagged dependent variable included to capture the dynamic nature in the equation. Similar to any other dynamic model specification, we assume the current level of rice yield depends on its past nature. As such, α_2 is expected to be positive. The $lnAH_{it}$ signifies the area harvested in the country i at time t. The higher the area harvested, the more rice produced. Given this, ∂_2 is expected to have a positive sign. Meanwhile, $lnFC_{it}$ is fertilizer consumption of country i at time t. The rice output is expected to has positive relationship with fertilizer consumption ($\emptyset_2$). On the other hand, CO2 is expected to affect rice production negatively and therefore γ_2 is expected to have a negative sign. The residual diagnostic tests are conducted on the model. The residual test confirms if the results are not spurious through the cross dependency. To test for cross-dependency, literature has prescribed the Pearson CD, Breusch-Pagan Chi-square and the Pearson LM normal tests.

Findings and Analysis
Results of panel regression for static and dynamic models are presented in Table 3, namely common effects (Pooled OLS), iterative OLS (IOLS), fixed effects (FEM) and random effects (REM).

Table 2: Results of Panel Static Models

Variables	(1) POLS	(2) IOLS	(3) REM	(4) FEM	(5) FEM
lnAH	0.105***	0.106***	0.149***	0.173	0.081
	(3.961)	(13.666)	(5.195)	(0.955)	(0.627)
lnFC	0.159***	0.162***	0.179***	0.186***	0.108***
	(4.948)	(13.220)	(5.520)	(5.040)	(3.863)
lnCO2	-0.063	-0.068***	0.030	0.040	-0.070
	(-0.948)	(-3.419)	(0.622)	(0.569)	(-0.876)
Constant	7.947***	7.922***	7.307***	6.924**	8.137***
	(28.589)	(80.931)	(17.450)	(2.540)	(4.242)
Observations	442	442	442	442	442
R-squared	0.636	0.629	0.6046	0.596	0.734
Number of Countries			9	9	9
VIF	3.70				
Breusch-Pagan LM		493.32***			
Hausman				35.11***	

Time-effect	No	Yes

Notes: 1. Robust t-statistics in parentheses
2. *** p<0.01, ** p<0.05, * p<0.1
3. Dependent variable: lnRY

According to Table 2, the rice yield function is relatively robust for all models as the goodness fit represented by R squared statistics are more than 50%. To analyze the more suitable function further, either POLS/IOLS or FEM, the F test is conducted. As the p-value of the F-test is lower than 1%, the null hypothesis is rejected, and FEM is used for further analysis. The further step is to test FEM and REM model using the Hausman Test. The result presented in Table 2 shows that the p-value is lower than 1%, meaning that we reject null hypothesis, and FEM is finally chosen as the appropriate static panel model for rice yield. The FEM with time effect shows more robust results with high R squared and more significant of variable coefficients. The results of FEM show that only Fertilizer consumption (lnFC) are statistically significant in affecting rice yield. The coefficient of 0.108 of equation 5, implying that increase of fertilizer consumption by 1 percent leads to an increase of rice yield about 11 percent in ASEAN countries.

Further analysis is done by adopting panel ARDL technique to investigate the long-term and short-term cointegration correlations between the determinants. The panel unit root tests are conducted and all variables are found to be stationary at first difference or I(1). The selected model suggested is ARDL (2,1,1,1) based on Akaike info criterion (AIC) statistics. The long-run and short-run estimations are presented in Table 3. The results show that two independent variables, namely fertilizer consumption and area harvested, are highly significant with positive sign. Observing the magnitude of the coefficients, it seems that the impact of area harvested on rice yield is bigger than the fertilizer consumption in the long-run. However, CO2 emission not significantly contribute to rice yield in long-run for ASEAN region. Nonetheless, none of the independent variables affect rice yield in the short-run. The importance of harvested area to rice yield is also supported by prior studies such as Dawe (2013) who found that the main determinant of (per capita) rice production in Southeast Asia is not rice yield per hectare, but rather the amount of per capita rice area harvested. In almost similar study, Affoh et al. (2019) found that the impact of total arable land was positive in Togo with a one percent increase in arable land led to an increase in rice supply in Togo by 0.05 percent. The empirical findings of Autoregressive Distributed Lag (ARDL) model by Chandio et.al (2018) further supported that area and fertilizer consumption for rice has a significant effect on the rice production in both short-run and long-run in Pakistan. Fertilizer is such a kind of production input whose demand cannot be avoided to obtain maximum yield or sustainable crop production from a piece of land even when other management technologies are evolved by researchers (Mustafi & Islam, 2008). In fact, according to Vlek and Byrnes (1986), Nitrogen fertilization is a key input in increasing rice production in East, South, and Southeast Asia.

