The Impact of Climate Change on Agricultural Productivity in Asian Countries: a heterogeneous panel data approach

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Abstract

While climate change is having serious impacts on agriculture and may require ongoing adaptation, short-term threats to global food security are also crucial for developing countries. This study aims to investigate how the effects of climate change on agricultural productivity vary depending upon the short-run and long-run in Asia over the period of 1980–2016. The results confirmed that there is a long-term relationship between agricultural productivity and climate change variables; however, only CO2 emissions could be linked to agricultural productivity in the short-term. Moreover, while the direction of this effect is positive for the short term, it turns into negative in the long term confirming that carbon fertilization in the atmosphere can to some extent have a positive effect on agricultural productivity.

Introduction

Changes in the world's climate will bring major shifts in food security. While the supply of food was increasing in Asia and the Pacific, rising incomes and emerging middle class continue to drive demand for food and agricultural commodities and resources (ESCAP, 2009). However, the shrinkage of agricultural areas day by day due to rapid urbanization, construction, climate and environmental factors, such as energy consumption, mining, urbanization, stands as an obstacle to a rapid growth in agricultural production. Climate change caused by emissions of greenhouse gases affects agricultural productivity cycles directly or indirectly through the temperature, amount of precipitation and sunshine duration. These changes have affected the productivity pattern of agricultural products and have become a leading source of worsened food insecurity, especially in developing countries. Climate change is to have a negative effect on agricultural productivity especially in least developed countries (UNCTAD, 2015). For instance, Cline (2007) examined three key factors on modeling changes in yields due to climate change for country-level impact estimates: carbon fertilization, trade and irrigation and demonstrated strong negative impacts that climate change brings on most developing countries. According to this, by the 2080s, global agricultural productivity may fall by 15.9% if global warming progresses at its current rate emphasizing that the developing countries are most at risk. In order to ensure food security and self-sufficiency in the agricultural sector, as well as to meet the increasing demand for food despite land degradation, a lot can be done in terms of incorporating numerous strategies for sustainable development.

Since climate change is a primary determinant for agricultural productivity on a sustainable basis, creating and managing sustainability performance in agricultural productivity to satisfy increased demands in agriculture and increase food availabilities is a major task for the global agricultural sector. Climate change might be a major concern to sustainability since it is having a measurable effect on agricultural productivity, especially in rain-fed farming areas. The effects of climate change such as changes in precipitation regime, temperature increase, drought and natural disasters lead to threats to productivity and growth rates in agriculture. However, conditions such as the level of nutrients in the soil and the amount of water must also be met in order to increase the yield. According to this, higher concentrations of atmospheric carbon dioxide and temperature boost crop yields by increasing the rate of

photosynthesis, which in turn contributes to higher growth and productivity. (Rosenberg, 1982; Kimball and Idso, 1983). But some research had found that CO_2 decreases the plant's concentrations of other internal compounds like vitamin B, protein and micronutrients (Ebi and Ziska, 2018).

Rainfed agriculture plays a critical role in food production, which covers 80% of the world's cultivated land, and is responsible for about 60% of crop production (UNESCO, UN-Water, 2020). The historic records show clear long-term warming trends across the world since the late 19th century (Hartmann et al. 2013). Changes in the mean level of temperature and rainfall may lead to stronger droughts, which adversely affect livestock and rainfed crops (Verner et al., 2018). On the other hand, it is expected that the carbon dioxide concentration accumulated in the atmosphere will have a positive contribution to the growth of certain agricultural products (Warrick, 1988). Overall, climate change makes agricultural productivity more vulnerable to climate impacts and could make it more difficult to grow crops and raise animals. It is certain that changes in rainfall levels due to climate change will have effects on agriculture. Soil moisture level should be ideal and agricultural area should be accessible to water. It is essential that these conditions come together and create an environment that is suitable for agriculture over the long term.

