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Abstract

This study empirically examines the impact of climate change and agricultural research and development (R&D) as well as their interaction on agricultural productivity in 12 selected Asian and Pacific countries over the period of 1990 – 2018. Results show that both proxies of climate change – temperature and precipitation – have negative impacts on agricultural productivity. Notably, agricultural R&D investments not only increase agricultural productivity but also mitigate the detrimental impact of climate change proxied by temperature on agricultural productivity. Interestingly, climate change proxied by precipitation initially reduces agricultural productivity until a threshold of agricultural R&D beyond which precipitation increases agricultural productivity. The findings imply useful policies to boost agricultural productivity by using R&D in the context of rising climate change in the vulnerable continent.

Key words: *Agricultural productivity; Asia and Pacific; Climate change; R&D; SGMM.*

JEL Classification: D24; O13; O33; Q16; Q54

1. Introduction

Agricultural sector plays a vital role in developing countries because of its large contribution to their gross domestic products (GDP) and employment. Therefore, productivity improvement in agriculture has become more important for sustainable economic development in developing world. However, agricultural productivity growth faces several challenges from worsening climate change such as global warming, salinity, soil acidity, flood, and wind erosion. Such challenges become more serious for those countries that are vulnerable to climate changes. Unfortunately, the Annual Global Peace Index (Institute for Economics & Peace, 2019) shows that all top nine countries facing the highest risk of multiple climate hazards belong to Asia – including Philippines, Japan, Bangladesh, Myanmar, China, Indonesia, India, Vietnam, and Pakistan. There is no doubt in the literature that climate change negatively affects economic growth (Fankhauser & Tol, 2005; Dell et al., 2008; Hoang & Huynh, 2021). How about its impact on agriculture? If there really is an adverse impact of climate change on agricultural productivity in Asia, how can policy makers deal with this dual problem?

Recent studies have given some evidences that investment in research and development (R&D) can promote agricultural Total factor productivity (TFP) in Australia (Salim & Islam, 2010) and in Bangladesh (Rahman & Salim, 2013). However, Salim et al. (2020) illustrate that that R&D has a significant positive impact on agricultural productivity in the long-run, but it is insignificant in the short run. Whereas, spending on agricultural R&D in Asian and Pacific countries is still modest. Whether investment in R&D can help improve agricultural productivity and lessen the detrimental impact of climate change on agricultural productivity?

The aim of this paper is to empirically investigate the impact of climate change and agricultural R&D as well as their interaction on agricultural productivity in 12 Asian and Pacific countries over the period of 1990 – 2018. We contribute to the literature in several ways. First, we examine how climate change affects agricultural productivity in Asian and Pacific countries – those are most vulnerable to climate change. Second, we assess the role of R&D in improve agricultural productivity as well as its moderating effect in reducing the harmful impact of climate change on agricultural productivity.

The remainder of this article is structured as follows. Section 2 reviews the literature and proposes hypotheses. The model, data and econometric methodology are described in section 3. Section 4 presents results and discussions. Conclusion and policy implications are provided in the final section.

2. Agricultural development, climate change, and agricultural R&D in Asian and Pacific countries

Agriculture has been an important sector of the economic and social development in Asian and Pacific economies with significant contributions to GDP, employment and poverty reduction (Anik et al., 2017; Briones, 2017; Liu et al., 2020). Over the period 1990-2018, the average GDP growth of 12 countries obtains 5.76%/year while annual agricultural growth was lower, with 2.93% on average. As shown in Table 1, the contribution of agriculture to GDP gradually declined from 29.38% to 22.11% and 17.95% in the three sub-periods 1990-2000, 2001-2010, and 2011-2018, respectively. Consequently, the agriculture employment (% of total employment) has been falling in the similar sub-periods from 59.06% to 50.62% and 42.86%.

Table 1. Agricultural development in Asian and Pacific countries

Period	GDP growth (annual %)	Agricultural growth (%)	Agriculture (% of GDP)	Agricultural employment (%)
1990-2000	5.32	2.49	29.38	59.06
2001-2010	6.16	3.68	22.11	50.62
2011-2018	5.80	2.62	17.95	42.86
Mean	5.76	2.93	23.15	50.85

Source: Authors' calculation based on World Bank database for 12 Asian and Pacific countries (Bangladesh, Cambodia, India, Indonesia, Laos, Malaysia, Myanmar, Nepal, Pakistan, Sri Lanka, Thailand, and Vietnam).

Low agricultural growth in 12 Asian and Pacific countries has been accompanied with the severe climate change in the region. As reported by the Institute for Economics and Peace (2019), nearly one million people in the world have been threaten by climate change with high exposure to environmental hazards such as cyclones, bushfires, floods, and rising sea levels. Most of them live in Asian region – home to 60% of the world's population. In 2019, Asia was the world's most disaster-prone region with many climate catastrophes. For example, many regions in Pakistan and India have been baked in a record-breaking heatwave of above 50 degrees Celsius, causing hundreds of deaths. The mighty Mekong which stretches on six countries (China, Myanmar, Thailand, Laos, Cambodia and Vietnam) is at risk of drying due to droughts and proliferating hydropower construction, threatening food security for more than sixty million people. In addition, rising sea levels and global warming threaten to engulf many coastal regions in Indonesia, India, Bangladesh, Thailand and Vietnam. Forest fires from Indonesia billow toxic smoke to Malaysia and Singapore, causing long-term damage to human lives. Besides, many Asia countries have been hit by typhoons due to the dense frequency of El Nino. As a result, people in these vulnerable regions can be hit hardest by climate change than anywhere.

