# Estimating the potential impact of climate change on energy crop productivity in Thailand: An empirical study of sugarcane, cassava, and oil palm using panel data analysis

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## Abstract

In recent years, biofuels have played an important role in the economic development of Thailand as a clean and environmentally-friendly source of energy that can be produced in the agricultural sector. Thailand has particularly high efficiency in energy crop production, making the country a valuable reserve energy source. The main purpose of this study is to examine the potential impact of climate change on energy crop productivity in Thailand, specifically for sugarcane, cassava, and oil palm, using panel data analysis from 1995 to 2020 at the provincial level throughout the country. The expected yield and variance of the yield are estimated using Just and Pope's procedure. The empirical results reveal that temperature and rainfall have different effects on the efficiency of energy crop production. The estimated potential impact indicates that higher temperatures above the average level affect energy crop productivity more than rainfall changes in different directions. The findings conclude that in order to maximize domestic energy crop productivity, it is necessary to prepare the cultivation areas to suit the local climate and weather conditions.

**Keywords:** Biofuel; Renewable Energy; Crop Yield; Weather; Projection; Production Function

## 1 Introduction

Climate change is a global challenge that has been discussed continuously in communities around the world as it causes numerous environmental and ecological problems such as heavy rain and severe storms, weather fluctuations, El Niño and La Niña phenomena, droughts, wildfires, floods, and landslides. There may also be habitat loss for various species, extinction of wildlife, and biodiversity loss, as well as the degradation of natural resources and the environment (e.g., forests, soils, water, air, seas, etc.). The severity of climate change may affect the economic and social systems of many nations globally. For example, production, especially in the agricultural sector, may be damaged by droughts and floods, which results in industrial sectors lacking the necessary raw materials to produce goods and services, as well as negative effects on farmers and other related stakeholders in the agricultural supply chain system. The export of agricultural products will be disrupted, and its volume will be declined accordingly. Therefore, the revenue of a country like Thailand will be decreased by the impact of climate change, which will eventually result in an economic slowdown and the loss of social welfare.

Climate change is mainly caused by the greenhouse effect, in which the Earth's atmosphere absorbs some of the Sun's heat, resulting in global warming and many negative consequences on economic, social, and environmental systems. The Intergovernmental Panel on Climate Change (IPCC) reports that climate change refers to the changes in the planet's temperature, precipitation (e.g., drizzle, rain, sleet, snow, hail, etc.), sea level, wind pattern, solar radiation, heatwave, and other measures of climatic indicators occurring over several decades or longer. Such measures can be identified based on statistical approaches generally used through the mean and variability of climate properties (UNFCCC, 2011; Hertel & Rosch, 2010; Sinnarong, 2017).

Greenhouse gases have major influences on climate change and are mainly from human activities, economic development, and changing social conditions. Agriculture is considered the most vulnerable sector to the impacts of climate change compared to other economic sectors, as it heavily relies on weather patterns for agricultural activities such as crop cultivation, livestock rearing, and fishery. These weather patterns are predicted to become increasingly extreme in the future (Mendelsohn, 2008). Agriculture has played an important role in Thailand's economic and social development throughout history because it is respected as a source of food supply, occupations for many Thai people, national revenue, and basic needs for human life. Most of the country's population relies on the agricultural sector, 47.38 percent, which can generate value-added to the overall economy by more than 43,575 million USD. According to statistical information, in 2020, Thailand received revenue from the exports of agricultural commodities equal to 38,344 million USD, which can be calculated as a proportion of 12.56 percent when comparing the gross domestic product (GDP). Thailand is a medium-sized country in Southeast Asia comprising 513,115 square kilometers, 46.54 percent or 23.88 million hectares, of which is devoted to agricultural concerns. Thailand is a leader in producing and exporting agricultural commodities to the world market, such as rice, cassava, natural rubber, oil palm, sugarcane, tropical fruits, vegetables, poultry, and fishery products (Office of Agricultural Economics, 2021a, 2021b, 2021c).

In recent years, Thailand has been influenced by weather variabilities, such as changes in the structure of daily rainfall and temperature patterns. For example, changes in the number of rainy days will influence the intensity of extreme events as well as changes in maximum, minimum, and average temperatures each year, which will influence and threaten the living conditions of humans and other species as a consequence. A report by the Thai Meteorological Department (2014) and Office of Agricultural Economics (2021d) revealed the changes in mean average temperature (averT), mean minimum temperature (minT), and mean maximum temperature (maxT) in Thailand. The mean temperature of the three series during the period from 1995 to 2020 at the provincial level is displayed in Figure 1. There are indications that all three series have had moderate fluctuations in each province for almost 26 years, which tended to change in a higher direction explicitly, especially for the maxT series. The annual total rainfall and number of rainy days by region in Thailand from 2011 to 2020 are shown in Table 1. There are also changes in the structure of daily rainfall in all regions, which have occurred over the past ten years, especially in terms of fewer rainy days and the greater intensity of daily rainfall.

**<<<Insert Figure 1>>>**

**<<<Insert Table 1>>>**

As mentioned previously, the climate in Thailand has been volatile and seems to be intensifying, thus affecting the productivity of Thailand's economy, especially agricultural production, which is highly vulnerable to climate change. Importantly, agriculture has long played a vital role in the economic and social development of Thailand as it is a major source of food production and basic human needs for living. Farmers and farming occupations are regarded as the backbone of the nation. Most of the population has been engaged in farming since their ancestors, with local agricultural wisdom passed down from generation to generation. In Thailand, agricultural commodities are used as a food source for direct consumption in the vast majority of households (e.g., rice, vegetables, fruits, seafood, chicken, pork, etc.) or used as raw materials for processing into commodities and products (e.g., rubber, cassava, sugarcane, oil palm, etc.). Besides, the agricultural sector can generate income and bring hundreds of billions of baht into the country annually, making Thailand one of the world's top producers and exporters of agricultural commodities (e.g., rice, rubber, cassava, sugarcane, tropical fruit, etc.). For these reasons, the government and private sectors have promoted Thailand as the "kitchen of the world", using the phrase in a national development strategy by pushing such policies into sector-by-sector economies, especially the agricultural sector, which is a production sector in the upstream level of the country (FAO, 2011; Ministry of Agriculture and Cooperatives, 2011).