Climate change also leads to multiple irregular agricultural production patterns. That is, addressing the threats from current climate risks are key to understand agricultural productivity, particularly in parts of Sub-Saharan Africa, south-eastern Asia and Western Asia (Bruinsma, 2003). Since developing countries are much more vulnerable to climate change than the developed countries, the importance of agricultural sustainable development is particularly crucial particularly in south Asia and southeast Asia. Agricultural output increased as a result of the Green Revolution, started in Asia in the 1960s under the leadership of the International Rice Research Institute (IRRI). Since then, the Asia and the Pacific region have experienced a rapid expansion and extensive structural changes with accompanying a remarkable progress in reducing food insecurity and malnutrition (FAO, 2018).

Figure 1. Agricultural Productivity Patterns

Asia region has made remarkable progress toward reducing food insecurity over the past quarter of a century. According to UNCTAD's Agricultural Productivity in the Least Developed Countries report, agricultural productivity in Asian least developed countries has surpassed that of African least developed countries since 2006 (UNCTAD, 2015). Some authors point out that the driving forces behind agricultural productivity growth in many Asian countries are technological progress that heavily rely on research and development (R&D) in food and agriculture and improvements in human capital (Chang and Zepeda, 2001; Thirtle et al., 2003). However, in comparison to the other major Asian economies, as can bee seen from Fig. 1, Japan's process of agricultural productivity change appears to be a bit of an outlier. According to the OECD's report on agricultural policy developments in all countries, Japan has reduced its support to agriculture, but more recently the change in support levels has been moderate (OECD, 2020). Additionally, Yamashita (2008) argues that the decline in agricultural productivity in recent years is due to the increased structural problems in the Japanese agriculture sector, stated earlier by the 1957 White Paper on Agriculture. It is also mentioned in the literature that more climate extremes tend to be

associated with more resilient agricultural productivity reducing economic growth in Asia and Africa (Stern 2007; Biemans et al. 2006; FAO, 2017). At the same time, since rapid economic development and heavy demand for environmental goods hinder the sustainability of natural resources, the threats to agricultural development posed by pollution and other forms of climate change and hereby the association of agricultural productivity to climate change should be addressed specifically on the basis of short and long term. So this raises crucial question and that is, to what extent are the climate change factors can affect agricultural productivity in the short-term and to what extent is it due to long-term patterns in Asia. Gornall et al. (2010) point out that long-term effects of climate variability include global food production and food security as well as changes in gene expression and enzyme activity in the shorter term. Besides this, rising carbon dioxide levels cause an increase of photosynthetic rates, crop yields, and agriculture efficiency. On the other hand, the rise in global temperature due mainly to the increasing concentrations of greenhouse gases in the atmosphere is likely to reduce yields in many areas (Allen, 1991; FAO, 2013; Sperry et al., 2019). Consequently, since the impact of elevated CO_2 levels on agriculture is complicated, in order to determine its net effect on agricultural productivity, a number of indicators related to climate change to be examined by considering the short and long term distinction. Empirical studies on the impact of climate variables on value-added agriculture is limited; but essential for policymakers to adopt the policies that reduce poor farmers' vulnerability to climate change. In this context, examining the consequences of climate change on agricultural productivity under short-term and long-term distinction, especially for certain Asian countries, will contribute to the active discussion in the recent literature on climate change and its implications for agriculture. For this purpose, this study aims to analyze the effects of climate change on agricultural productivity for selected Asian countries by applying advanced panel data techniques include three different tests, namely, mean group (MG) introduced by Pesaran and Smith (1995), pooled mean group (PMG) developed by Pesaran et al. (1999), and dynamic fixed effect (DFE) estimators. The novelty of this approach is that it focuses on the short and long-run effect of three climate variables as CO_2 level, average annual temperature and rainfall on agricultural productivity in Asian countries. Primary energy consumption per capita and total fertilizers by nutrients used in agricultural sector were also used as control variables.

