Assessing the impact of climate change on the agricultural economy in Thailand: An empirical study using panel data analysis

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Abstract

This study estimates the impact of climate change on the economic growth of the agricultural sector and its variability using a panel dataset from 1995 to 2019 for 76 provinces in Thailand. The panel data analysis consists of unit root tests for identifying stationary characteristics, autoregressive distributed lag (ARDL) bounds for analyzing cointegration, and pool mean group (PMG) estimation for detecting long-run and short-run effects. The cointegration results indicate the existence of long-run equilibrium in the agricultural economy and its variability to climatic and non-climatic variables. Results from the PMG estimation suggest that extreme weather events have a negative impact on the agricultural economy, but increased total rainfall has a positive association with the agricultural economy. The increases in mean average and mean minimum temperatures will reduce the variability of agricultural growth. The obtained results suggest that the productivity of agricultural households and water resources increases the agricultural revenue and reduces its variability for long-term development in the agricultural sector of Thailand.

Keywords Cointegration; ARDL; PMG; Climatic Change; Agriculture; Global Warming

Introduction

Climate change is a concern for many countries around the world and generally has a negative impact on the economy, society, and environment. Climate variability is becoming more serious with heavy rains, flooding, droughts, rising sea levels, and El Niño-Southern Oscillation (ENSO). This may, therefore, result in the occurrence of serious global epidemics. In addition, extreme climate and weather events have a profound impact on ecosystems and biodiversity, including air pollution, and pose a threat to life in terms of affecting both health and livelihoods, creating food and drinking water shortages, and so on. The causes of climate change can be attributed to the fluctuation of the Earth's average temperature rise due to the greenhouse effect, which influences changes with respect to other climatic factors, such as precipitation, sunlight, wind patterns, heatwaves, etc. Hence, governments across the world have enacted proactive measures to adapt to climate change on various levels of economic development in order to minimize the potential consequences that might occur. For all these reasons, climate change is seen as a global issue that needs to be addressed seriously and rapidly, requiring cooperation from all countries of the world.

Thailand is also facing challenges to its sustainable development due to the impact of climate change. The country has been suffering from natural disasters more than before, with notable events being the 2004 tsunami, the great flood in 2011, and the extreme droughts during the past couple of years. In particular, the great flood in 2011, caused by the La Niña phenomenon, was estimated to cause damage to the Thai economy of approximately US$ 6.23 billion. The impact dramatically affects the export sector because most of the flooded areas were in the major industrial estates located in the central region of Thailand. It was found that the total value of exported products, which can be grouped into four categories, including automobiles, electronics, electrical appliances, and agricultural commodities, decreased by US$ 2.5 billion. At that time, the country had shortages of consumer goods and products of many different types, which resulted in headline inflation as high as 3.9 percent in 2011 (Fiscal Policy Office 2011). As mentioned previously, it would therefore be concluded that climate change has a tremendously negative effect on economic growth as a whole, including making more people's livelihoods more difficult and destroying the environment as well.

Climate change is an important challenge for the agricultural development of Thailand because agricultural outputs depend on climatic conditions such as rainfall, temperature, solar radiation, and humidity. In recent years, Thailand has constantly faced droughts. The factors that mainly cause droughts occur from natural conditions such as faults in circulation forms within the monsoon trough as well as human actions, such as greenhouse gas emissions, deforestation, encroachment on natural water resources, improper land use, and so on. In 2016, Thailand faced a severe drought, partly from the accumulated drought since 2015, due to the El Niño phenomenon that caused temperatures to rise above normal and delayed the monsoons, resulting in agricultural activities not having enough water, especially to grow crops during the planting season. The impact of the drought crisis during the period 2015-2016 affected 187,351 farmers, damaging 474,409 hectares of agricultural land, with total estimated damage of US$ 468.72 million (Department of Water Resources 2017). The Department of Disaster Prevention and Mitigation reported that agricultural areas had been damaged by disasters caused by climate change in the past 24 years (from 1989 to 2012), mainly from floods, droughts, and windstorms. It was found that 2.72 million hectares of agricultural land had been damaged in 1994 by droughts, 4.64 million hectares had been damaged in 2001 by floods, 16,000 hectares had been damaged during the period 2009-2011 by windstorms, and 1.6 million hectares had been damaged during the period 2010-2011 by floods, respectively. In summary, the damage to agriculture due to droughts, floods, and windstorms in the past 24 years (from 1989 to 2012) was approximately US$ 5.77 billion (Department of Disaster Prevention and Mitigation 2013; Ministry of Agriculture and Cooperatives 2017). Hence, the effect of climate change has explicitly affected the efficiency of agricultural production in Thailand.