In the past, it could be seen that the main purposes of agriculture in growing crops were for direct consumption as food, raw materials for the production of animal feed, raw materials to feed into the industrial sector, etc. At present, the agricultural sector has increasingly focused on growing crops for use in the energy sector due to the increasing demand for energy crops to produce biofuels. Using biofuels generates less carbon dioxide and air pollution compared to fossil fuels. The governments and private sectors in many countries are concerned with environmental and global warming issues. Therefore, promoting and supporting the use of renewable energy (e.g., wind energy, hydropower, solar energy, geothermal energy, biofuels, etc.) has been considered to replace fossil fuel energy (e.g., coal, petroleum, natural gas, etc.). Particularly, the use of crops to produce renewable energy has been considered a clean energy option. It can be used as a source of renewable fuel at all times. The use of crops to produce this alternative energy, also called "biofuel or bioenergy", is mostly derived from agricultural commodities such as oil palm, sugarcane, cassava, corn, soybeans, etc. Biofuels in Thailand derived from agricultural production can be classified into two main categories: (1) ethanol is used as a mixture with benzyl oil for gasohol. Domestically, most ethanol is produced from sugarcane and cassava. (2) biodiesel is used in combination with kerosene or diesel for palm-diesel production. Most of the biodiesel produced domestically comes from oil palm. However, the use of ethanol and biodiesel to replace gasoline and diesel in the transport sector currently accounts for only ten percent of the country's total demand (Department of Alternative Energy Development and Efficiency, 2021).

In recent years, the demand for agricultural raw materials to produce alternative biofuel energy is likely to increase because the use of biofuels reduces pollution problems and is environmentally friendly. It is also an alternative energy source that will help solve the problem of fossil fuel shortage in the near future. It can be used as an unlimited replacement for traditional energy that human beings can produce naturally. This is especially important for Thailand, which is known as a country that has a high potential to grow energy crops for the production of biofuels (i.e., ethanol and biodiesel), namely sugarcane, cassava, and oil palm. A report of agricultural statistics in Thailand by the Office of Agricultural Economics (2021b) indicated that sugarcane production amounted to 76 million tons from 1.71 million hectares of harvested area, accounting for 13.14 percent of the world market share. Based on this amount, a certain amount of sugarcane and molasses was used as raw materials, 3.56 million tons and 0.85 million tons, respectively, to produce ethanol equal to 924.63 million liters. During the same period, the production of cassava in Thailand amounted to 30 million tons from 1.43 million hectares of harvested area, accounting for 76.34 percent of the world market share. Based on this amount, cassava was used as raw materials in the amount of 3.46 million tons to produce ethanol, equal to 553.04 million liters. Meanwhile, the production of oil palm was 15.66 million tons, accounting for 2.65 million tons of crude palm oil, from 0.94 million hectares of harvested area, accounting for only 0.45 percent of the world market share since it was produced primarily for domestic use. Based on this amount, crude palm oil was used as raw materials in a certain amount of 1.36 million tons or equivalent to 7.70 million tons of oil palm to produce biodiesel, equal to 1,843.19 million liters (Department of Alternative Energy Development and Efficiency, 2021).

Climate change is a factor that influences Thailand's energy crop productivity, including sugarcane, cassava, and oil palm. More severe global warming will result in the increased frequency and intensity of extreme weather events, which will affect the efficiency of energy crop production as well. For example, studies by Knox et al. (2010), Baez-Gonzalez et al. (2018), Sonkar et al. (2020), and Vera et al. (2020) estimated the impact of climate change on sugarcane production in Swaziland, Mexico, India, and Brazil, respectively. The results confirmed that climate variability had influenced sugarcane productivity in the countries used in the studies. In addition, studies by Okoro et al. (2017), Chankong et al. (2019), and Sarkar et al. (2020) found that climate change affected the efficiency of oil palm production in Nigeria, Thailand, and Malaysia, respectively. Nonetheless, Jarvis et al. (2012) found that climate conditions had a positive effect on cassava production in the case of Nigeria. On the other hand, Pipitpukdee et al. (2020) concluded that the changes in climate factors would have a negative impact on harvested areas and the yield of cassava in Thailand. For these reasons, the main purpose of this study is to analyze the potential impact of climate change on energy crop productivity in Thailand, particularly for sugarcane, cassava, and oil palm. In order to assess the capacity to produce sufficient energy crops to replace fossil fuels and meet the demand for household consumption, animal feed, raw materials for various industrial sectors, and energy production, it is important to formulate policy implications for the appropriate use of renewable energy. The study's outcomes will help raise awareness among the Thai government and other stakeholders, as well as create adaptation guidelines and policies for Thailand's agriculture and energy consumption sectors to address climate change issues in the future.

## 2 Methodology

### 2.1 Model specification

This study applies Just and Pope's (1978, 1979) stochastic production function (SPF) based on panel data analysis for detecting the impact of climate and weather variability on energy crop productivity in Thailand, specifically for sugarcane, cassava, and oil palm. Just and Pope's procedure assumes that the expected mean yield and variance of the yield can be expressed in equation (1).

$$Y_{it} = f(X_{it,k}, \beta_k) + u_{it} = f(X_{it,k}, \beta_k) + h(X_{it,k}, \alpha_k)^{0.5}.\varepsilon_{it} \quad (1)$$

where $Y_{it}$ is the energy crops produced in the agricultural sector of Thailand, namely, sugarcane, cassava, and oil palm, f(.) is the mean yield function, $X_{it}$ is the vector kth explanatory variables, $\beta_k$ and $\alpha_k$ are the vectors of estimated parameters, $u_{it}$ is the heteroskedastic disturbance term, h(.) is the yield variance function, $\varepsilon_{it}$ is the random error term with zero mean and variance of $\sigma^2$. The subscript (it) represents a panel dataset that consists of province i at time period t. Based on equation (1), the expected mean yield $[E(Y_{it}) = f(X_{it,k}, \beta_k)]$, and variance of the yield $[Var(Y_{it}) = Var(u_{it}) = h(X_{it,k}, \alpha_k).\sigma^2]$ can be independently influenced by climatic and non-climatic variables.

To estimate the SPF in equation (1), Just and Pope (1978, 1979) proposed the feasible generalized least squares (FGLS) and maximum likelihood estimator (MLE). The MLE is a consistent and more efficient estimator than FGLS, particularly for a small sample size (Saha et al., 1997). However, this study provides a large sample size for all provinces that produce each energy crop over a period from 1995 to 2020. Therefore, FGLS and MLE are used to estimate equation (1).

The analysis of this study starts with a three-stage estimation of the FGLS. In the first stage, the ordinary least squares (OLS) technique is utilized to capture the residual from the expected mean yield equation to produce the variance of the yield because the $\sigma^2$ is an unobserved variable. The formulation of the expected mean yield can be expressed in equation (2).

$$\begin{aligned} Y_{it} = {} & \beta_0 + \beta_1 A_{it} + \beta_2 averT_{it} + \beta_3 minT_{it} + \beta_4 maxT_{it} + \beta_5 Rf_{it} + \beta_6 Rfd_{it} \\ & + \beta_7 averVT_{it} + \beta_8 minVT_{it} + \beta_9 maxVT_{it} + \beta_{10} Trend + u_{it} \end{aligned} \quad (2)$$

where Y is the output of crop yield (kilogram/hectare: kg/ha) for sugarcane, cassava, and oil palm, A is the harvested area (hectares: ha), averT is the annual mean average temperature (degree Celsius: °C), minT is the annual mean minimum temperature (degree Celsius: °C), maxT is the annual mean maximum temperature (degree Celsius: °C), Rf is the annual total rainfall (millimeter: mm.), Rfd is the average rainfall intensity (millimeters/day: mm./d), and Trend is the time trend representing the effect of technology improvement during the period of study, and averVT, minVT, and maxVT are the variations of averT, minT, and maxT, respectively. For the mean yield equation based on the Cobb-Douglas function, all variables, therefore, have transformed into logarithm form to explain marginal effects (it is commonly called the elasticity between the variables) of climatic and non-climatic variables to the expected crop yield.