To the Food and Agriculture Organization of the United Nations (FAO), climate change refers to "a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period" and it is caused not only by natural factors, but also by human activities[1]. Climate change can be measured by two popular indicators, including temperature and precipitation (Alagidede et al., 2016). These two indicators are also employed in our research.

The temperature and agricultural growth on average in 12 Asian and Pacific countries are graphically scattered in Figure 1.

[1] See more at: http://www.fao.org/nr/climpag/cli_cha_0_en.asp

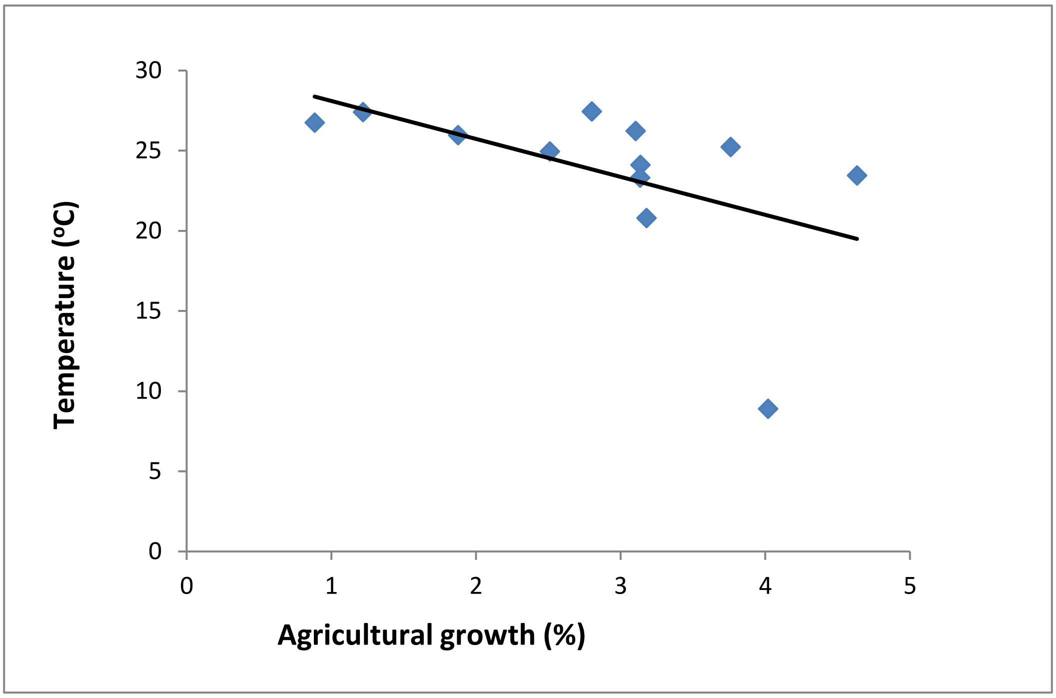

Figure 1. The temperature and agricultural growth on average in 12 Asian Pacific countries (1990-2018) (*Sources: FAO; World Bank, 2020)*

As depicted in Figure 1, there seems to be a negative linear relationship between the temperature and agricultural growth in 12 Asian Pacific countries. Whether this relationship may be moderated by agricultural R&D? According to Hall and Scobie (2006), the stock of knowledge – widely acknowledged as the main driver of productivity growth – can be proxied by spending on R&D because R&D generate the increase of knowledge (Griliches, 1979; Islam & Salim, 2009). Our calculations from using the Agricultural Science and Technology Indicators (ASTI) database indicate that annual R&D investments in agriculture in 12 Asian and Pacific countries on average have increasingly fluctuated between 3.3 and 4.9 USD billion per 100,000 farmers from 2000 to 2018. It is accounted for an annual increase of 2.2%, compared with 2.5% for the total global spending growth on agricultural research on average during 2010–2016 (Beintema et al., 2020). Earlier, the total global spending on agricultural research grew by 2.9 percent per year on average during 2000–2010. It can be seen that the annual growth of R&D investments in agriculture in 12 Asian and Pacific countries is still lower than the global growth on average while these countries are the most affected ones by the climate change in the world. Figure 2 graphically shows the relationship between R&D investments per 100,000 farmers (thousand constant 2011 US dollars) and agricultural value added per worker (constant 2011 US dollars) in 12 Asian and Pacific countries on average during 2000 – 2018.