Table 3: Results of Panel ARDL: Long Run and Short Run Estimation (Selected model: ARDL (2,1,1,1))

Variable	Coefficient (t-statistic)
Long-run Equation	
Dependent Variable: lnRY	
lnAH	0.577***
	(4.197)
lnFC	0.239***

	(10.80)
lnCO2	-0.043
	(-0.969)

Short-run Equation
Dependent Variable: D(lnRY)

ECT$_{t-1}$	-0.143***
	(-4.049)
D(lnRY)t-1	-0.124*
	(-1.654)
D(lnAH)	0.026
	(0.296)
D(lnFC)	-0.018
	(-0.904)
D(lnCO2)	0.0083
	(244)
Constant	0.150***
	(3.002)
N	420
Root MSE	0.082
Akaike info criterion	-2.591
Schwarz criterion	-2.063
Hannan-Quinn criterion	-2.383

Notes: 1. ***, **, * denote rejection of null hypothesis at 1%, 5%, and 10% level of significance
2. t-statistics in parentheses
3. Model selection method: AIC

The panel ARDL estimation also provides short-run equation for each country in study. The results are displayed on Table 4. Looking at individual country, the impact of area harvested, fertilizer consumption and CO2 emission (all three independent variables) on rice yield are significant in several ASEAN countries among the nine countries in study. Those countries are Malaysia, Brunei, Cambodia, Laos, Myanmar, Philippines and Vietnam. Only fertilizer consumption and CO2 emission contribute significantly to rice yield for Indonesia and only area harvested and fertilizer consumption affect rice yield significantly in the case of Thailand.

The area harvested positively affect rice yield in Malaysia, Cambodia, Myanmar, Philippines and Thailand but negatively affect rice yield in the case of Brunei, Laos, and Vietnam in short-run. In Laos, rice production is the main farming accounting for over 80% of the total cultivated area (Bestari et al., 2006). Rice is grown in three main farming systems, namely, the rainfed lowland, irrigated lowland, and rainfed upland systems. Under French colonial rule (1893–1945) there was little effort to increase rice production (Schiller et al., 2006). The negative impact of area harvested on rice yield in Laos could be contributed by the fact that almost all rice was produced under rainfed conditions and subject to periodic droughts and (in the lowlands) floods and most of the lowland wet-season crop was still based on traditional low-yielding varieties (Inthapanya et al., 2006). As in Vietnam, USDA forecasts Vietnam 2020/21 rice production at 27.0 million metric tons (milled basis), down 1 percent from 2019 and down 2 percent from the 5-year average. Harvested area is forecast at 7.4 million hectares, down 1 percent from year 2019 and down 3 percent from the 5-year average. Since 2016/17, rice area in Vietnam has declined on an annual basis. This is because the rice area is

being converted to uses such as urban and commercial development or transitioning to more profitable crops.

Meanwhile, though Brunei Darussalam paddy rice area harvested fluctuated substantially in recent years, it tended to decrease through 1971 - 2020 period ending at 853 ha in 2020. There is also limited or no availability of proper water in the area and the major issue of water supply in Brunei is due to the lack of proper irrigation available for rice farmers (Galawat & Yabe, 2012). Although Thailand is still one of the main exporters of rice, over the last five years the country has seen a decline in production and total rice harvested area. Malaysia, relative to the other SEA countries, has shown an almost constant trend for rice production and harvested area from 2000 to 2016. Indeed, palm oil has always been a bigger contributor to the national GDP of Malaysia and this can be seen over time, as the oil palm harvested area has increased tremendously while the paddy harvested area remained relatively constant. Vietnam has been an exceptional case, whereby it has shown the highest growth in rice production at the back of a relatively slower increase in paddy land area. For the Philippines, since the 1990s, it has shown a gradual increase in production and harvested area.