Even though the impact of climate change on national income has been analyzed in the previous literature, only a few studies have been conducted at the sub-sectoral level of the economy. This study differs from previous studies, which have largely emphasized assessing the impact of climate change on productivity rather than value-added in the agricultural sector. Therefore, this study examines the factors that determine the aggregate values of the agricultural sector in Thailand, namely, non-climatic (i.e., agricultural land use and households) and climatic (i.e., rainfall and temperature) variables. The study includes 76 provinces that cover the agricultural areas of the country. The data collection is fully accessed from Thailand's Office of Agricultural Economics in the form of time series data over the period of 1995 to 2019. The findings could provide useful information for policy planning to determine measures in order to support and mitigate climate change impacts as well as adaptation and climate resilience in the agricultural sector. Thus, the main purpose is to estimate the impact of climate and weather variability on the economic growth of the agricultural sector in Thailand using panel data analysis. The remainder of this study is structured as follows. The following literature review section provides previous studies related to this issue. Then, the methodology section describes panel datasets and econometric techniques, such as testing stationarity using common unit root and individual unit root tests, analyzing cointegration using general-to-specific ARDL bounds tests, and estimating short-run and long-run coefficients using the PMG estimation. The empirical results are presented in the empirical analysis and discussion section. Finally, the conclusion and policy recommendations section presents concluding remarks and implications.

Literature review

From the literature review related to climate change and agriculture, most recent studies have analyzed the effect of climate and weather variability on the efficiency of agricultural output in the form of yield and its variance using Just and Pope's stochastic production function. Just and Pope (1978, 1979) introduced an analysis technique of panel data using climatic and non-climatic factors that are associated with the yield and the variance of the yield. The estimation utilized maximum likelihood (MLE) and feasible generalized least squares (FGLS), which was more efficient and accurate than a classical panel data technique. However, Saha et al. (1997) suggested that the MLE was more efficient and unbiased than the FGLS in cases of a small sample size. For an example of previous studies that used the MLE, Chen et al. (2004) analyzed the impacts of precipitation and temperature on crop yields such as corn, cotton, sorghum, soybean, and wheat in the U.S. The results revealed that the effect of climate change influenced crop yields and their variance differently. Moreover, Kim and Pang (2009), Aye and Ater (2012), and Poudel et al. (2014) confirmed that the variability of climate and weather factors affected crop productivity, with these effects having different associations, both positively and negatively. Numerous studies have employed a three-step FGLS method to estimate climatic factors affecting crop productivity; the study of Sarker et al. (2019) evaluated the impact of climate change on the rainfed Aman rice yields in Bangladesh using Just and Pope's procedure. The panel datasets over 48 years for the district levels were analyzed using the linear and quadratic functions. The results indicated that changes in temperature and rainfall series would be a risk factor for Aman rice productivity in Bangladesh. Guntukula and Goyari (2020) estimated the impacts of climatic variables on major crop yields of rice, cotton, jowar, and groundnut in Telangana using a panel dataset from 1956 to 2015. The results of Guntukula and Goyari (2020) were consistent with the findings of Sarker et al. (2019), indicating that changes in temperature and rainfall affected the efficiency of crop production. In addition, Sinnarong et al. (2019) and Pipitpukdee et al. (2020) confirmed that climate and weather factors were negatively associated with crop yields in Thailand in the projections of rice and cassava, respectively.

To assess the impact of climate change on crop production, Zaied and Zouabi (2016) and Attiaoui and Boufateh (2019) applied a panel cointegration test to capture the short-run and long-run effects of climatic factors on agricultural commodities such as cereal and olive oil in Tunisia. The results indicated that increases in climate and weather variability would reduce Tunisian olive oil production. Attiaoui and Boufateh's (2019) findings also confirmed that temperature and rainfall had a negative effect on cereal farming in Tunisia, and these factors were likely to reduce crop productivity. However, Warsame et al. (2021) studied the impact of climate change on crop production in Somalia using time series analysis. The results of the cointegration test suggest that rainfall increased crop productivity in the long-term period but reduced crop productivity in the short-term period. At the same time, the temperature harmed both long-term and short-term crop yields. Abbas (2020) argued that temperature changes were not associated with the efficiency of cotton production in Pakistan using cointegration analysis.