The rest of this paper is structured as follows: Sect. 2 discusses how to describe the previous literature related to a problem, methodology, model specification and data are presented in Sect. 3, the empirical results are discussed in Sect. 4, and finally we draw some general conclusions in Sect. 5.

Literature Review

The importance of seeking relevance between global warming and agricultural productivity is concerned not just with the uncertainty in climate projections but also with the shifts in environmental conditions that can lead to potential risks causing further jeopardized the food security in developing countries (Rosegrant et al., 2008; Khor, 2009; Dudu and Cakmak, 2018). More importantly, the impact of climate change on agricultural productivity indirectly causes significant changes in consumption trends through prices, such as higher animal feed costs due to drought result in higher meat prices and consequently, lower meat consumption. Hence, it is crucial for policy makers in the agriculture sector to assess the

impacts that climate change will have on agricultural productivity. Essentially, the effects of climate change on agriculture can be analyzed from different perspectives within different contexts, notably “Ricardian Approach” and “Time Series/Panel Data Approach” (Mandelsohn, 2008).

Ricardian approach focuses on the estimates of the cost of climate changes analyzing associations between land value and agro-climatic variables using net revenue climate response function under the assumption that that land rent would reflect the long-term net productivity of farmland on the basis of survey or country-level data (Mendelsohn et al., 1994, 1996; Mendelsohn & Dinar, 1999, 2003; Liu et al., 2004; Gbetibouo and Hassan, 2005; Schlenker et al., 2005; Seo et al., 2005; Mano and Nhemachena, 2007; Deressa and Hassan, 2009; Lippert et al., 2009; De Salvo et al., 2013; Closset et al., 2014; Mishra and Sahu, 2014; Van Passel et al., 2017; Trinh, 2018; Sadiq et al., 2019; DePaula, 2020; De Siano et al., 2020; Jawid, 2020; Nicita et al., 2020; Ortiz-Bobea, 2020). The time series/panel data models have become popular in recent years, as more data is available. This approach has been used to examine the association between weather and net income (Chang, 2002; Deschenes & Greenstone, 2007; Gay et al., 2007; Gupta et al., 2012; Sarker et al., 2012; Barnwal and Kotani, 2013; Guntukula, 2020; Guntukula and Goyari, 2020). However, while these studies examine the issue with food production and net revenues focusing on farm net revenue, net agricultural revenue, land value, net agricultural income, yields of grain or cereal yield etc., only a few studies have addressed short-term and long-term effects of climate change on agricultural productivity based on advanced panel data techniques. For instance, Zaied and Cheikh (2015) analyzed the short-run and long-run association between agriculture production and climate change in Tunisia from 1979–2011. Using the panel data cointegration method, the study concluded that while the long-run effect of temperature on the crop production is generally negative, the effect of precipitation is positive. Besides, they concluded that an increased annual temperature decreases both cereal and date productions. Zhai et al. (2017) have assessed the wheat productivity response to climate change and technological progress on the wheat yield per unit area during 1970 to 2014 in China using ARDL model. The findings showed a long-run relationship among climate change, technical progress, and the wheat yield per unit area and positive land size impact on the per unit area wheat yield in the short run. Another empirical study has been conducted in Tunisia from the period of 1975–2014 by Attiaoui and Boufateh (2019), which investigated the long-term and short-term effects of climate change on cereal farming using Pooled Mean Group (PMG) estimation method. Findings revealed that climate change can negatively affect cereal production, mostly due to the shortage of rainfall, whereas current temperature level has a positive impact on cereal production in Tunisia. More recently, Chandio et al. (2020) have analyzed the short-run and long-run impacts of climate change on agricultural output in China over the period of 1982–2014. They used annual climate change and other control variables by using the ARDL model. Findings showed that while CO2 emissions, land area under cereal crops, fertilizer consumption and energy consumption have a positive impact on the agricultural output both in the short-run and long-run, temperature and rainfall have a negative effect on agricultural output in the long-run but positive in the short-run. Finally, Abbas (2020) applied an autoregressive distributed lag (ARDL) model bounds testing to investigate the short-term and long-term relationships between climate change, the area under cultivation, fertilizer consumption, and cotton production in Pakistan from 1980 to 2018. According to the

results, there is no evidence on increasing cotton yield through increased temperatures in the long run in Pakistan.