The expected variance is assumed to be the exponential function as $E(\sigma^2_{it}) = \exp(Z'_{it}\alpha)$. In the second stage, the OLS squared residual as the representative of variance yield is performed in natural logarithmic form, $\ln(\hat{u}^2_{it})$ to be regressed by the explanatory variables, as expressed in equation (3).

$$\begin{aligned} \ln(\hat{u}^2_{it}) = {} & \alpha_0 + \alpha_1 A_{it} + \alpha_2 averT_{it} + \alpha_3 minT_{it} + \alpha_4 maxT_{it} + \alpha_5 Rf_{it} + \alpha_6 Rfd_{it} \\ & + \alpha_7 averVT_{it} + \alpha_8 minVT_{it} + \alpha_9 maxVT_{it} + \alpha_{10} Trend + v_{it} \end{aligned} \quad (3)$$

In the third stage, the expected crop yield based on equation (2) is re-estimated using the predicted error $(\hat{v}_{it})$ from the second step to weigh for generating the FGLS estimation. The advantage of this stage is beneficial for projecting the potential impact of changes in crop productivity for the future using the conditions of climate and weather information. To compare the estimation of the FGLS, however, the limited information maximum likelihood (LIML) estimation (commonly called the MLE method) is considered to analyze the expected crop yield. The log-likelihood function can be expressed in equation (4).

$$\mathrm{lnL} = -\frac{1}{2}\left[\mathrm{n.ln}(2\pi)\sum_{i=1}^{n}\ln(h(X_i,\alpha)^2) + \sum_{i=1}^{n}\frac{\left(Y_i - f(X_i,\beta)\right)^2}{h(X_i,\alpha)^2}\right]. \tag{4}$$

where α and β are the estimated parameters in a single-stage maximization under the assumptions of $Y_i \sim N(f(X_i,\beta)), h(X_i,\alpha)^2$, and $\varepsilon_i \sim N(0,1)$. The log-likelihood function is utilized: (1) to compare expected mean yield with the FGLS estimation and (2) to find out the most appropriate projection model for the potential impacts of climatic and non-climatic factors on energy crop productivity. The measures of root mean square error (RMSE) and mean absolute percentage error (MAPE), calculated using equation (5) and equation (6), respectively, are used to select the most appropriate projection model, as follows.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}.\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

$$\mathrm{MAPE} = \frac{1}{n}.\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{6}$$

where $y_i$ is the actual value, $\hat{y}_i$ is the predicted value, i is the sequence of observed information, and n is the total number of observations.

The scenarios for the climatic changes assume that temperature has increased by 1°C, 2°C, and 3°C in all three series simultaneously by increasing from the average level, together with the changes in total rainfall, to increase and decrease from the average level by 100 mm., 200 mm., and 300 mm., respectively. Moreover, the study sets the default to the yield projections based on temperature and rainfall at the average level, or it does not change in temperature (± 0°C) and total rainfall (± 0 mm.). Therefore, the projection consists of 28 scenarios in each case for three energy crops, with 84 scenarios in total. Further, this study assumes that other non-climatic factors do not change or remain constant over the projection scenarios, as well as other climatic factors equal to the mean value over the time projection.

### 2.2 Data and variables

The unbalanced panel datasets for climatic and non-climatic variables are considered from 1995 to 2020 at the provincial level of Thailand, obtained from the Office of Agricultural Economics in various forms. The study areas consist of 46 sugarcane-growing provinces, 49 cassava-growing provinces, and 66 oil palm-growing provinces, out of the total of 76 provinces in Thailand, excluding Bueng Kan because there is missing and unavailability of data as well as the fact it is recently established as a new province.

**<<<Insert Figure 2>>>**

Figure 2 displays an example picture of the distribution maps for energy crop production in Thailand, including sugarcane, cassava, and oil palm. It shows the distribution of energy crop production in 2020 at the provincial level, where the production areas with the most color concentrates are defined as a province with production higher than the average country's production.

**<<<Insert Table 2>>>**

The summary statistics for the panel data series in Table 2 present descriptive statistics for the variables used, such as mean value (mean), minimum value (min), maximum value (max), and standard deviation (S.D.). The samples utilized for analysis of sugarcane, cassava, and oil palm contained 1162 observations, 1221 observations, and 985 observations, respectively. A brief description of crop yields and climatic features can be summarized as follows. The annual average yield of sugarcane is 61144.662 kg/ha under the climatic conditions for the mean average temperature of 27.529°C, mean minimum temperature of 22.790°C, mean maximum temperature of 33.490°C, and total rainfall of 1135.653 mm. The annual average yield of cassava is 18652.500 kg/ha under the climatic conditions for the mean average temperature of 27.298°C, mean minimum temperature of 22.453°C, mean maximum temperature of 33.396°C, and total rainfall of 1151.245 mm. The annual average yield of oil palm is 11113.849 kg/ha under the climatic conditions for the mean average temperature of 27.518°C, mean minimum temperature of 23.008°C, mean maximum temperature of 33.232°C, and total rainfall of 1586.008 mm.

### 2.3 Pre-estimation of panel unit root and specification tests

Before performing the panel data analysis, there has to be testing for stationarity to prevent spurious results, as the panel dataset consists of a time trend component (Granger & Newbold, 1974). The common unit root process of Levin, Lin, and Chu (LLC) has been considered for testing the properties of panel datasets (Levin et al., 2002), which can be expressed as equation (7).

$$\Delta Z_{it} = \alpha_i + \rho Z_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta Z_{it-j} + \delta_i t + \theta_t + e_{it} \tag{7}$$

where Z is the panel dataset, subscript i is the index for the provincial level, subscript t is the time period, $\Delta$ is the order of integration, p is the lag length of the time series to be selected by the Schwartz information criterion, $\alpha_i$ and $\theta_t$ are the unit-specific fixed effects and unit-specific time effects, respectively, and e is the disturbance term. If the null hypothesis ($H_0$) of $\rho$ equal to zero for all i is rejected, then the variable will contain stationary property.

The results of panel unit root using the LLC procedure were presented in Table 3 based on the model, including the constant and time trend components in testing, as presented in equation (7). However, all variables used in Table 3 were in a linear form, and it was adjusted to the logarithm function to present the nature of the panel datasets.

**<<<Insert Table 3>>>**

The results of the panel unit root tests in Table 3 showed that all variables of Y, A, averT, minT, maxT, Rf, Rfd, averVT, minVT, and maxVT for sugarcane, cassava, and oil palm equations, had statistical significance at the 0.01 level. This implied that all variables were stationary at the level stage with the contained unit root I(0) process. Hence, the variables could be used in this order to analyze the classical panel regression model.