As of fertilizer consumption, the positive relationship to rice yield is apparent for Indonesia, Laos, Myanmar and Philippines in short-run. The negative relationship however traced for Malaysia, Brunei, Cambodia, Thailand and Vietnam. From the mid-1990s there has been a steady growth in the Lao rice sector in terms of area, production, and yield which made the country notionally self-sufficient in rice in 1999, when total paddy production reached 2.1 million tonnes, compared to only 1.4 million tonnes in both 1985 and 1995. The overall trend has been attributable to the widespread use of improved rice varieties and management practices, especially the use of fertilisers (Schiller, 2008). Meanwhile, Cambodian rice farmers face serious constraints in productivity and output quality, which include the lack of purified seeds; lack of access to commercial credit; high interest rates; limitations of irrigation; and high costs of energy, fertilizers, pesticides, etc. Chemical fertilizer use is extremely low and native soils are often very infertile. The average amount of fertilizer use in Cambodia is below the nationally recommended rate (Blair & Blair, 2010). The Food and Agricultural Organization of the United Nations (FAO) estimates that Cambodia has the lowest rate of fertilizer use for rice in Southeast Asia, with around 30% of the total area while farmers on average applied 108 kg in Thailand, which shares similar soil and temperature conditions with Cambodia.

Most importantly, CO_2 emission negatively affects rice yield in short-run in the case of Myanmar and Philippines. However, the positive impact is marked in majority of countries such as Malaysia, Brunei, Cambodia, Indonesia, Laos and Vietnam in the short-run. Past studies projected that increased atmospheric CO_2 concentration would have a mixture of positive and negative effects on rice production, consumption, distribution as well as national development (Peterson, 2019; Wang et al., 2021; Ujiie et al., 2019; Muehe et al., 2019). Climatic impacts on agriculture span a wide range of attributes and outcomes depending on the specific climate scenario, geographical location, and nature of study. In China for example, while major climate changes were predicted for China, to a certain extent warming would be beneficial for yield increasing in the country due to diversification of cropping systems. In the case of Japan, the positive effects of CO_2 on rice yields would generally more than offset any negative climatic effects (MOSTE, 2001).

Nonetheless, several studies projected that increased atmospheric carbon dioxide (CO_2) concentration along with temperature, precipitation, soil conditions, and solar radiation would have mixed impacts on rice yields. Under a high CO_2 emission scenario (CO_2 at 900 ppm),

rice and soybeans in the U.S. will have a 135% increase in yield in 2100 due to the CO2 fertilization effect (Petersen, 2019). A study by Tan et al. (2021) which assess the impact of climate variables (i.e., minimum and maximum temperature and precipitation) on rice yield in Malaysia and the variance of the impact during the main season and off-season indicated that precipitation was not statistically significant in all model specifications for both the main and off-season. While the maximum temperature was found to be negatively associated with yield during the off-season, the minimum temperature showed a positive effect in both cropping seasons.

Though CO2 might have positive impact in the short term in some countries, the main concern is definitely on the long-run implication. Lobell et al. (2008) who evaluated climate change impacts on 18 different crops in 12 food-insecure regions revealed that rice productions in Brazil, Central America, and Southeast Asia are projected to record losses of up to 5% by 2030. Other crops such as wheat in South Asia, the Sahel, Southern Africa, Brazil, and Central Africa, as well as maize in Southern Africa and groundnut in Western Africa, would also likely be affected by such losses. A study by Rosenzweig et al. (2014) in assessing the impacts of climate change on multiple crops worldwide indicated that climate change impacts are severe in tropical areas, particularly for annual C3 crops such as rice. In a global assessment of climate change and socioeconomic impacts on agriculture up to 2080 using different models, it was found that the critical asymmetric impacts of climatic and socioeconomic factors would increase existing gaps in food production and consumption between developed and developing countries (Fischer et al., 2005)