While climate change has a direct impact on productivity in agriculture, it also indirectly impacts the economic value of the agricultural sector. Following the Ricardian approach, Benhin (2008) estimated climatic and non-climatic factors affecting the average farm revenue of farmers in South Africa. The results indicated that increases in annual mean temperature and precipitation would increase net crop revenue. These findings were in line with Hossain et al. (2019), which found that the increase in temperature and rainfall had a positive relationship with net income from crop farming in Bangladesh. On the other hand, Huong et al. (2019) revealed that changes in temperature and rainfall were negatively associated with net revenue by studying the impact of climate variability on the economic value of household revenue in northwest Vietnam using the Ricardian concept. Furthermore, Lanzafame (2014) investigated the effects of temperature and rainfall on economic growth in Africa using an econometric procedure. An autoregressive distributed lag (ARDL) model was applied to estimate the annual panel dataset from 1962 to 2000 for 36 African countries using the mean group (MG) estimator. The results revealed that there were short-run and long-run relationships between temperature and economic growth, while rainfall was less closely associated with economic growth. Alagidede et al. (2016) also examined the linkage of temperature and rainfall to economic growth in sub-Saharan Africa by applying a panel cointegration test. The pool mean group (PMG) estimator was considered to estimate the panel dataset based on the ARDL model with the Cobb-Douglas production function. The results indicated that the economic growth was significantly affected negatively in the short-run and long-run by temperature. Accordingly, this study has drawn upon the previous literature by investigating the impact of climate change on the economic growth of the agricultural sector at the provincial level in Thailand. The ARDL model based on the Cobb-Douglas concept has been considered to estimate the linkage of climatic and non-climatic factors to the aggregate values of the agricultural economy in Thailand.

Methodology

Numerous studies on the issue of climate change have mainly focused on the impacts of temperature and rainfall variability on crop yields that were mentioned previously. However, the effect of climate variables not only affects crop outputs of a country but also influences economic value in different economic sectors (Lanzafame 2014; Alagidede et al. 2016; Dafermos et al. 2018; Rezai et al. 2018). For instance, Lanzafame (2014) and Alagidede et al. (2016) studied the effects of climatic variables on the national income of African countries. These studies employed the panel cointegration methodology to capture the long-run and short-run effects of climate change on economic growth. In this study, an augmented neoclassical Cobb-Douglas production function in equation (1) is considered to detect the impacts of climatic and non-climatic variables on the economic growth of the agricultural sector. The Cobb-Douglas structure using the aggregate values of the agricultural sector, which applies the natural logarithmic function, is modified from the studies of Lanzafame (2014) and Alagidede et al. (2016), as expressed in equation (2).

$$Y_{it} = A_{it}^{\beta_1}.L_{it}^{\beta_2}.CF_{it}^{\beta_3} \tag{1}$$

$$\ln Y_{it} = \alpha_0 + \beta_1 \ln A_{it} + \beta_2 \ln L_{it} + \beta_3 \ln CF_{it} + e_{it} \tag{2}$$

where Y is the agricultural economy represented by the gross provincial product (GPP) of the agricultural sector (million Thai baht), α and β are the estimated parameters, e is the random error term with zero mean and constant variance, A is the agricultural land use (rai: 6.25 rai equals one hectare), L is the number of agricultural households, and CF represents the climatic factors, including Rf as the amount of total rainfall in a year (millimeters: mm), Rfd as the rainfall intensity (millimeters/day: mm/day), AverT as the mean average temperature (degrees Celsius: °C), MinT as the mean minimum temperature (degrees Celsius: °C), and MaxT as the mean maximum temperature (degrees Celsius: °C). The subscript (it) represents a panel dataset that consists of the province i at the time period of t over the period of 1995 to 2019. The descriptive statistics of the variables used are reported in Table 1.

<<< Insert Table 1 >>>

The panel variables of the agricultural economy (Y), agricultural land use (A), agricultural households (L), mean average temperature (AverT), mean minimum temperature (MinT), mean maximum temperature (MaxT), rainfall (Rf), and rainfall intensity (Rfd) display summary statistics, including mean (Mean), maximum (Max), minimum (Min), and standard deviation (S.D.). The study includes 76 provinces that cover the agricultural areas of the country. The panel dataset comprises 1,900 observations in total collected from the Office of Agricultural Economics, Thailand.