This brief review of the nexus between climate change and agricultural output suggests that there is no doubt that climate change might have a possible impact on agricultural productivity. However, they do not sufficiently address or comprehensively explain climate change-related agricultural productivity on a short-term basis as well as on a long-term basis. This research aims to investigate the long-run and short-run association between climate change and agricultural productivity in the context of selected Asia countries.

Methodology, Model Specification And Data

This study adopts a panel-data approach covering 11 Asian countries over the period 1980-2016, to examine the dynamic relationship between agricultural productivity and some primary climate change indicators. This section can be divided into two subsections. The first subsection gives a brief summary of the method and some comment on its appropriateness. The second subsection is used to describe the model specification and data-related issues.

1. Methodology

Referring to the technique introduced by Pesaran et al.(1999), the dynamic heterogeneous panel regression model can be into an error correction modeling format using panel autoregressive distributed lag (ARDL) model. As Pesaran and Shin (1999) argued, panel ARDL model is applicable in a condition that variables are integrated of integrated of order zero or one, I(0) or I(1), respectively or a combination of both; moreover, the potential endogeneity bias and small sample problem tends to be irrelevant and very small. Therefore, the dynamic panel model in error-correction form based on panel ARDL (p,q) approach, with p as the lag of the dependent variable and q as the lag of the independent variables, is formulated accordingly as follows (Pesaran et al. 1999; Loayza and Ranciere, 2006):

$$\Delta(y_i)_t = \sum_{j=1}^{p-1} \gamma_j^i \Delta(y_i)_{t-j} + \sum_{j=0}^{q-1} \delta_j^i \Delta(X_i)_{t-j} + \varphi^i \left[(y_i)_{t-1} - \left\{ \beta_0^i + \beta_1^i (X_i)_{t-1} \right\} \right] + \varepsilon_{i,t} \qquad (1)$$

where y is the real agricultural value added in agriculture, forestry and fishing, X is the vector set of explanatory variables including carbon dioxide (CO2) levels, average annual temperature and rainfall primary energy consumption per capita and total fertilizers by nutrients used in agricultural sector, γ and δ are the short-run dynamic coefficients related to dependent variable and its determinants respectively, β represents the long-run coefficients, φ shows the speed of adjustment in the long-run. Lastly, i and t represent country and time respectively. The bracketed values represent the long-run regression as follows:

$$(y_i)_t = \beta_0^i + \beta_1^i (X_i)_{t-1} + \mu_{i,t} \qquad \text{where} \quad \mu_{i,t} \sim I(0) \qquad (2)$$

There are different types of methods to estimate the above model. According to Pesaran et al. (1999), the autoregressive distributed lag (ARDL, p,q) model includes the mean group (MG) and pooled mean group (PMG) estimators as well as the dynamic fixed effect (DFE) model. The MG estimation includes separate regressions for each country with all the coefficients to vary and being heterogeneous in the short- and long-terms. That is, the MG model does not impose any restrictions on the cross-sectional parameters and hence, ignores any possible homogeneity of some parameters across countries. The PMG model allows the short-run coefficients, error variances and the regression intercept to be heterogenous, but constraints the long-run estimates to vary across cross-sections, which is a prominent difference between the PMG and MG technique. Finally, The dynamic fixed effect (DFE) model presumes all slope coefficients (both short run and long run) to be homogeneous across countries allowing panel-specific intercepts except the constant term (intercept). However, Baltagi et al. (2000) clarify that this model is subject to potentially inconsistent and misleading estimates caused by the endogeneity existing between the lagged dependent variable and error term. To find the efficient model to provide reliable results, the Hausman h-test that based on panel ARDL approach that measures the efficiency and consistency has been used to analyze whether there are significant differences among the PMG, MG, as well as the DFE. Under the null hypothesis of log-run homogeneity, the difference between PMG and MG or PMG and DFE estimation is not significant; that is, the efficient estimator under the null hypothesis is PMG. Otherwise, if the null hypothesis is rejected, then the efficient estimator, MG or DFE, is preferred respectively.