Table 4: Short-run Equation by Country

Variable	Coefficient (t-statistic)				
	Malaysia	**Brunei**	**Cambodia**	**Indonesia**	**Laos**
ECT_{t-1}	-0.169***	-0.109***	-0.124***	-0.409***	-0.102***
	(-28.88)	(-5.88)	(-105.00)	(-47.57)	(-61.67)
D(lnRY)t-1	-0.403***	-0.322***	-0.249***	0.241***	-0.235***
	(-21.38)	(-7.132)	(-33.33)	(21.76)	(-8.736)
D(lnAH)	0.356***	-0.380***	0.159***	0.016	-0.133***
	(18.92)	(-7.968)	(45.08)	(1.153)	(-8.736)
D(lnFC)	-0.151***	-0.031***	-0.018***	0.0051***	0.004***
	(-49.79)	(-11.70)	(-79.70)	(9.311)	(17.17)
D(lnCO2)	0.111***	0.074**	0.0058***	0.091***	0.011*
	(18.09)	(3.476)	(6.766)	(70.17)	(2.874)
Constant	0.188	0.501	0.171*	0.072	0.222**
	(2.117)	(1.507)	(2.526)	(0.089)	(4.694)
	Myanmar	**Philippines**	**Thailand**	**Vietnam**	
ECT_{t-1}	-0.123***	-0.091***	-0.037***	-0.119***	
	(-74.87)	(-55.92)	(-24.45)	(-31.76)	
D(lnRY)t-1	0.119***	-0.0087	0.289***	0.033	
	(8.378)	(-0.518)	(-17.09)	(1.899)	
D(lnAH)	0.289***	0.081**	0.211***	-0.362**	
	(19.89)	(4.315)	(12.17)	(-5.005)	
D(lnFC)	0.0008**	0.074***	-0.045***	-0.002*	
	(3.402)	(30.960)	(-23.57)	(-2.486)	
D(lnCO2)	-0.014***	-0.239***	0.0009	0.034***	
	(-6.868)	(-18.77)	(0.107)	(22.082)	

Constant	0.093	0.052	0.012	0.041
	(1.345)	(1.464)	(1.758)	(0.617)

Conclusion

Although rice production in the ASEAN region has been showing progress with further growth expected in the future, there has been a growing concern over the escalating signs of climate change that could adversely affect the production of rice. The serious threat which climate change could pose on the production of the region's staple food must therefore be assessed closely. Thus, this study attempts to assess the impact of climate change on food security measured in terms of rice yield, with the focus being on ASEAN member countries. Panel data are collected on nine ASEAN countries and static panel data equations are estimated, namely random (REM), fixed effects (FEM) and Pooled Ordinary Least Square (POLS) model. Besides, the panel ARDL technique is also attempted to investigate the long-term and short-term cointegration correlations between the variables. The FEM with time effect shows more robust results than other models and it shows that only Fertilizer consumption (lnFC) are positive and statistically significant in affecting rice yield in ASEAN region. The results from panel ARDL show that fertilizer consumption and area harvested, are highly significant with positive sign in the long-run but none of the independent variables affect rice yield in the short-run.

The panel ARDL estimation also provides short-run equation for each country in study. The study finds that the area harvested positively affect rice yield in Malaysia, Cambodia, Myanmar, Philippines and Thailand but negatively affect rice yield in the case of Brunei, Laos, and Vietnam in short-run. As of fertilizer consumption, the positive relationship to rice yield is exist in Indonesia, Laos, Myanmar and Philippines in short-run. The negative relationship however traced for Malaysia, Brunei, Cambodia, Thailand and Vietnam. CO_2 emission negatively affects rice yield in short-run in the case of Myanmar and Philippines. However, the positive impact is marked in majority of countries such as Malaysia, Brunei, Cambodia, Indonesia, Laos and Vietnam in the short-run. The mixed results of impact of CO_2 on rice yield among majority of ASEAN member countries in short-run signify the positive CO_2 fertilization effect in the region over the adverse impact of temperature increase on rice yield. In long-run, however, the negative effects are projected by several studies which consequently will translate into decline in rice yield in tropical areas.

In brief, the government of each ASEAN countries needs to take necessary actions and develops innovative programs in order to boost agriculture production in these countries. Land management policy, primarily incorporated with the expansion strategy is required. It is suggested to put a restriction of shifting cultivation land to industrial area in the policy. Creating special Act to encourage urban farming implementation is also necessary, for example by providing incentives to farmers who attempt to apply urban farming in the city. ASEAN region cannot avoid high risk from climate change in the long-run but some efforts to minimize the bad impact can certainly be sought through the adaptation and mitigation strategy. Accordingly, government can transfer some incentives through crop insurance program for farmers in order to secure their work from extreme climate change. Since ASEAN countries have similar geographical topology, agricultural technology can be shared to achieve effective and efficient adaptation to climate change as well as to increase food security condition collectively. Greater collaboration between developing and least-developed countries in the region to address the issues in agriculture and rice production is very crucial to solve food insecurity problem in the long-term.

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