This study applies panel cointegration using an autoregressive distributed lag (ARDL) structure which is well-known as a bounds cointegration analysis, proposed initially by Pesaran et al. (1996, 2001). The main advantage of the panel bounds cointegration using the ARDL structure is to capture long-run and short-run dynamic effects, even though the relationship of the variables is questionable as it features a mixture of stationary and non-stationary datasets. In other words, the variables can be cointegrated without a purely I(1) process which is different from the traditional cointegration tests, such as the methods of Kao (1999) and Pedroni (2004).

Therefore, for the first step in estimating panel cointegration, it needs to be confirmed that the variables are not integrated more than order one, with the expectation of containing the stationary I(1) or I(0) process. A common unit root (e.g., LLC) and an individual unit root (e.g., IPS, ADF-Fisher, PP-Fisher) are used to analyze the characteristics of the panel dataset before performing the cointegration. The pooled mean group (PMG) estimation of Pesaran et al. (1999) is considered for the ARDL model regarding the homogeneity of the long-run coefficients to be identical for all provinces, and for heterogeneity of the short-run coefficients to be random. To estimate the long-run and short-run effects, there are two steps included (Attiaoui et al., 2017; Attiaoui and Boufateh 2019): (1) confirmation of the existence of cointegration using the ARDL bounds test, and then (2) detection of the short-run response using the error correction model (ECM).

To confirm the existence of cointegration, according to Pesaran et al. (1996, 2001), the bounds model, including previous lags of endogenous and exogenous variables, is structured as ARDL (p, q, …, q) as expressed in equation (3).

$$\Delta \ln Y_{it} = \alpha_0 + \beta_1 \ln Y_{it-1} + \beta_2 \ln A_{it-1} + \beta_3 \ln L_{it-1} + \beta_4 \ln CF_{it-1}$$

$$+\sum_{j=1}^{p-1}\beta_5\Delta\ln Y_{it-j}+\sum_{j=0}^{q-1}\beta_6\Delta\ln A_{it-j}+\sum_{j=0}^{q-1}\beta_7\Delta\ln L_{it-j}+\sum_{j=0}^{q-1}\beta_8\Delta\ln CF_{it-j}+e_{it} \quad (3)$$

where p and q are the lag lengths of the time period for endogenous and exogenous variables selected from the Akaike information criterion (AIC) and the Schwarz information criterion (SIC).

The null hypothesis (H_0) of the ARDL bounds tests is based on the F-statistics or the Wald coefficient test that provides the absence of a long-run relationship as H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$, as well as the alternative hypothesis (H_A) for indicating the presence of a long-run relationship as H_A: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq 0$. The outputs of the bounds test can be derived from three conclusions. First, if the computed F-statistic value of the Wald coefficient is greater than the upper critical bounds value, then the null hypothesis of the absence of cointegration is rejected. It can be concluded that all of the variables included in the specification ARDL model contain the I(1) process. On the other hand, if the computed F-statistic value is less than the lower bounds, the null hypothesis of the absence of cointegration cannot be rejected. However, if the computed F-statistic value falls within the bounds, then this would indicate that any absence or presence of cointegration is inconclusive.

To detect the short-run dynamic effects, the ARDL based on the ECM structure is applied with the specified model, which can be expressed in equation (4).

$$\Delta\ln Y_{it}=\alpha_0+\sum_{j=1}^{p-1}\beta_1\Delta\ln Y_{it-j}+\sum_{j=0}^{q-1}\beta_2\Delta\ln A_{it-j}+\sum_{j=0}^{q-1}\beta_3\Delta\ln L_{it-j}+\sum_{j=0}^{q-1}\beta_4\Delta\ln CF_{it-j}+\gamma ECT_{it-1}+\omega_{it} \quad (4)$$

where ECT is the error correction term (ECT) or the part of disequilibrium that is derived from the long-run relationship, γ is the speed of adjustment of the model returning to the equilibrium state, and ω is the white noise $\sim N(0, \sigma^2)$. In addition, this study captures the expected variance (e_{it}^2) of lnY from equation (2) to estimate the variability or risk of economic value in the agricultural sector, which is influenced by climatic and non-climatic factors, following the same process as the analysis of lnY.