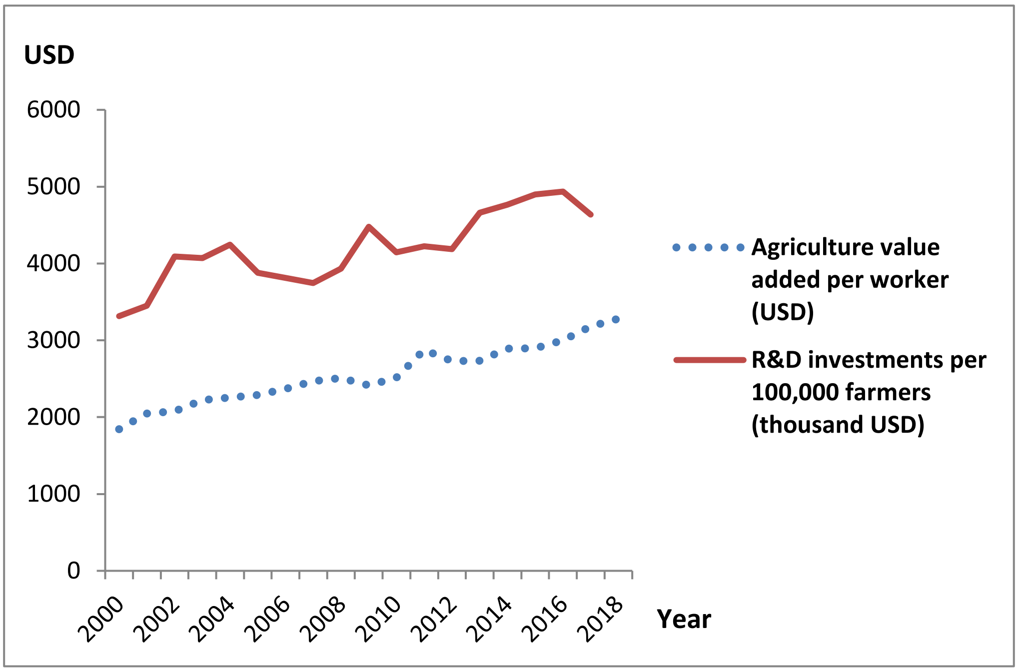

Figure 2. R&D investments in agriculture and agricultural value added per worker in 12 Asian and Pacific countries on average during 2000 – 2018 *(Source: ASTI, 2020; World Bank, 2020)*

3. Literature review and hypotheses

3.1. The impact of climate change on agricultural productivity

Agricultural sector may possibly be affected by climate change for its sensitivity to changes in the weather. One of early studies on this done by Adams et al. (1990) shows that crop yields are adversely affected by high temperature and low precipitation in the US over the period 1951–1980.

However, the impact of temperature and precipitation on agricultural productivity is different in different countries. In cold countries, warmer temperatures may improve agricultural productivity but rising precipitation has an inverse effect on it. In hot countries, agricultural productivity may benefit from higher precipitation, but may lose from higher temperatures. For example, on the one hand, the rising temperature increases yields of potatoes, wheat, oats and barley for the period 1958–2001 at county level in Norway; while the rising precipitation reduces the yields due to excess soil moisture or reduced sunlight associated with more cloud cover (Torvanger et al., 2004). Similarly, Kokic et al. (2005) forecast that under a scenario of an increase in temperature and a decline in rainfall, wheat yield is projected to increase by 7 to 16 per cent in Australia.

On the other hand, Nastis et al. (2012) conclude that rising average temperatures statistically reduce agricultural productivity, whereas higher precipitation increases average agricultural output during the past three decades in Greece. Similar results are found in Bangladesh (Salim et al., 2020). Cases of other Asian and Pacific countries are still the research gap in the literature.

Most of countries in our samples of Asia and Pacific have the tropical climate zone. According to data from the National Oceanic and Atmospheric Administration (NOAA), Asia saw 2019 as its third warmest year on record, with a temperature of 1.68 degrees Celsius above the 1910–2000 average[2]. Most of the time, temperature spikes cause extreme weather patterns. For example, many regions in Pakistan and India have been baked in a record-breaking heatwave of above 50 degrees Celsius, causing hundreds of deaths; while torrential rains lashed other regions in Bangladesh, India, Pakistan and Nepal, inducing worst floods. Higher temperatures are likely to reduce crop yields because: i) the life cycle of most cereals are shorten, ii) most cereal crops

[2] See more at: https://www.ncdc.noaa.gov/sotc/global/201913

can only endure narrow temperature ranges, iii) the length of the growing season is reduced, and iv) the senescence become more quickly (Porter, 2005). When the climate crisis makes annual rainfall and monsoons - so important to the region's agriculture - more erratic, droughts and water shortages are more severe. Therefore, droughts and water shortages may reduce yields of important crops in the region due to the lack of water for crop growing. However, excess precipitation may also cause damages to crop production (Rosenzweig et al., 2002) because many Asia countries have been hit by typhoons due to the dense frequency of El Nino.

Therefore in the context of selected Asia Pacific countries, we hypothesize that:

Hypothesis 1: Agricultural productivity in Asian and Pacific countries is adversely affected by temperature and precipitation, ceteris paribus.

3.2. The impact of R&D on agricultural productivity

Agricultural productivity is affected not only by climate change but also by agricultural R&D. Some empirical studies generally indicate that R&D investments can improve agricultural productivity by channels of creating innovation and new knowledge (Alene, 2010; Rahman & Salim, 2013). For example, Alene (2010) finds that agricultural R&D significantly affects productivity in African agriculture over the period 1970–2004 With an annual return rate of 33%; and rather than efficiency change, technical progress is the principal source of productivity growth for the regional agriculture. Similarly, Rahman & Salim (2013) conclude that technological progress mainly contributes to agricultural TFP growth in Bangladesh while technical efficiency improvement is negligible. In addition, Adetutu and Ajayi (2020) reveal that agricultural productivity is strongly influenced by both domestic and foreign R&D through the mechanism of knowledge shocks for a sample of 30 sub-Sahara African countries during the period 1981–2011, albeit the productivity impact of domestic R&D