**<<<Insert Table 4>>>**

The panel specification tests in Table 4 consisted of the White heteroskedasticity, Wooldridge test for autocorrelation, and normality of residuals based on equation (2) using the panel OLS estimation. The results of White's test for heteroskedasticity using the LM statistic showed that the null hypothesis of "heteroskedasticity not present" was rejected with a statistical significance level of 0.01 for all three crop models. The Wooldridge test for autocorrelation in panel data also rejected the null hypothesis of "no first-order autocorrelation" with a statistical significance level of 0.01 for all three crop models. The $\chi^2$ statistic was utilized to test the normal distribution, and it was found that both models, sugarcane and oil palm, could reject the null hypothesis of "error was normally distributed" with a statistical significance level of 0.01, except in the case of cassava, which could not reject the null hypothesis considering the statistical significance of 0.05 level. From the specification tests presented in Table 4, it was confirmed that the classical panel OLS estimation was unsuitable for estimating the expected yield equation. Therefore, this study estimated the mean yield of sugarcane, cassava, and oil palm using the FGLS and MLE, as suggested by Just and Pope (1978, 1979).

## 3 Empirical results

### 3.1 Impact of climate change on mean yield and variance of the yield

The coefficients were evaluated for statistical significance at the 0.05 and 0.01 levels to characterize the relationship between the variables. Since the yields of the mean equation were based on the Cobb-Douglas function, it described the relationship as a percentage change or elasticity between variables. The estimated coefficients using the FGLS estimation of the mean yield equations for sugarcane, cassava, and oil palm were presented in Table 4. The non-climatic variables displayed that the harvested areas for sugarcane, cassava, and oil palm had a positive association with the mean yields with elasticities of 0.011, 0.016, and 0.162, respectively. Furthermore, technology improvement in the sugarcane, cassava, and oil palm equations had a positive association to mean yields with elasticities of 0.008, 0.018, and 0.094, respectively.

**<<<Insert Table 5>>>**

The results of climatic variables affecting the mean yields in Table 5 showed that mean average temperature was negatively associated with the yield of sugarcane, but it seemed to be positively associated with the yield of oil palm. When the mean average temperature increased by one percent, the yield of sugarcane reduced by 1.190 percent, but the yield of oil palm increased by 17.987 percent. However, if one percent of the mean minimum temperature increased, it reduced the yield of oil palm by 8.707 percent. An increase in mean maximum temperature by one percent led to an increase in the yield of cassava by 0.439 percent. The effect of total rainfall was found to be associated with crop yields in a positive relationship for the yield of cassava, but it seemed to be associated with a negative relationship for the yield of oil palm. If one percent of total rainfall increased, then it led to an increase in the yield of cassava by 0.040 percent, and it reduced the yield of oil palm by 1.614 percent. However, rainfall intensification showed a positive impact on only the yield of oil palm. If the average rainfall per time increased by one percent, it increased the yield of oil palm by 0.345 percent. The variability of mean average temperature was positively associated with the yield of sugarcane, but it was negatively associated with the yield of oil palm. The variability of mean minimum temperature was negatively associated with the yield of oil palm. In addition, the variability of mean maximum temperature was negatively associated with the yields of sugarcane and cassava.

The estimated coefficients using the LIML estimation of the mean yield equations for sugarcane, cassava, and oil palm were presented in Table 6. The non-climatic variables displayed that the harvested areas for sugarcane, cassava, and oil palm had a positive association with the mean yields with elasticities of 0.011, 0.016, and 0.124, respectively. Besides, technology improvement in the sugarcane and cassava equations had a positive association to mean yields with elasticities of 0.008 and 0.018, respectively.

**<<<Insert Table 6>>>**

The results of climatic variables affecting the mean yields in Table 6 showed that mean average temperature had a negative effect only on the yield of sugarcane. An increase of one percent in the mean average temperature reduced the yield of sugarcane by 1.131 percent. There was no association between the mean minimum temperature and the yields of all three crops. For mean maximum temperature, there was a positive association only with the yield of cassava. An increase of one percent in the mean maximum temperature also increased the yield of cassava by 0.439 percent. The effect of total rainfall showed that an increase of one percent in total rainfall reduced the yield of sugarcane by 0.035 percent and increased the yield of cassava by 0.040 percent. There was no association between rainfall intensification and the yields of all three crops. The variability of mean average temperature was associated with the yields of sugarcane in a positive direction and oil palm in a negative direction. The variability of mean minimum temperature was negatively associated with the yield of oil palm. Moreover, the variability of mean maximum temperature was negatively associated with the yields of sugarcane and cassava.

Based on the results in Table 5 and Table 6, the appropriate prediction method to estimate the potential impact of climate change on sugarcane, cassava, and oil palm productivity was the LIML estimation because it gave the lowest value for the RMSE and MAPE in all crop yield equations.

**<<<Insert Table 7>>>**

The estimated variance equations for sugarcane, cassava, and oil palm were presented in Table 7. It was found that the non-climatic variable of the harvested area was negatively associated with the variance of oil palm yield. Technology improvement was positively associated with the variance of sugarcane yield but negatively associated with the variance of oil palm yield. There were only two relationships between the climatic variables and variances in crop yields. Firstly, total rainfall was positively associated with the variance of oil palm yield. Secondly, the variability of mean maximum temperature was positively associated with the variance of sugarcane yield. The fact that the adjusted R-squared statistic is very small is not surprising because the variances of the crop yields might be due to other factors not included in the expected yield or the variance of the yield. The output of the adjusted R-squared statistic is consistent with previous studies, including Cabas et al. (2010), Weersink et al. (2010), Poudel and Kotani (2013), Sinnarong et al. (2019), and Shayanmehr et al. (2020).

### 3.2 Potential impact of climate change on energy crop productivity

The estimated potential impacts of temperature and rainfall on energy crop productivity in Table 8 showed that sugarcane was expected to increase productivity at the average temperature level (± 0°C), while total rainfall tendencies were lower than the average level (-100 mm. to -300 mm.). The results also indicated that increased temperature change had a negative effect on sugarcane productivity at higher levels. Additionally, changes in total rainfall within the range of +300 mm. to -300 mm. had little effect on yield fluctuations compared to temperature changes. When the temperature increased by 3°C and the total rainfall increased by 300 mm., the productivity of sugarcane was predicted to be reduced by a maximum of 11.073 percent. On the other hand, if the temperature remained at the average level (± 0°C) and the total rainfall decreased by 300 mm., the productivity of sugarcane was expected to increase slightly by about 1.142 percent.