Empirical analysis and discussion

First, to prevent a spurious relationship from occurring before performing panel data analysis, we need to verify the characteristics of the panel dataset because it might be influenced by the time effect (Granger and Newbold 1974). Even though the ARDL bounds test does not require stationarity of all variables in the same order, it is necessary to confirm that the variables should not be integrated more than order one or I(1) level. To handle this issue, a common unit root of Levin, Lin, and Chu (LLC) and an individual unit root of Im, Pesaran, and Shin (IPS), ADF-Fisher, and PP-Fisher are employed to identify the order of integration in each panel dataset. The Schwarz information criterion (SIC) is considered to determine the optimal lag selection in testing. The panel dataset for all unit root tests using the model, including a constant and time trend, can be used to reject the null hypothesis of non-stationarity when the p-values from the analysis are below the 0.05 level. Suppose the hypothesis of non-stationarity cannot be rejected; in that case, it is necessary to include more than one order of integration to perform the unit root tests again until the results approach stationarity.

<<<Insert Table 2>>>

The results of the LLC, IPS, ADF-Fisher, and PP-Fisher unit root tests in Table 2 indicated that the variables have different test outputs. The unit root tests of lnY, lnA, and lnL cannot be used to reject the hypothesis at the I(0) level because the p-values in parenthesis are greater than the 0.05 level, except for lnA, which can be used to reject the hypothesis at I(0) level only when testing under the LLC method. Then, the first order of integration or the I(1) level must be tested again, and it was found that the variables of lnY, lnA, and lnL can be used to reject the hypothesis, which means that these three variables contain unit roots at the stationary I(1) level, except for lnA which contains I(0) for a common unit root test and I(1) for an individual unit root test. However, the variables of lnAverT, lnMinT, lnMaxT, lnRf, lnRfd, and $\ln e^2$ are found to reject the hypothesis at the I(0) level as there are p-values in parenthesis below the 0.05 level. Hence, it can be concluded that the variables of lnAverT, lnMinT, lnMaxT, lnRf, lnRfd, and $\ln e^2$ contain unit roots at the stationary I(0) level. The results in Table 2 confirm that the variables used in this study can be integrated with not more than order one, which is in compliance with the conditions of the ARDL bounds test.

<<<Insert Table 3>>>

According to the unit root results, this study can apply the ARDL bounds test for establishing cointegration based on lnY and the variance of lnY ($\ln e^2$) equations, including the independent variables of lnA, lnL, lnAverT, lnMinT, lnMaxT, lnRf, and lnRfd in analysis. The ARDL bounds structure estimates a general-to-specific cointegration. The F-statistic value can be calculated using the Wald coefficient test. The results of general-to-specific ARDL bounds tests shown in Table 3 indicate that the equations of lnY and lne^2 have F-statistic values of 8.624 and 10.961, respectively, with a statistical significance at the level of 0.01. The computed F-statistic values of lnY and the variance of lnY (lne^2) equations are greater than the upper critical bounds value or I(1) level in all cases of Pesaran et al.'s (2001) statistical table. Thus, the null hypothesis of the absence of cointegration is rejected. The results in Table 3 suggest that the lnY and lne^2 equations included in the specification ARDL model have cointegration with the variables of lnA, lnL, lnAverT, lnMinT, lnMaxT, lnRf, and lnRfd.

The results of the long-run and short-run effects of climatic and non-climatic variables on the economic growth of the agricultural sector and their variability are presented in Table 4. The PMG estimation based on the ARDL structure is performed using the Cobb-Douglas function. The assumptions from the PMG control are that the long-run coefficients are to be homogeneous for all provinces, and the short-run coefficients are to be heterogeneous for provincial-specific effects.