is qualitatively and statistically stronger. Earlier, Hall & Scobie (2006) show evidence that both domestic and foreign investments in R&D contribute to agricultural productivity via the channel of spill-over effects in New Zealand from 1926-27 to 2000-01. However, Mullen & Cox (1995) and Binenbaum et al. (2008) discover that public R&D investments for agriculture reduce the rate of return in Australia. Salim & Islam (2010) also confirm insignificant impact of R&D spending on agricultural productivity in Western Australia in the short run. This negative impact of R&D can be due to: i) knowledge and innovation exhibit declining returns to scale (Bitzer & Kerekes, 2008); and ii) local conditions (such as institutional bottlenecks, intellectual property rights and development levels) may hamper the absorption of innovation efforts (Johnson & Evenson, 2000; O'Gorman, 2015).

In the context of Asian and Pacific countries with beginning levels and scale of R&D investments, we argue the beneficial effects of R&D on agricultural productivity. Thus, we confirm that:

Hypothesis 2: R&D investments in agriculture have a positive impact on agricultural productivity, ceteris paribus.

3.3. The role of R&D in moderating the adverse impact of climate change on agricultural productivity

Based on prior studies, a number of solutions has been proposed to deal with climate change in Asia, such as: attracting FDI inflows and improving institutional quality (Huynh & Hoang, 2019; Huynh & Ho, 2020), conducting appropriate fiscal policies (Huynh, 2020), and utilizing free-market economy, property rights, and government integrity (Huynh & Hoang, 2021). However, the role of R&D in moderating the adverse impact of climate change on agricultural productivity is still a research gap in the literature.

The agricultural productivity impact of climate change can depend on other factors such as kinds of crops (Torvanger et al., 2004) or development levels (Mendelsohn et al., 2001). For instance, Mendelsohn et al. (2001) postulate that the agricultural impact of climate change depends on a country's stage of development due to the substitution between capital and climate. Results from this study show that climate sensitivity of agriculture tends to be lower in developed countries compared to developing or less developed countries. In other words, increasing development reduces climate sensitivity from the development of new technology. Therefore, investments in R&D in agriculture can help mitigate the adverse impacts of climate change on agricultural productivity for the reasons as follows: i) R&D generates stocks of knowledge and diffuse modern technologies in agriculture, ii) more agricultural facilities and techniques are invented for climate change adaption, iii) new seeds and hybrid plants can endure to climate change, and iv) R&D optimizes the input use and save resources for facing climate change and for utilizing in other economic sectors.

Therefore, we postulate that:

Hypothesis 3: Institutional quality mitigates the detrimental impact of climate change on agricultural productivity, ceteris paribus.

4. Empirical model, data and econometric methodology

4.1. Empirical model and data

Most empirical studies on productivity and growth (Jorgenson & Griliches, 1967; Nishimizu & Page, 1982) base on Cobb–Douglas production function - which defines a relationship between a vector of maximum outputs and a vector of various combinations of inputs. The standard Cobb–Douglas production function with material augmented is given as follows:

$$Y_{it} = TFP_{it}.L_{it}^{\alpha}.K_{it}^{\beta}.M_{it}^{\gamma} \tag{1}$$

where t and i are year and country, respectively. Y is total output; TFP is total factor productivity; L, K and M are inputs for labour, capital and other materials, respectively. α, β and γ are the contribution of labour, capital and materials in the output.

Dividing the both sides of Eq. (1) by numbers of labours, we have:

$$(Y/L)_{it} = (TFP/L)_{it}.L_{it}^{\alpha-1}.(K^{\beta}/L)_{it}.(M^{\gamma}/L)_{it} \quad (2)$$

In our study, we postulate that TFP in agriculture is affected by climate change (C) and R&D activities (RD) and. Therefore, we have:

$$(TFP/L)_{it} = A_{it}.C_{it}^{\lambda 1}.RD_{it}^{\lambda 2} \quad (3)$$

where A is the given technological progress; $\lambda 1$ and $\lambda 2$ represent the weight of C and R&D, respectively.

Substituting Eq. (3) into Eq. (2), we get:

$$(Y/L)_{it} = A_{it}.L_{it}^{\alpha}.K_{it}^{\beta}.M_{it}^{\gamma}.C_{it}^{\lambda 1}.RD_{it}^{\lambda 2} \quad (4)$$

We call P = Y/L: The agricultural productivity of labour. Taking the logarithm for both sides of Eq. (4), the following equation is generated:

$$LnP_{it} = LnA_{it} + \alpha LnL_{it} + \beta LnK_{it} + \gamma LnM_{it} + \lambda_1 LnC_{it} + \lambda_2 LnRD_{it} \quad (5)$$

To examine the impact of climate change, R&D and their interaction on agricultural growth, we rearrange Eq. (5) as follows:

$$LnP_{it} = \lambda_0 + \lambda_1 LnC_{it} + \lambda_2 LnRD_{it} + \lambda_3 LnC_{it} * LnRD_{it} + LnZ'_{it}\,\gamma_j + \varepsilon_{it} \quad (6)$$

where λ_0 stands for given technological levels of country i at year t (LnA_{it}); $LnC_{it}*LnRD_{it}$ is the interaction between climate change and R&D; Z_{it} is a vector of control variables of inputs (L, K, M), including labour, capital, fertilizer consumption and land; and ε_{it} is the error term.