2. Model specification and data issues

This research is intended to estimate short-run and long-run relationship between agricultural productivity and climate change variables without being able to observe the short-run and long-run relevant components of variables employed. Agricultural productivity was measured using agriculture, forestry and fishing value added per unit of input, as identified in the World Bank data catalog. Based on Climate Change Indicators in the United States Report by the U.S. Environmental Protection Agency (EPA, 2016), average annual temperature, average annual rainfall and CO2 emission levels were used in the model as a proxy for climate change indicators. Besides, primary energy consumption per capita and total fertilizers by nutrients used in agricultural sector were also added as control variables. To obtain evidence on the potential impact of climate change on agricultural productivity, the current study incorporates an interaction between agriculture, forestry and fishing value added per unit of input and relevant climate change indicators and control variables as follows:

$$AGR_t = f(CO2_t, TEMP_t, RF_t, EC_t, FE_t) \qquad (3)$$

where AGR is the agriculture, forestry, and fishing, value added (constant US$) as a proxy for agricultural productivity; CO2 is the CO2 emissions (metric tons per capita); Temp is the temperature as measured °C , RF is the average annual rainfall (mm per year); EC represents the primary energy consumption (gigajoules per capita); and finally, FE represents total fertilizers by nutrients used in agricultural sector measured as tones. To alleviate the multicollinearity problem, all the variables have been transformed into natural logarithmic forms. The study is based on a panel data set of 11 Asian countries as China, India, Indonesia, Japan, Malaysia, Pakistan, Philippines, South Korea, Sri Lanka, Thailand and Vietnam over the period 1980-2016 with a total of 407 observations. The data sources include the FAOSTAT database, the World Bank Group Climate Change Portal, the BP Statistical Review of World Energy and the World Bank national accounts data.

Empirical Results

Before going into the main estimation of the panel ARDL estimators, panel unit root tests were conducted to verify the stationarity of the variables used as in the literature due to their superiority to time series unit root tests. Although *ARDL* is applicable for variables with a mixture of integration of I(0) and of I(1), unit root tests still need to be undertaken to ensure that the variables are not I(2) so as to avoid spurious

results. Therefore, in this paper, we examine non-stationarity of our data by the use of two well-known panel unit root tests; Im, Pesaran and Shin (IPS) (2003) and Levin Lin and Chu (LLC) (2002). The LLC test has a null hypothesis of the common unit root process presence, while null hypothesis for the IPS test is the presence of individual unit root process in series. If the results are statistically significant under the LLC and IPS test, that is to say that all our series are non-stationary. The results of the unit root tests are presented in Table 1 showing mix results regarding the existence of unit-root in their levels for the variables that are employed in the model. Since all the variables are stationary in their first differences, the common components of variables all turn out to be integrated of order one, or I(1).

Table 1
Unit root tests

Series	**Levin Lin & Chu**			**Im-Pesaran-Shin**
	No Trend	**Trend**	**No Trend**	**Trend**
		Level		
lnAGR	-2.903***	-1.135*	2.171	-0.550
lnCO2	-2.281**	-0.132	1.712	1.381
lnTEMP	-3.503***	-5.883***	-3.451***	-7.615***
lnRF	-7.218***	-6.311***	-8.880***	-7.948***
lnEC	-2.673***	0.745	1.198	3.302
lnFE	-6.056***	-2.529***	-2.065**	-1.170
		First Difference		
lnAGR	-7.919***	-7.179***	-9.923***	-9.488***
lnCO2	-6.863***	-6.257***	-8.627***	-7.884***
lnTEMP	-17.659***	-14.905 ***	-19.913***	-18.377***
lnRF	-14.067***	-11.266***	-18.514***	-17.014***
lnEC	-5.518***	-6.135***	-7.469***	-8.202***
lnFE	-13.192***	-13.094***	-15.769***	-16.615***
Note: ***, (**) and * represent significance at 1%, 5%, and 10%, respectively.				