<<<Insert Table 4>>>

The long-run coefficients show that agricultural households and total rainfall have a significant positive effect on the agricultural economy. A one percent increase in the number of agricultural households will increase the agricultural economy by 0.335 percent, and a one percent increase in total rainfall will increase the agricultural economy by 2.491 percent. However, mean minimum temperature, mean maximum temperature, and rainfall intensity have a significant adverse effect on the agricultural economy. A one percent increase in the mean minimum temperature, mean maximum temperature, and rainfall intensity will reduce the agricultural economy by 6.223 percent, 6.238 percent, and 0.944 percent, respectively. There is no long-run association of agricultural economy with agricultural land use and mean average temperature when considering the statistical significance at the level of 0.05. The variability of the agricultural economy in Table 4 indicates that agricultural households and mean average temperature have a significant negative effect on the variability of the agricultural economy. A one percent increase in the number of agricultural households will decrease the variability of the agricultural economy by 0.094 percent, and a one percent increase in mean average temperature will lead to a reduction in the variability of the agricultural economy by 2.565 percent. However, agricultural land use has a significant positive effect on the variability of the agricultural economy. A one percent increase in agricultural land use will lead to increased variability of the agricultural economy by 0.128 percent. There is no long-run association of agricultural economy variability with mean minimum temperature, mean maximum temperature, total rainfall, and rainfall intensity when considering the statistical significance at the level of 0.05. The results of short-run coefficients in Table 4 indicate that changes in mean average temperature and total rainfall are positively associated with the agricultural economy, while changes in rainfall intensification are negatively associated with the agricultural economy. In addition, variability of the agricultural economy is positively associated with the agricultural households but negatively associated with the mean minimum temperature. Responding to sudden shocks, the models of the agricultural economy and variability of the agricultural economy both have small convergence coefficients (ECT_{it-1}) of 0.063 and 0.248, respectively, with a negative sign as expected, and statistical significance to indicate an adjustment to the equilibrium state that is not immediately returned to the steady-state.

From the results of the long-run coefficient analysis above, it is found that the climatic and non-climatic factors that positively affect the agricultural economy, considering the magnitude of the impact, are the increases in total rainfall and agricultural households, respectively. The findings point out that rainfall is a climatic factor that positively influences the aggregate values of the agricultural sector, with most of Thailand's agricultural production structure being crops such as rice, cassava, Para rubber, oil palm, sugarcane, etc. (Office of Agricultural Economics 2021). There is a need to use a lot of water for growing these crops, especially in rainfed agriculture, which accounts for approximately 78 percent of the country's total arable land. In addition, some agricultural areas are found to be unsuitable for crop production, especially in the Northeast, which occupies almost a third of the country. This is due to the fact that most of the aforementioned agricultural areas are outside irrigated areas, have arid soil conditions, and have low productivity compared to other regions of the country. This is consistent with the findings of Holst et al. (2013), which found that an increase in rainfall by 100 mm would result in increased grain yields in cases of northern and southern China. Therefore, increased total rainfall will result in an adequate water supply for cultivation and thus increase agricultural productivity (Holst et al. 2013; Sinnarong et al. 2018), which will ultimately result in increased income for the agricultural sector. Meanwhile, the climatic factors that negatively affect the agricultural economy, considering the magnitude of the impact, are the increase in mean maximum temperature, mean minimum temperature, and rainfall intensity, respectively. The findings can explain that mean maximum and mean minimum temperatures have a negative effect on the productivity of agriculture because, during the period of maximum and minimum temperature increases, it will affect plant growth, which will ultimately affect crop revenue. This finding is in line with the study of Alagidede et al. (2016), which found that higher temperatures could affect economic performance in Sub-Saharan Africa. Akram and Gulzar (2013) also confirmed that temperature harms economic growth and efficiency of agricultural production, consistent with the studies by Cabas et al. (2010), Aye and Ater (2012), and Holst et al. (2013), which found that temperature increased could reduce the productivity of agriculture. The distribution of rainfall is also important for plant growth. Rainfall intensity has a detrimental effect on crops, causing crop damage and flooding as well as causing the soil to lose its fertility and nutrients due to the leaching of the soil surface. The variability in rainfall intensity has a direct negative effect on crop productivity (Nciizah and Wakindiki 2014). This finding is in line with the study of Poudel and Kotani (2013), which found that variability of rainfall generally has adverse impacts on crop productivity, consistent with the Weersink et al.'s (2010) results, which found that variation in seasonal rainfall has a negative effect to the yields of corn, soybean, and winter wheat. Hence, the rainfall intensity ultimately affects the income of the agricultural sector indirectly. The short-run coefficient analysis reveals that climatic factors positively influencing the agricultural economy, considering the magnitude of the impact, are mean average temperature, and the increase in total rainfall, while the intensity of total rainfall has a negative influence on the agricultural economy. The findings show that changing climate factors such as decreases in mean average temperature and total rainfall, as well as increases in rainfall intensification each year, will affect the efficiency of agricultural production, which will reflect the agricultural value accordingly. For this reason, governments and related stakeholders can use these findings, along with annual climate predictions, to effectively plan to optimize seasonal cultivation patterns for producing crops, such as changing crop varieties to suit the climatic conditions, for example, switching to crops that need less water, particularly during periods of drought (i.e., cultivating maize instead of rice), changing techniques and cropping patterns to suit water sufficiency and temperature conditions, and reserving water availability for cultivation during the dry season. Therefore, it is concluded that optimizing cultivation patterns in each crop year will mitigate the effects of climate change on agricultural productivity, thereby reducing the risk and income damage to the agricultural economy.