Because we use the mean annual temperature (TEM) and the annual rate of precipitation (PRE) to measure climate change, the Eq. (6) can be written as:

$$LnP_{it} = \lambda_0 + \lambda_1 LnTEM_{it} + \lambda_2 LnRD_{it} + \lambda_3 LnTEM_{it}*LnRD_{it} + \lambda_4 LnPRE_{it} + \lambda_5 LnPRE_{it}*LnRD_{it} + LnZ'_{it}\gamma_j + \varepsilon_{it} \quad (7)$$

This is our baseline model. The description of variables in the model is provided as follows:

The dependent variable is agricultural productivity (P), measured by agricultural value added per worker (constant 2011 US dollars) from World Development Indicators – WDI (World Bank, 2020). The independent variables are: i) climate change, proxied by the mean annual temperature (TEM) and the annual rate of precipitation (PRE) collected from the University of East Anglia's Climate Research Unit [3]; and ii) R&D activities, represented by the total R&D spending on agriculture extracted from Agricultural Science and Technology Indicators database (ASTI, 2020)[4]. Because we hypothesize that climate change reduces agricultural productivity while R&D activities promote it, it is expected that λ_{11} and λ_4 are positive and λ_2 negative.

Besides, the interaction terms between TEMP and RD as well as between PRE and RD capture the role of RD in moderating the effect of climate change on agricultural productivity. This role can be calculated by taking the partial derivatives of Eq. (7) with respect to TEMP and PRE, respectively:

$$\frac{\partial(LnP_{it})}{\partial(LnTEMP_{it})} = \lambda_1 + \lambda_3 \, \mathrm{LnRD}_{it} \tag{8}$$

$$\frac{\partial(LnP_{it})}{\partial(LnPRE_{it})} = \lambda_4 + \lambda_5 \, \mathrm{LnRD}_{it} \tag{9}$$

Because of the postulation that TEMP and PRE decrease agricultural productivity, and the R&D activities reduce the disadvantageous impact of TEMP and PRE on agricultural productivity, we expect that λ_1 and λ_4 are negative, λ_3 and λ_5 positive ; with $/\lambda_1/ > \lambda_3$, and $/\lambda_4/ > \lambda_5$.

Control variables (Z) consist of Labour (L), Capital (K), Fertilizer consumption

[3] See: http://www.cru.uea.ac.uk/data/

[4] See: https://www.asti.cgiar.org/

(F), and Arable land (LAND). These are key determinants of agricultural productivity in the literature, being consolidated as follows:

Labour: Labour is a key factor of economic growth and productivity (Barro, 2000). Labour is then considered not only number of labourers but also the quality of labour, and the improvement in labour quality will bring higher productivity. Farmers with higher education are more able to apply and perform effectively more productive techniques of production (Azhar, 1991; Parikh & Shah, 1994). The contribution of labour to agricultural productivity was empirically demonstrated by Adams & Bumb (1979), Salim & Islam (2010), Ahmad & Heng (2012), Nastis et al. (2012), Salim et al. (2019), and Liu et al. (2020). In our study, labour (L) and labour quality (EDU) are measured by employment in agriculture (% of total employment) and average total years of schooling for adult population, respectively, collected from WDI (World Bank, 2020) and Human Development Report (United Nations Development Programme, 2018).

Capital (K): Being a main determinant of productivity like labour, capital was found having a strong contribution to agricultural productivity in India (Adams & Bumb, 1979). However, it was found insignificantly positive in South and Southeast Asian countries (Liu et al., 2020), showing that capital formation in agriculture has not clearly and significantly contributed to the growth of agricultural production. Evenly, the impact of capital on agricultural productivity is negative in the case of Greece (Nastis et al., 2012) due to an overutilization of tractors when farmers got large subsidies after Greece's accession to the European Union. We use tractors per 100 sq. km of arable land (World Bank, 2020) as an indicator for the capital input.

Fertilizer consumption (F): Fertilizer is believed to boost agricultural productivity by enhancing natural soil nutrients (Azhar, 1991; Nastis et al., 2012; Shita et al., 2020).

Nevertheless, the negative impact is possible when the use of fertilizer exceeds the optimal amount, causing harm to plants (Ahmad & Heng, 2012). In this research, fertilizer consumption is measured by kilograms per hectare of arable land (World Bank, 2020).

Arable land (LAND): Although being considered as one of the most important natural resources, arable land has inconclusive impacts on agricultural productivity. On the one hand, farmers with larger farm size are more productive than those with smaller one, because they can adopt agricultural technologies to a higher level and greater scale (Barker & Herdt, 1978; Rahman & Salim, 2013; Chandio et al., 2016; Shita et al., 2020). On the other hand, Ekbom (1998) proves that farmers with smaller farm size have more incentive to enhance productivity for feeding their households with limited conditions. However, scale is also found having no impact on productivity (Karanja et al., 1999). We measure arable land by hectare per person, collected from the WDI (World Bank, 2020).

We collected all data in the model (7) for 12 Asian and Pacific countries over the period of 1990 – 2018, including Bangladesh, Cambodia, India, Indonesia, Laos, Malaysia, Myanmar, Nepal, Pakistan, Sri Lanka, Thailand, and Vietnam. Reasons for this sample selection are: i) most of these countries have been listed in the top countries facing the highest risk of multiple climate hazards (Institute for Economics & Peace, 2019); ii) these countries have similar climate conditions and development levels; and iii) data of these countries are available for the empirical model.