Besides panel unit root tests, it is also necessary to investigate the existence of a possible long run relationship between the variables. Using the convention in the literature, panel residual cointegration technique suggested by Pedroni (1999, 2004) under the null hypothesis of no cointegration against the

alternative of cointegration with allowance for heterogeneity with four panel and three group test statistics and Kao (1999) under the null hypothesis of no cointegration between the series allowing for cross-sectional dependence and heterogeneity.

Table 2
Pedroni residual cointegration test

	Dependent Variable: lnAGR	
Trend assumption	**No deterministic trend**	**Deterministic intercept and trend**
Alternative hypothesis: common AR coefficients (within-dimension)		
Panel v-Statistic	-1.594288	3.484340***
Panel rho-Statistic	1.339442	1.043972
Panel PP-Statistic	0.168634	-4.112804***
Panel ADF-Statistic	0.231837	-4.516746***
Alternative hypothesis: individual AR coefficients (between-dimension)		
Group rho-Statistic	2.369164	2.456783
Group PP-Statistic	0.943026	-2.135678***
Group ADF-Statistic	0.987881	-1.993011***

*Automatic lag length selection based on SIC with a max lag of 9. *** represents significance at 1% .

For the model with intercept, we have only five statistics, from seven, indicating the rejection of the no cointegration null hypothesis. Following Pedroni (1999, 2004), who points out that both the panel-ADF and group-ADF statistics are more reliable in a constant plus trend, we can conclude that there is cointegration among the variables in the model since at least four statistics are significiant, as can be seen in Table 2. The evidence on cointegration is consistent with the Kao test in Table 3; the Kao residual cointegration test strongly rejects the null hypothesis of no cointegration. With the results of both tests, it can be concluded that there is a long-run relationship among the variables used in the model.

Table 3
Kao residual cointegration test

	t-statistics	**p-value**
ADF	-2.464727	0.0069

Table 4 presents the results of baseline estimates obtained from MG, PMG, and DFE estimators for a linear specification of the effects of climate change on agricultural productivity. The Hausman test was used to test the null hypothesis of homogeneity restriction on the long-run coefficients based on the comparison between the Pooled Mean Group and the Mean Group estimators, as the respective Hausman h-test p-values of 8.61 and 0.10 for MG and DFE are both insignificant. This suggests that the PMG estimators are consistent and more efficient than MG and DFE. Thus, the PMG long-run results are interpreted and discussed. Summarizing the findings from Table 4, the long-run estimates of all variables are significant at the 1% significance level. The results indicates that in the long-run, the coefficient of CO_2 emission level and temperature level are both significant and negative at a 1% significance level, indicating a negative impact of main climate change indicators on agricultural productivity. Specifically, a 1% increase in CO_2 emission level would lead to a reduction in agricultural productivity by 1.94% and 1% increase in temperature would cause to lower productivity by 2.28 % and vice-versa. In contrast, the results also showed that, rainfall and the control variables as energy and fertilizer consumption have all positive impact on productivity, by about 0.95, 2.42 and 0.69 % respectively in the long run. Our findings on the negative long-term effect of rising temperature and positive long-term effect of rainfall on agricultural productivity is consistent with those of Zaied and Cheikh (2015) and Attiaoui and Boufateh (2019).