Conclusion and policy recommendations

The agricultural sector is essential to economic development in Thailand as it is responsible for the production of food for humans and animals, as well as raw materials for other industrial sectors. Agriculture in the country is particularly vulnerable due to its dependence on climatic factors such as rainfall, temperature, humidity, sunlight, and so on, especially crop production, which represents most of the agricultural revenue from this sector, which is directly and normally affected by weather and climate fluctuations. Climate change has a direct impact on agricultural productivity, which also affects agricultural revenue. Thus, the main purpose of this study is to assess the impact of climate change on the agricultural economy in Thailand. The panel datasets were obtained from 1995 to 2019 for 76 provincial levels. The ARDL-PMG estimation is employed using the Cobb-Douglas structure to detect the impacts of non-climatic factors such as agricultural land use and agricultural households, as well as climatic factors such as mean average temperature, mean minimum temperature, mean maximum temperature, total rainfall, and rainfall intensification, on the agricultural economy and the variability of the agricultural economy.

First, the results of general-to-specific ARDL bounds tests confirm the existence of long-run equilibrium in the agricultural economy and its variability. This means that climatic and non-climatic factors have a long-term association with the agricultural economy and variability of the agricultural economy in Thailand. Second, the long-run estimation presents that the positive factors affecting the agricultural economy are the increase in total rainfall and agricultural households. At the same time, the negative factors affecting the agricultural economy are the increase in mean maximum temperature, mean minimum temperature, and rainfall intensity. The factor contributing to the higher variability of the agricultural economy in the long-run association is the increase in agricultural land use. The factors that reduce the variability of the agricultural economy are the increases in mean average temperature and agricultural households. Third, the short-run estimation presents that the positive factors affecting the agricultural economy are mean average temperature and total rainfall. The negative factor affecting the agricultural economy is the increase in rainfall intensification. The factor contributing to the higher variability of the agricultural economy in the short-run association is the increase in agricultural households, but the mean minimum temperature is shown to reduce the variability of the agricultural economy.

The findings highlight the contributing factors to long-term increases in the agricultural economy and reducing variability in the agricultural economy. This study confirms that extreme events, such as the increase in mean maximum temperature, mean minimum temperature, and rainfall intensification, severely affect the agricultural economy, but an increase in total rainfall will help mitigate that impact and will increase the growth of the agricultural sector in the short-term and long-term period. Hence, from the findings of this study, it can be concluded that agricultural households with better access to water resources can contribute to raising the agricultural revenue of the country. Although extreme events such as increases in maximum and minimum temperatures and rainfall intensification will affect agricultural productivity, having sufficient water resources such as irrigation and rainfall for agriculture will mitigate the effects of such extreme events. In addition, the government and related stakeholders should raise awareness of climate change as it affects the economic growth of the country, which may have serious impacts on the economy, society, and environment in the near future. The growth of the agricultural sector must be calculated in terms of its effect on the environment, as agricultural production is one of the key factors for global warming. There should be appropriate agricultural production supervision and control measures to mitigate the negative impact on the environment to the greatest possible extent, such as using fertilizers properly to reduce carbon dioxide emissions or using suitable production techniques that help reduce environmental pollution as well as transferring responsibility for these impacts to the contributors such as farmers or producers, consumers, manufacturers, traders, and others throughout the agricultural supply chain. For the limitations, this empirical study provides an indirect analysis of the impact of climate and weather variability on the agricultural economy, so it would be worthwhile to focus directly on the efficiency of agricultural production, while other function forms, estimators, methods, and climatic factors might be considered in order to analyze the appropriate model to be most suitable for estimation.

Table 1 Summary statistics of the variables

Variable	Mean	Max	Min	S.D.	Obs.
Y (million baht)	11,628	74,734	810	10,282	1,900
A (rai)	1,970,765	9,079,441	109,406	1,441,063	1,900
L (household)	76,944	344,880	1,930	58,317	1,900
AverT (°C)	27.415	29.773	22.342	1.003	1,900
MinT (°C)	22.798	31.950	15.858	1.535	1,900
MaxT (°C)	33.255	35.900	29.708	0.976	1,900
Rf (mm)	1,302.769	5,883.500	210.560	665.914	1,900
Rfd (mm/day)	8.489	30.886	2.570	3.475	1,900

Source: Office of Agricultural Economics, Thailand.