**<<<Insert Table 8>>>**

In contrast, cassava was expected to decrease productivity at the average level of temperature, and total rainfall tendencies were lower than the average level (-100 mm. to -300 mm.). The results in Table 8 indicated that increased temperature change resulted in higher cassava productivity. It was concluded that higher temperatures and increased total rainfall exposure significantly increased the productivity of cassava. When the temperature increased by 3°C and the total rainfall increased by 300 mm., the productivity of cassava was predicted to increase by a maximum of 5.795 percent. If the temperature remained at the average level (± 0°C) and the total rainfall decreased by 300 mm., the productivity of cassava was slightly reduced by about 1.335 percent. Regarding oil palm productivity, it was found that an increase of 3°C from the average level of temperature resulted in a very high yield increase. With changes in total rainfall in the range of +300 mm. to -300 mm., there was little effect on yield fluctuations compared to temperature changes. When the temperature increased by 3°C and the total rainfall decreased by 300 mm., the productivity of oil palm was predicted to increase by a maximum of 11.038 percent. If the temperature remained at the average level (± 0°C) and the total rainfall increased by 300 mm., the productivity of oil palm was slightly reduced by about 0.176 percent.

## 4 Conclusion and policy implications

Nowadays, climate and weather fluctuations affect the productivity of Thailand's agricultural sector, especially in terms of energy crop production, which will impact the stability of alternative energy in the future. Sugarcane, cassava, and oil palm are energy crops that play an important role in the development of agricultural economies and renewable energy sources, being the main biofuels of Thailand. The purposes of this study are to (1) estimate the impact of climate change on the efficiency of energy crop production in Thailand and (2) project the potential impact of climate change on energy crop productivity in Thailand, specifically sugarcane, cassava, and oil palm. Unbalanced panel datasets from 1995 to 2020 at the provincial level of Thailand are utilized to satisfy the purposes using Just and Pope's procedure. The FGLS and MLE are considered to detect the expected crop yields and variances of the crop yields. The empirical results indicate that the MLE is appropriate for estimating mean yields because it gives the lowest values for the RMSE and MAPE statistics. The selected models are also used to estimate the potential impacts of climate factors on energy crop productivity under specific scenarios.

The estimated impact of climate change on mean yield shows that mean temperature series and total rainfall are negatively associated with the yield of sugarcane but positively associated with the yield of cassava. Moreover, this study confirms that the variability of temperature series affects the yields of the energy crops in a negative direction, except for the variability of mean average temperature in sugarcane yield, which is found to have a positive relationship. Besides, variances of the crop yields show that total rainfall has a positive association with the variance of oil palm yield, and variability of mean maximum temperature has a positive association with the variance of sugarcane yield. The findings of the study conclude that changes in climate variables affect the productivity of energy crops differently, which is consistent with previous studies on seasonal crops. For example, Guntukula and Goyari (2020) have found that maximum temperature adversely affects the yields of rice, cotton, and groundnut, while minimum temperature positively affects the yields of these crops. The study has also found that rainfall has been unfavorable to the yields of cotton and groundnut. Hence, Guntukula and Goyari's (2020) findings confirm that climate variability affects the yields of seasonal crops differently. In addition, Poudel and Kotani's (2013) results have supported that changes in temperature and rainfall affect crop productivity differently depending on the crop species and cultivated areas. Based on the analysis of temperature and total rainfall changes, the projection of energy crop productivity reveals that the greatest positive effect will be on oil palm productivity, followed by cassava, when the temperature rises above the average level. It can be assumed that the efficiency of oil palm and cassava production will be more suitable for those areas in Thailand with higher temperatures than the average level. On the other hand, it is found that a higher temperature level will significantly reduce sugarcane productivity. However, the changes in total rainfall volume in the range of +300 mm. to -300 mm. have little effect on production efficiency in terms of energy crops. When the volume of total rainfall changes, whether an increase or decrease from the average level, it will have only a slight impact on cassava productivity, followed by sugarcane and oil palm, respectively. The study has found that sugarcane and cassava cultivations are planted in the same area, as shown in Figure 2. In the event that higher temperatures will affect sugarcane production, cassava should be promoted instead of sugarcane as it is a crop that responds better to temperature increases. This replacement may be the result of the substitution of crop rotations in case of higher temperature, which results in a higher yield of cassava. Therefore, the findings of the potential impact analysis confirm that changes in temperature series and total rainfall will affect Thailand's crop patterns, especially energy crop production. For these reasons, the agricultural sector and farmers should formulate policy implications to support Thailand's adaptation to climate change in order to maintain a balance of sufficient renewable energy to meet sustainable consumption in the country.

In the past decade, Thailand has designated suitable areas for growing major economic crops, including sugarcane, cassava, oil palm, and others, which are classified by region, province, district, and sub-district. The most suitable areas for certain crops will emphasize the suitability of land use, the production inputs according to the crop conditions, and other relevant factors such as the legal forest area, the irrigated area, and so forth (Land Development Department, 2013). Determining suitable cropping areas for the cultivation of energy crops does not take into account the climate and weather factors, which are highly important for crop productivity. Based on the findings of this study, determining the most suitable areas for growing crops, especially energy crops, must include the climatic variables in the conditions when determining potential areas for energy crop production. Therefore, the recommendations suggest that the government and related stakeholders should allocate the planted areas of energy crops suitable for climate and weather conditions, considered in conjunction with Thailand’s biofuel and renewable energy policy formulations. In addition, alternative energy processing industries should be promoted along with energy crop cultivation sources. Renewable energy crops should be promoted and encouraged more to replace fossil energy soon, reduce airborne pollution, and better protect the environment, as well as reduce the import of fuel from foreign countries. However, food security in the country should be highly considered along with promoting the use of biofuels; if agricultural production potential is used too much for alternative energy production, biofuel crops may upset the balance in crop production for human consumption and use in other industrial sectors.

## Declarations

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Availability of data and materials** The datasets analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request.

**Competing interests** The authors declare that they have no competing interests

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## References

Baez-Gonzalez, A. D., Kiniry, J. R., Meki, M. N., Williams, J. R., Alvarez Cilva, M., Ramos Gonzalez, J. L., & Magallanes Estala, A. (2018). Potential impact of future climate change on sugarcane under dryland conditions in Mexico. *Journal of Agronomy and Crop Science*, 204(5), 515-528. https://doi.org/10.1111/jac.12278

Cabas, J., Weersink, A., & Olale, E. (2010). Crop yield response to economic, site and climatic variables. *Climatic Change*, 101(3-4), 599-616. https://doi.org/10.1007/s10584-009-9754-4

Chankong, J., Sittisuntikul, K., Sinnarong, N., & Autchariyapanitkul, K. (2019). Impact of climate change on oil palm production in southern Thailand. *RMUTSV Research Journal*, 11(1), 54-66.

Department of Alternative Energy Development and Efficiency. (2021). *Renewable energy*. Retrieved June 9, 2021, from https://www.dede.go.th/more_news.php?cid=34&filename=index

FAO. (2011). *Thailand and FAO achievements and success stories*. FAO Regional Office for Asia and the Pacific.

Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, 2(2), 111-120. https://doi.org/10.1016/0304-4076(74)90034-7

Guntukula, R., & Goyari, P. (2020). Climate change effects on the crop yield and its variability in Telangana, India. *Studies in Microeconomics*, 8(1), 119-148. https://doi.org/10.1177/2321022220923197

Hertel, T. W., & Rosch, S. D. (2010). Climate change, agriculture, and poverty. *Applied Economic Perspectives and Policy*, 32(3), 355-385. https://doi.org/10.1093/aepp/ppq016

Jarvis, A., Ramirez-Villegas, J., Campo, B. V. H., & Navarro-Racines, C. (2012). Is cassava the answer to African climate change adaptation?. *Tropical Plant Biology*, 5(1), 9-29. https://doi.org/10.1007/s12042-012-9096-7

Just, R. E., & Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics*, 7(1), 67-86. https://doi.org/10.1016/0304-4076(78)90006-4

Just, R. E., & Pope, R. D. (1979). Production function estimation and related risk considerations. *American Journal of Agricultural Economics*, 61(2), 276-284. https://doi.org/10.2307/1239732

Knox, J. W., Díaz, J. R., Nixon, D. J., & Mkhwanazi, M. (2010). A preliminary assessment of climate change impacts on sugarcane in Swaziland. *Agricultural Systems*, 103(2), 63-72. https://doi.org/10.1016/j.agsy.2009.09.002

Land Development Department. (2013). *The announcement of the ministry of agriculture and cooperatives on zoning appropriate for rice, cassava, rubber, oil palm, sugarcane, and maize*. Retrieved June 9, 2021, from https://www.ldd.go.th/NewsIndex/Zoning_Plant/index.htm

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, 108(1), 1-24. https://doi.org/10.1016/S0304-4076(01)00098-7

Mendelsohn, R. (2008). The impact of climate change on agriculture in developing countries. *Journal of Natural Resources Policy Research*, 1(1), 5-19. https://doi.org/10.1080/19390450802495882

Ministry of Agriculture and Cooperatives. (2011). *Agricultural Development Plan during the 11th National Economic and Social Development Plan (2012-2016)*. Office of Agricultural Economics, Ministry of Agriculture and Cooperatives, Thailand.

Office of Agricultural Economics. (2021a). *Indicators: Agricultural economics of Thailand in 2020*. Center of Agricultural Information, Office of Agricultural Economics, Thailand.

Office of Agricultural Economics. (2021b). *Agricultural economic information by commodity in 2020*. Center of Agricultural Information, Office of Agricultural Economics, Thailand.

Office of Agricultural Economics. (2021c). *Thailand foreign agricultural trade statistics in 2020*. Center of Agricultural Information, Office of Agricultural Economics, Thailand.

Office of Agricultural Economics. (2021d). *Agricultural statistics of Thailand 2020*. Center of Agricultural Information, Office of Agricultural Economics, Thailand.

Okoro, S. U., Schickhoff, U., Boehner, J., Schneider, U. A., & Huth, N. I. (2017). Climate impacts on palm oil yields in the Nigerian Niger Delta. *European Journal of Agronomy*, 85, 38-50. https://doi.org/10.1016/j.eja.2017.02.002

Pipitpukdee, S., Attavanich, W., & Bejranonda, S. (2020). Impact of climate change on land use, yield and production of cassava in Thailand. *Agriculture*, 10(9), 402. https://doi.org/10.3390/agriculture10090402

Poudel, S., & Kotani, K. (2013). Climatic impacts on crop yield and its variability in Nepal: Do they vary across seasons and altitudes?. *Climatic Change*, 116(2), 327-355. https://doi.org/10.1007/s10584-012-0491-8

Saha, A., Havenner, A., & Talpaz, H. (1997). Stochastic production function estimation: Small sample properties of ML versus FGLS. *Applied Economics*, 29(4), 459-469. https://doi.org/10.1080/000368497326958

Sarkar, M. S. K., Begum, R. A., & Pereira, J. J. (2020). Impacts of climate change on oil palm production in Malaysia. *Environmental Science and Pollution Research*, 27(9), 9760-9770. https://doi.org/10.1007/s11356-020-07601-1

Shayanmehr, S., Henneberry, S. R., Sabouni, M. S., & Foroushani, N. S. (2020). Drought, climate change, and dryland wheat yield response: An econometric approach. *International Journal of Environmental Research and Public Health*, 17(14), 5264. https://doi.org/10.3390/ijerph17145264

Sinnarong, N. (2017). Economics and climate change: From concept and analytical tools to public policy in agriculture. *University of the Thai Chamber of Commerce Journal Humanities and Social Sciences*, 37(3), 142-162.

Sinnarong, N., Chen, C. C., McCarl, B., & Tran, B. L. (2019). Estimating the potential effects of climate change on rice production in Thailand. *Paddy and Water Environment*, 17, 761-769. https://doi.org/10.1007/s10333-019-00755-w

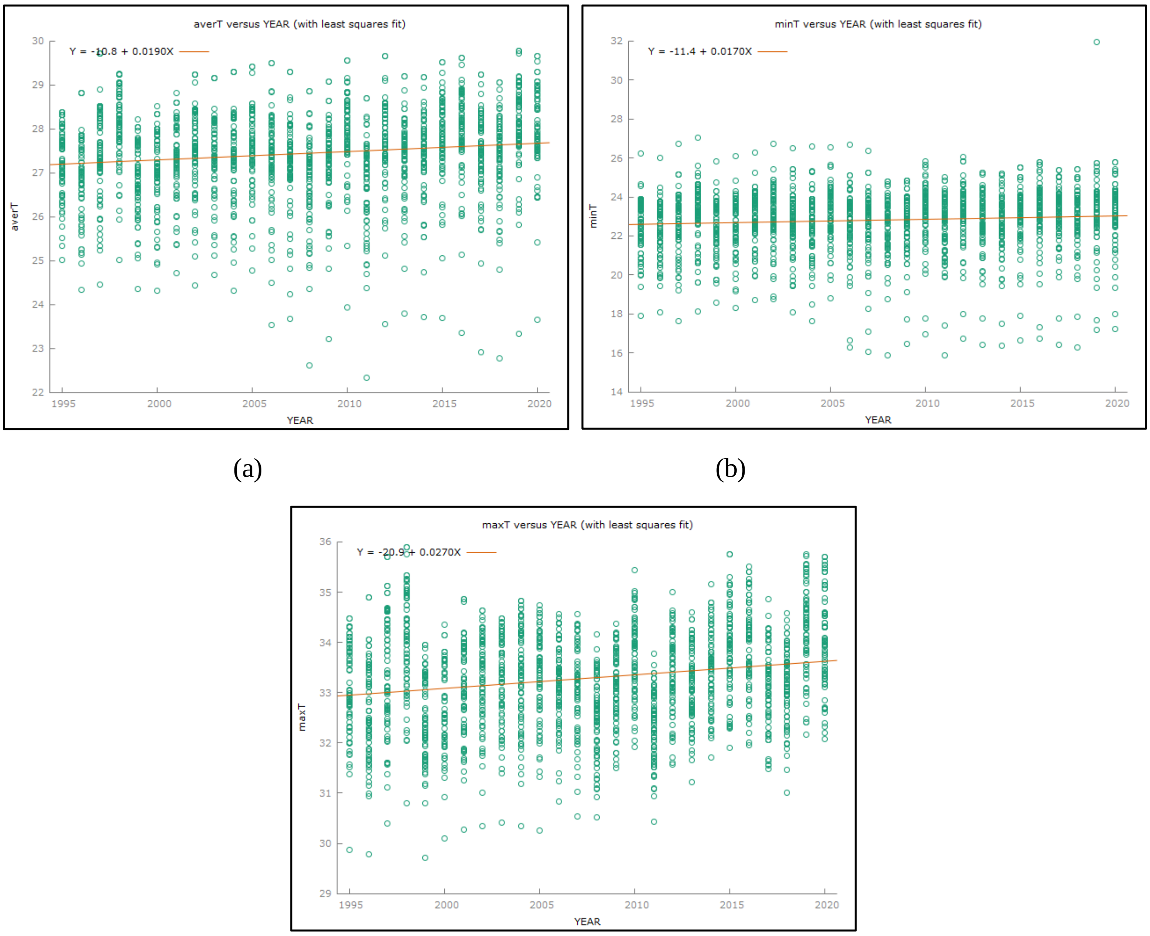
Sonkar, G., Singh, N., Mall, R. K., Singh, K. K., & Gupta, A. (2020). Simulating the impacts of climate change on sugarcane in diverse Agro-climatic zones of northern India using CANEGRO-Sugarcane model. *Sugar Tech*, 22(3), 460-472. https://doi.org/10.1007/s12355-019-00787-w