Table 4
Agricultural productivity: The dynamic model

	PMG		MG		DFE	
	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
Long-run coefficients						
lnCO2	-1.943***	0.613	-0.554**	0.282	0.273	0.521
lnTEMP	-2.285***	0.698	-0.477	2.143	-3.950	2.548
lnRF	0.954***	0.325	0.321	0.220	0.669	0.545
lnEC	2.428***	0.612	0.808**	0.317	-0.134	0.497
lnFE	0.692***	0.116	0.277	0.175	0.431**	0.171
Short-run coefficients						
Error-correction coefficient	-0.039**	0.018	-0.224***	0.069	-0.042***	0.015
ΔlnCO2	0.141***	0.037	0.153***	0.052	0.021	0.032
ΔlnTEMP	-0.336	0.249	-0.228	0.275	0.022	0.074
ΔlnRF	-0.031	0.030	-0.048*	0.026	-0.018	0.014
ΔlnEC	-0.127***	0.044	-0.185**	0.083	0.012	0.047
ΔlnFE	0.026	0.027	0.001	0.022	0.014	0.014
Intercept	-0.138	0.092	1.648**	0.761	0.058**	0.292
Country	11		11		11	
Observation	396		396		396	
Hausman Test			8.61		0.10	
p-value			0.12		0.999	
Note: ***, (**) and * represent significance at 1%, 5% and 10% respectively.						

If we turn our attention to the short-run results shown in Table 4, only the coefficients of the impact of CO2 emissions and energy consumption are significant at 1% level. However, the significant effects are observed in opposite directions in comparison with the long-term for both CO_2 emission and energy consumption. That is, while the impact of CO_2 emission on agricultural productivity was positive and the impact of energy consumption on agricultural productivity was negative in the short-run, these effects

turned out to be negative and positive, respectively. This contradiction in our findings could be supported by the assessment of Goudriaan and Unsworth (1990) suggested that while increasing concentrations of atmospheric CO2 promote plant growth and agricultural productivity without increasing the water demand for crop transpiration, global warming and climate change vulnerability may tend to reverse positive direct CO2 effects in the long-run. The empirical results also reveal that the coefficients of temperature, rainfall and fertilizer consumption were insignificant in influencing agricultural productivity in the short run.

Conclusion

Agricultural vulnerability to climate change depends not only on acceptable temperature ranges and patterns of rainfall, but also on concentration of carbon dioxide in the atmosphere. Indeed, climate change poses a challenge to agricultural productivity and its effects vary according to the regional risks and adaptation and type of production system as well as depending on the dynamic characteristics of climatic indicators. However, the uncertainties about climate impacts appear to have both short-run and long-run components. This research contributes to the agricultural productivity-climate change literature by focusing on a selection of Asian countries which adopted the '*Green Revolution*' model in the 1960s by introducing high-yielding varieties of food through the intensification of the arable lands through massive investments in irrigation. The aim and novelty of this study is to investigate how the effects of climate change on agricultural productivity vary depending upon the short-run and long-run in Asia over the period of 1980–2016. Overall, the results confirmed that there is a long-term relationship between agricultural productivity and climate change variables; however, only CO2 emissions could be linked to agricultural productivity in the short-term. Moreover, while the direction of this effect is positive for the short term, it turns into negative in the long term confirming that carbon fertilization in the atmosphere can to some extent have a positive effect on agricultural productivity.

Nevertheless, it is evident that both carbon emissions and annual temperature have an adverse effect on agricultural productivity in the long-run, which further has implications on food security for countries, policy interventions that seek to overcome global warming in agriculture sector need to be based on sustainable land management to prevent land degradation and to improve land use management, climate-friendly agricultural practices to increase the capacity to adapt to climate change and, most importantly, the adaptation and dissemination of low carbon emission technologies within the framework of efficient use of agricultural and forest areas. These findings can form a base for further research such as productivity responses to nitrogen, carbon dioxide, and temperature interactions.