Definitions, measurements and summary statistics for all variables are presented in Table 2.

Table 2. Definition and summary statistics

Variables	Definitions and measurements	Mean	St.var	Min	Max	Obs

P	Agricultural productivity, value added per worker (constant 2011 US dollars)	2438.5	3894.8	369.9	19208.9	315
TEMP	Temperature (^{O}C)	23.71	4.85	8.0	28.0	300
PRE	Precipitation (mm/month)	1851.5	753.8	175.8	3642.5	300
RD	Agricultural R&D spending per 100,000 farmers (million constant 2011 US dollars)	4.231	10.519	0.035	45.815	264
L	Employment in agriculture to total (%)	51.416	17.863	10.665	86.66	336
EDU	Average total years of schooling for adult population (years)	10.449	64.633	-18.109	1877.372	336
K	Agricultural machinery, tractors per 100 sq. km of arable land	77.733	97.846	1.198	480.522	276
F	Fertilizer consumption, kilograms per hectare of arable land	294.67	480.72	1.36	2182.53	276
LAND	Arable land per person (hectare)	0.145	0.087	0.027	0.412	324

4.2. Econometric methodology

After testing the data stationarity of all variables, we employ three methods including Pooled Ordinary Least Squares (OLS), Fixed Effects (FE) and Random Effects (RE) to estimate the empirical model (7) with the procedure as follows. *First*, we perform Pooled OLS and RE estimations. *Second*, we use the Breusch–Pagan Lagrange multiplier test for RE with the null hypothesis of no country-specific effects in intercepts (Breusch & Pagan, 1980). Pooled OLS is applied if there is no significant difference across countries (no panel effect). If the null hypothesis is rejected, we choose RE. *Third*, we perform FE estimation and use the Hausman test to compare FE to RE with the null hypothesis that difference in coefficients is not systematic (Hausman, 1978). RE can be used to control unobserved time-variant country-specific effects. If the null hypothesis is rejected, we employ FE to remove unobserved time-invariant country-specific effects. *Fourth*, we also check heteroscedasticity by using the Breusch–Pagan Lagrange multiplier test after RE (Breusch & Pagan, 1979), and the modified Wald test after FE (Greene, 2000). In addition, the Wooldridge test or the

Breusch-Pagan LM test of independence is employed for checking the serial autocorrelation in panel data (Wooldridge, 2010). Fifth, the Feasible Generalized Least Squares (FGLS) is employed to correct the presence of autocorrelation within panels and heteroscedasticity across panels (Greene, 2012).

5. Empirical results and discussions

Prior to regression, we employ Fisher stationary test based on Phillips–Perron unit root test (Choi, 2001), and Hadri Lagrange multiplier stationarity test (Hadri, 2000) for examining the data stationarity with the null hypothesis that the variable is not stationary or gets unit-root. Our results reject the null hypothesis for LnP, LnTEMP, LnPRE, LnRD, LnEDU, LnF and LnLAND, specifying that these variables are stationary at levels. However, we fail to reject the null hypothesis for L and LnK, indicating that these variables get unit-roots and thus they must be first-differenced to be stationary for further statistical analysis. The results for unit-root tests are presented in Table 3.

Table 3. Unit-root tests for all variables.

Variables	Phillips – Perron (Chi squares)	Hadri Lagrange (Z-stat)
LnP	197.34***	18.93***
LnTEMP	206.95***	15.99***
LnPRE	234.08***	13.23***
LnRD	53.91***	17.58***
L	14.84	5.73
D.L	286.38***	38.11***
LnEDU	59.87***	55.35***
LnK	11.81	6.55
D.LnK	51.91***	28.54***

LnF	52.27***	16.82***
LnLAND	147.69***	52.35***

****Indicates the rejection of the unit-root hypothesis at the 1% significant level.*

The empirical model (7) is estimated in three specifications. We examine the impacts of temperature, precipitation, and agricultural R&D spending on agricultural productivity in the first specification (1.1). Next, interaction terms between temperature and agricultural R&D spending as well as between precipitation and agricultural R&D spending are added in the second specification (1.2). Finally, in the third specification (1.3) – our baseline one, other control variables are included.

Following the five steps described in the section 4.2 (Econometric methodology), we obtain the estimation results and relevant tests presented in Table 4. Results from the Breusch–Pagan Lagrange multiplier test and the Hausman test reject the null hypotheses of no country-specific effects in intercepts and of no time-variant country-specific effects, respectively, indicating that FE estimations are appropriate for all three specifications. Besides, results from the modified Wald test and the Wooldridge test after FE prove the presence of heteroscedasticity but the absence of autocorrelation in the three specifications. Thus, we use FGLS to correct the presence of heteroscedasticity across panels.