Thai Meteorological Department. (2014). *The charts of climate information*. Retrieved June 9, 2021, from https://www.tmd.go.th/en/climate.php?FileID=7.

UNFCCC. (2011). *Fact sheet: Climate change science - The status of climate change science today*. Retrieved June 9, 2021, from https://unfccc.int/files/press/backgrounders/application/pdf/press_factsh_science.pdf.

Vera, I., Wicke, B., & Hilst, F. V. D. (2020). Spatial variation in environmental impacts of sugarcane expansion in Brazil. *Land*, 9(10), 397. https://doi.org/10.3390/land9100397

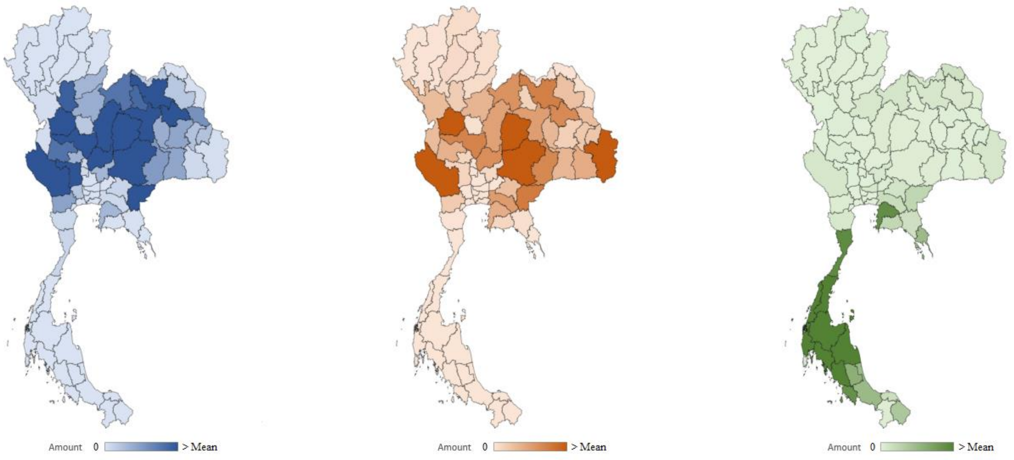
Weersink, A., Cabas, J. H., & Olale, E. (2010). Acreage response to weather, yield, and price. *Canadian Journal of Agricultural Economics*, 58(1), 57-72. https://doi.org/10.1111/j.1744-7976.2009.01173.x



(a) (b)

(c)

**Fig. 1** Mean temperature for averT (a), minT (b), and maxT (c)



(a) Sugarcane (b) Cassava (c) Oil Palm

**Fig. 2** Production maps of sugarcane (a), cassava (b), and oil palm (c) in 2020

**Table 1** Annual total rainfall and the number of rainy days by region from 2011 to 2020

| Year | Whole Kingdom | Northern | Northeastern | Central | Southern |
|---|---|---|---|---|---|
| 2011 | 1,731 (174) | 1,504 (173) | 1,627 (160) | 1,574 (159) | 2,670 (229) |
| 2012 | 1,365 (172) | 1,202 (162) | 1,048 (158) | 1,559 (165) | 2,230 (220) |
| 2013 | 1,443 (162) | 1,181 (150) | 1,239 (161) | 1,648 (150) | 2,249 (200) |
| 2014 | 1,260 (153) | 1,052 (148) | 1,095 (151) | 1,301 (132) | 2,091 (201) |
| 2015 | 1,333 (157) | 929 (144) | 1,052 (148) | 1,285 (137) | 2,068 (199) |
| 2016 | 1,530 (164) | 1,211 (155) | 1,129 (154) | 1,330 (145) | 2,451 (202) |
| 2017 | 2,092 (146) | 1,558 (134) | 1,753 (127) | 1,661 (131) | 3,395 (193) |
| 2018 | 1,596 (131) | 1,221 (124) | 1,190 (101) | 1,559 (131) | 2,412 (167) |
| 2019 | 1,341 (110) | 956 (97) | 1,064 (82) | 1,288 (106) | 2,057 (157) |
| 2020 | 1,639 (123) | 991 (97) | 1,424 (110) | 1,614 (116) | 2,526 (170) |

Note: The numbers in parentheses ( ) are the average number of rainy days. A unit of rainfall is in millimeters.