Table 2 The results of panel unit root tests

Variable	LLC		IPS		ADF-Fisher		PP-Fisher	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
lnY	2.436	-28.481	3.069	-26.332	98.180	821.284	93.371	1132.060
	(0.992)	(<0.001)	(0.998)	(<0.001)	(0.999)	(<0.001)	(0.999)	(<0.001)
lnA	-2.756		-1.204	-19.943	177.920	636.959	163.904	966.739
	(0.002)		(0.114)	(<0.001)	(0.073)	(<0.001)	(0.240)	(<0.001)
lnL	13.170	-21.911	6.946	-17.453	125.453	582.076	74.291	663.410
	(1.000)	(<0.001)	(1.000)	(<0.001)	(0.943)	(<0.001)	(1.000)	(<0.001)
lnAverT	-30.116		-28.516		893.831		1567.120	
	(<0.001)		(<0.001)		(<0.001)		(<0.001)	
lnMinT	-22.029		-20.988		667.874		1456.920	
	(<0.001)		(<0.001)		(<0.001)		(<0.001)	
lnMaxT	-26.908		-23.882		745.133		1396.190	
	(<0.001)		(<0.001)		(<0.001)		(<0.001)	
lnRf	-11.338		-11.688		404.166		429.987	
	(<0.001)		(<0.001)		(<0.001)		(<0.001)	
lnRfd	16.546		-18.279		593.208		1173.100	
	(<0.001)		(<0.001)		(<0.001)		(<0.001)	
$\ln e^2$	-6.402		-10.483		382.741		397.688	
	(<0.001)		(<0.001)		(<0.001)		(<0.001)	

Note: The values in ( ) are the corresponding p-values.

Table 3 The results of general-to-specific ARDL bounds tests

Variable	F-statistic	p-value	Conclusion
lnY	8.624	<0.001	Cointegration
lne^2	10.961	<0.001	Cointegration

Bounds test (F-statistic)	0.01 level		0.05 level		0.1 level	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
Case I	2.45	3.79	1.91	3.11	1.66	2.79
Case II	2.62	3.77	2.11	3.15	1.85	2.85
Case III	2.79	4.10	2.22	3.39	1.95	3.06
Case IV	2.93	4.06	2.38	3.41	2.13	3.09
Case V	3.15	4.43	2.55	3.68	2.26	3.34

Note: Bounds (F-statistic) tests refer to Pesaran et al. (2001).

Table 4 The results of long-run and short-run effects using PMG estimation

Variable	Model: lnY			Model: lne^2		
	Coefficient	t-statistic	p-value	Coefficient	t-statistic	p-value
Long-run coefficient						
lnA	0.120	0.842	0.399	0.128	4.187	<0.001
lnL	0.335	2.054	0.040	-0.094	-3.189	0.001
lnAverT	9.144	1.921	0.054	-2.565	-1.972	0.048
lnMinT	-6.223	-2.837	0.004	0.913	1.648	0.099
lnMaxT	-6.238	-2.237	0.025	1.501	1.853	0.064
lnRf	2.491	13.398	<0.001	-0.031	-1.224	0.221
lnRfd	-0.944	-4.977	<0.001	-0.023	-0.661	0.508
Short-run coefficient						
ECT_{it-1}	-0.063	-10.414	<0.001	-0.248	-9.651	<0.001
ΔlnA	0.222	0.781	0.434	0.017	0.047	0.962
ΔlnL	-0.087	-1.779	0.075	0.297	3.007	0.002
ΔlnAverT	1.470	2.249	0.024	1.955	1.695	0.090
ΔlnMinT	-0.139	-0.368	0.712	-1.078	-2.023	0.043
ΔlnMaxT	-0.230	-0.534	0.593	-0.455	-0.588	0.556
ΔlnRf	0.066	2.533	0.011	0.172	1.806	0.071
ΔlnRfd	-0.096	-3.817	<0.001	-0.100	-1.762	0.078
No. of province	76			76		
No. of observations	1900			1900		

Δ is the first order of integration.

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Declarations

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