Table 4. Estimation results for Eq. (7) by FE and FGLS

Dependent variables: LnP						
Regressors	(1)		(2)		(3)	
	FE	FGLS	FE	FGLS	FE	FGLS
LnTEMP	-1.178***	-0.851***	-1.122**	-1.315***	-1.335***	-1.004***
	(4.44)	(9.66)	(2.57)	(4.68)	(3.44)	(2.57)
LnPRE	-0.1174***	-0.148**	-0.211***	-0.299*	-0.237**	-0.218*
	(4.02)	(2.34)	(3.74)	(2.48)	(2.35)	(1.95)

LnRD	0.337***	0.559***	0.585***	0.709***	0.770***	0.522***
	(6.37)	(4.80)	(4.75)	(4.33)	(5.31)	(3.93)
LnTEMP*LnRD			0.313**	0.409**	0.456**	0.412*
			(2.73)	(2.53)	(2.17)	(1.94)
LnPRE*LnRD			0.267***	0.225***	0.396*	0.289***
			(3.80)	(6.03)	(6.02)	(6.26)
D.L					0.094***	0.036**
					(3.17)	(2.07)
LnEDU					0.257*	0.336***
					(1.98)	(2.83)
D.LnK					1.759	1.041
					(1.81)	(1.75)
LnF					0.087*	0.037*
					(1.96)	(1.93)
LnLAND					0.418***	0.359***
					(4.06)	(4.79)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.491***	6.041***	3.572***	5.081***	4.115***	6.825***
Observation	285	285	285	285	249	249
Hausman	145.68***		178.55***		159.44***	
Wooldridge	183		139		152	
MW-P	0.000	0.175	0.000	0.287	0.000	0.216
LM-P	0.627		0.542		0.463	

*Absolute T-statistics appear in parentheses. ***, ** and * indicate significance at 1%, 5% and 10%, respectively. MW-P: P-value of Modified Wald test. LM-P: P-value of Breusch-Pagan LM test.*

Results in Table 4 provide interesting findings as follows.

First, both proxies of climate change – temperature and precipitation – have negative impacts on agricultural productivity at statistically significant levels of 1% – 10% in the three specifications, confirming our first hypothesis. The negative effect of temperature on agricultural productivity found in our study is consistent with Nastis et al. (2012) and Salim et al. (2020), respectively for cases of Greece and Bangladesh – countries with similar hot climate conditions to those in our samples. However, this finding is contrary to those of Torvanger et al. (2004) and Kokic et al. (2005) who show that agricultural productivity gets benefit from higher temperatures in Norway and Australia due to their cold weather. Meanwhile, the negative impact of precipitation on agricultural productivity in our research – which supports prior findings by Salim et al. (2020) – can be explained that excess precipitation may also cause damages to crop production although crops need water for growing, or torrential rains may lead to floods which are detrimental for agriculture.

Second, the second hypothesis in our research is supported when R&D investments in agriculture have a positive impact on agricultural productivity in all specifications with a statistically significance of 1%. This finding is contrast to previous studies by Mullen & Cox (1995) and Binenbaum et al. (2008) who find that public R&D investments for agriculture reduce the rate of return in Australia, which can be due to inefficiency, declining returns to scale of knowledge and innovation, or local conditions. However, our finding is in accord with those by Alene (2010), Rahman & Salim (2013), and Adetutu & Ajayi (2020). To these authors, the beneficial effects of R&D on agricultural productivity can be gained through channels of creating innovation and new knowledge, spill-over effects or through the mechanism of knowledge shocks. In the context of Asian and Pacific countries with beginning levels and scale of R&D investments, the beneficial effects of R&D on agricultural productivity can be explained when declining returns to scale of knowledge and innovation have not happened yet.

Third, the most interesting finding is the important role of agricultural R&D investments in moderating the negative impacts of climate change on agricultural productivity. The coefficients of interaction terms between temperature and agricultural R&D spending (λ_3) as well as between precipitation and agricultural R&D spending (λ_5) are statistically found negative at significant levels of 1% – 10% in the specifications

(1.2) and (1.3), supporting the third hypothesis that R&D investments mitigate the negative impact of climate change on agricultural productivity.

For the interaction between temperature and agricultural R&D investments, results show negative λ_1, positive λ_3, and $/\lambda_1/ > \lambda_3$, indicating that temperature reduces agricultural productivity, and the rise in agricultural R&D investments lessens the detrimental impact of temperature on agricultural productivity. In particular, as showed in Eq. (8), the total impact of temperature on agricultural productivity is the sum of λ_1 and (λ_3*LnRD). Based on results by FGLS in the specification (1.3) in Table 4, the total impact of temperature on agricultural productivity at different levels of R&D investments can be computed. Without agricultural R&D investments, a 1% increase in temperature leads to 1.004% decrease in agricultural value added per worker. At the maximum value of agricultural R&D investments (45.815), agricultural value added per worker decreases by only 0.571% when temperature rises by 1%. Thus, the total impact of temperature on agricultural productivity decreases by 43.053% when agricultural R&D investments rise from zero to its maximum value.

For the interaction between precipitation and agricultural R&D investments, results show negative λ_4, positive λ_5, and $/\lambda_4/ < \lambda_5$, demonstrating that precipitation reduces agricultural productivity until the threshold of agricultural R&D investments beyond which precipitation increases agricultural productivity. This threshold can be calculated by setting Eq. (9) = 0 and using estimation results from FGLS of the baseline specification (1.3) in Table 4. The threshold of agricultural R&D investments is 2.126 million constant 2011 US dollars per 100,000 farmers per year. This finding on the beneficial impact of precipitation can be explained in the context of 12 selected Asian and Pacific countries when agricultural R&D investments are utilised. Most of 12 selected countries have the tropical climate zone with hot weather where droughts and water shortages are more severe although sometimes floods and torrential rains happen. However, if these countries invest more in agricultural R&D for preventing floods and landslides, as well as utilising torrential rains for irrigation system, precipitation can be promoted to increase agricultural productivity.