Declarations

Ethical Approval

Not applicable

Consent to Participate

Not applicable

Consent to Publish

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Competing Interests

The author declare that they have no competing interests

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Figures

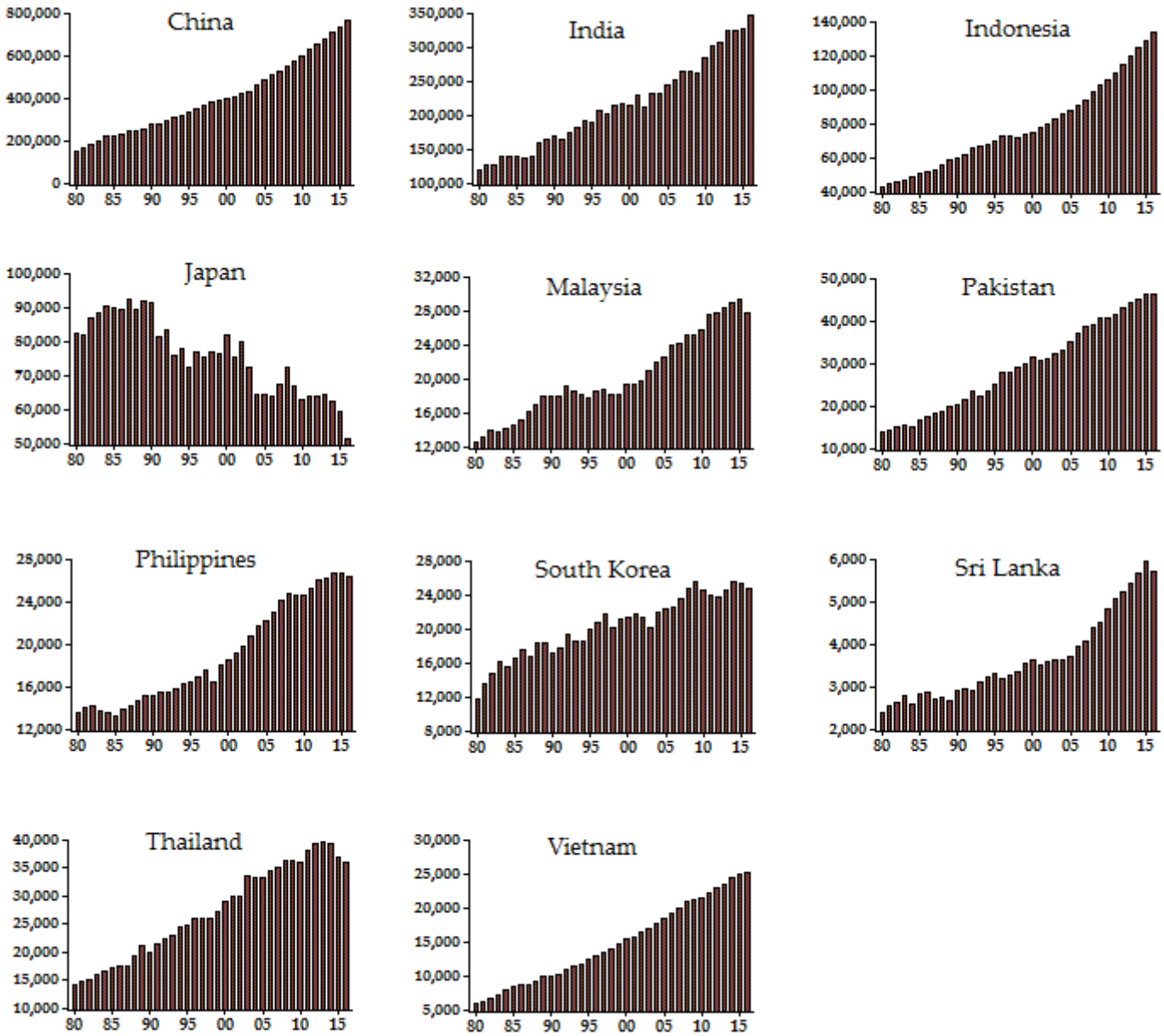

Figure 1

Agricultural Productivity Patterns