Fourth, other determinants of agricultural productivity are confirmed in the context of 12 selected Asian and Pacific countries, consisting of labour employed in agriculture, education, fertilizer consumption, and arable land. Our results on the contribution of labour and education to agricultural productivity are in line with those by Adams & Bumb (1979), Salim & Islam (2010), Ahmad & Heng (2012), Nastis et al. (2012), Salim et al. (2019), Liu et al. (2020); Azhar (1991), and Parikh & Shah (1994). Fertilizer consumption is found to boost agricultural productivity since it is expected to enhance natural soil nutrients, as confirmed in the literature by Azhar (1991), Nastis et al. (2012), and Shita et al. (2020). Besides, the positive impact of arable land on agricultural productivity in our study supports the notion that farmers with larger farm size are more productive than those with smaller one, because they can adopt agricultural technologies to a higher level and greater scale (Barker & Herdt, 1978; Rahman & Salim, 2013; Chandio et al., 2016; Shita et al., 2020). However, the physical capital proxied by tractors per 100 sq. km of arable land is found insignificantly positive, showing that capital formation in agriculture has not clearly and significantly contributed to the growth of agricultural production. This finding is similar to that by Liu et al. (2020).

Robustness check

The impact of climate change on agriculture has been fundamentally examined in the literature. However, the potential feedback effect of agriculture on climate change – though being rarely investigated – is still inevitable. The contribution of agriculture to climate change can be induced by many sources such as: nitrous oxide coming from manure and fertilizers, methane coming from wetland and livestock, and carbon dioxide coming from deforestation. Therefore, we use the two-step System Generalized Method of Moments (SGMM) as a robustness check of the estimation to control the endogeneity issue in our empirical model. By performing SGMM, the lagged levels of dependent variable and the first difference of independent variables are used as instruments for differenced equation, while for level equation it is instrumented by the lagged differences of the dependent variable. As proposed by Arellano and Bond (1991), two kinds of tests will be conducted for the post-estimation of SGMM. First, the Sargan test is carried out to check the validity of instruments and specifications. Second, conducting the Arellano and Bond test aims at examining the hypothesis that the errors from the estimations are first-order correlated (AR1) but not second-order correlated (AR2). Besides, we include year dummies in Eq. (2) for regressions to control the overall effects of technological changes over time. The restricted number of lags is also performed to control the issue of instrument proliferation. Results and relevant tests are reported in Table 5. Our results remain consistent and robust.

Table 5. Estimation results for Eq. (7) by SGMM

Dependent variables: LnP			
Regressors	(2.1)	(2.2)	(2.3)
LnP(-1)	0.962***	1.112***	0.983***
	(11.49)	(9.38)	(10.09)
LnTEMP	-0.966***	-0.821**	-1.115**
	(2.98)	(2.80)	(1.99)
LnPRE	-0.213**	-0.122***	-0.331***
	(2.18)	(3.34)	(4.41)
LnRD	0.432***	0.385**	0.622**
	(5.17)	(2.27)	(2.20)
LnTEMP*LnRD		0.252***	0.436**
		(2.67)	(2.24)

LnPRE*LnRD		0.101**	0.203***
		(1.92)	(2.62)
D.L			0.054*
			(1.95)
LnEDU			0.219**
			(2.25)
D.LnK			1.294
			(1.37)
LnF			0.062*
			(2.01)
LnLAND			0.296***
			(3.84)
Year dummies	Yes	Yes	Yes
Constant	1.513***	1.851***	1.492***
AR(1)-P	0.033	0.049	0.016
AR(2)-P	0.774	0.424	0.483
Sargan test-P	0.528	0.622	0.533

*Absolute T-statistics appear in parentheses. ***, ** and * indicate significance at 1%, 5% and 10%, respectively. AR(1)-P: P-value of first-order correlation. AR(2)-P: P-value of second-order correlation. Sargan test-P: P-value of Sargan test.*

6. Concluding remark and policy implications

This study empirically sheds light on the impact of climate change and agricultural R&D investments as well as their interaction on agricultural productivity in 12 selected Asian and Pacific countries over the period of 1990 – 2018. Results from estimation methods of FE, FGLS and SGMM show that both proxies of climate change – temperature and precipitation – have negative impacts on agricultural productivity. Notably, agricultural R&D investments not only increase agricultural productivity but also mitigate the detrimental impact of climate change proxied by temperature on agricultural productivity. Interestingly, climate change proxied by precipitation initially reduces agricultural productivity until a threshold of agricultural R&D beyond which precipitation increases agricultural productivity. These results strongly confirm the important role of R&D investments in the context of rising climate change and low agricultural productivity in Asian and Pacific countries. Within context of climate change, farmers need sciences more than ever. Governments should more invest and encourages private sectors to invest in agro-ecology research to provide farmers with tools and techniques for efficiency and productivity.

Furthermore, policies aiming at enhance agricultural productivity in the continent should focus on improving the quality of agricultural workforces so that farmers can apply and utilize the achievements from R&D more effectively. Besides, the optimization of agricultural inputs such as fertilizer consumption and arable land should be closely considered for the improvement of agricultural productivity.

Compliance with ethical standards

Conflict of interest: The authors declare that they have no conflict of interest.

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