Source: Office of Agricultural Economics (2021c)

**Table 2** A summary of statistics for the variables

| Variable | Mean | Min | Max | S.D. |
|---|---|---|---|---|
| Sugarcane equation | | | | |
| Y (kg/ha) | 61144.662 | 34035.071 | 92462.250 | 10014.093 |
| A (ha) | 26798.765 | 153.280 | 132879.840 | 31408.388 |
| averT (°C) | 27.529 | 24.692 | 29.296 | 0.824 |
| minT (°C) | 22.790 | 16.658 | 25.625 | 1.273 |
| maxT (°C) | 33.490 | 30.917 | 35.900 | 0.917 |
| Rf (mn.) | 1135.653 | 281.620 | 3434.400 | 418.888 |
| Rfd (mm./d) | 7.961 | 2.570 | 24.018 | 2.725 |
| averVT | 3.827 | 0.350 | 10.857 | 1.925 |
| minVT | 6.901 | 0.815 | 20.294 | 3.520 |
| maxVT | 4.041 | 0.338 | 11.504 | 2.081 |
| Cassava equation | | | | |
| Y (kg/ha) | 18652.500 | 10443.718 | 29873.140 | 3320.741 |
| A (ha) | 25887.540 | 37.120 | 317396.000 | 39391.145 |
| averT (°C) | 27.298 | 22.769 | 29.296 | 1.015 |
| minT (°C) | 22.453 | 16.275 | 25.625 | 1.470 |
| maxT (°C) | 33.396 | 30.433 | 35.900 | 0.973 |
| Rf (mn.) | 1151.245 | 210.560 | 3434.400 | 412.318 |
| Rfd (mm./d) | 7.984 | 2.570 | 22.979 | 2.683 |
| averVT | 4.229 | 0.350 | 11.323 | 2.181 |
| minVT | 7.757 | 0.815 | 24.798 | 4.052 |
| maxVT | 4.219 | 0.338 | 12.681 | 2.165 |
| Oil palm equation | | | | |
| Y (kg/ha) | 11113.849 | 180.688 | 29000.000 | 5166.539 |
| A (ha) | 12393.402 | 1.440 | 208188.160 | 32419.810 |
| averT (°C) | 27.518 | 22.769 | 29.708 | 0.864 |
| minT (°C) | 23.008 | 16.275 | 31.950 | 1.359 |
| maxT (°C) | 33.232 | 30.433 | 35.750 | 0.987 |
| Rf (mn.) | 1586.008 | 434.260 | 5883.500 | 778.116 |
| Rfd (mm./d) | 9.349 | 2.883 | 30.886 | 3.877 |
| avert | 2.734 | 0.084 | 11.229 | 2.473 |
| minT | 5.875 | 0.064 | 1230.394 | 39.299 |
| maxT | 3.438 | 0.246 | 12.681 | 2.346 |

Source: Office of Agricultural Economics

**Table 3** Panel unit root tests

| Variable | Sugarcane | | Cassava | | Oil Palm | |
|---|---|---|---|---|---|---|
| | LLC | Prob. | LLC | Prob. | LLC | Prob. |
| Y | -7.788 | <0.001 | -7.788 | <0.001 | -9.366 | <0.001 |
| A | -3.183 | <0.001 | -3.183 | <0.001 | -3.633 | <0.001 |
| averT | -14.642 | <0.001 | -14.642 | <0.001 | -21.852 | <0.001 |
| minT | -11.007 | <0.001 | -11.007 | <0.001 | -12.509 | <0.001 |
| maxT | -15.633 | <0.001 | -15.633 | <0.001 | -16.988 | <0.001 |
| Rf | -3.759 | <0.001 | -3.759 | <0.001 | -9.478 | <0.001 |
| Rfd | -6.162 | <0.001 | -6.162 | <0.001 | -10.765 | <0.001 |
| averVT | -18.004 | <0.001 | -18.004 | <0.001 | -17.712 | <0.001 |
| minVT | -10.978 | <0.001 | -10.978 | <0.001 | -12.014 | <0.001 |
| maxVT | -21.865 | <0.001 | -21.865 | <0.001 | -43.744 | <0.001 |

Note: The panel datasets are tested for the unit root in the linear form of the variables.

**Table 4** Panel specification tests

| Specification test | Sugarcane | Cassava | Oil Palm |
|---|---|---|---|
| Heteroskedasticity | 233.956 (<0.001) | 106.298 (<0.001) | 188.908 (<0.001) |
| Autocorrelation | 23.590 (<0.001) | 31.925 (<0.001) | 8.788 (<0.001) |
| Normality | 52.907 (<0.001) | 3.429 (0.180) | 272.555 (<0.001) |

Note: The numbers in parentheses ( ) are the p-value.

**Table 5** FGLS estimation of the mean yield equation

| Variable | Sugarcane | | Cassava | | Oil Palm | |
|---|---|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E |
| constant | 14.806** | 0.884 | 7.169** | 0.529 | -22.669** | 6.104 |
| A | 0.011** | 0.003 | 0.016** | 0.002 | 0.162** | 0.016 |
| averT | -1.190** | 0.441 | 0.330 | 0.255 | 17.984** | 3.036 |
| minT | 0.213 | 0.175 | -0.200 | 0.116 | -8.707** | 1.364 |
| maxT | -0.126 | 0.330 | 0.439* | 0.202 | 2.257 | 2.564 |
| Rf | -0.032 | 0.018 | 0.040** | 0.012 | -1.614** | 0.141 |
| Rfd | -0.006 | 0.019 | 0.009 | 0.013 | 0.345* | 0.149 |
| averVT | 0.054* | 0.026 | -0.018 | 0.017 | -0.657** | 0.120 |
| minVT | -0.030 | 0.022 | 0.025 | 0.013 | -0.396** | 0.068 |
| maxVT | -0.054** | 0.017 | -0.062** | 0.011 | -0.025 | 0.107 |
| Trend | 0.008** | 0.001 | 0.018** | <0.001 | 0.094** | 0.007 |
| Adjusted R-squared | 0.122 | | 0.660 | | 0.900 | |
| S.E. of Regression | 0.160 | | 0.109 | | 1.293 | |
| RMSE | 9227.340 | | 2027.331 | | 13056.556 | |
| MAPE | 12.164 | | 8.735 | | 72.716 | |

* and ** are the statistical significance levels of 0.05 and 0.01, respectively.

**Table 6** LIML estimation of the mean yield equation

| Variable | Sugarcane | | Cassava | | Oil Palm | |
|---|---|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E |
| constant | 14.874** | 0.853 | 7.201** | 0.523 | 6.439** | 2.218 |
| A | 0.011** | 0.003 | 0.016** | 0.002 | 0.124** | 0.007 |
| averT | -1.131** | 0.427 | 0.324 | 0.253 | 1.159 | 1.061 |
| minT | 0.182 | 0.170 | -0.198 | 0.115 | 0.621 | 0.478 |
| maxT | -0.168 | 0.320 | 0.439* | 0.200 | -1.081 | 0.839 |
| Rf | -0.035* | 0.017 | 0.040** | 0.012 | -0.010 | 0.055 |
| Rfd | -0.004 | 0.019 | 0.009 | 0.013 | -0.001 | 0.055 |
| averVT | 0.056* | 0.025 | -0.016 | 0.017 | -0.123** | 0.044 |
| minVT | -0.032 | 0.022 | 0.024 | 0.013 | -0.054* | 0.023 |
| maxVT | -0.054** | 0.016 | -0.063** | 0.011 | -0.045 | 0.036 |
| Trend | 0.008** | 0.001 | 0.018** | <0.001 | 0.005 | 0.003 |
| Adjusted R-squared | 0.141 | | 0.664 | | 0.544 | |
| S.E. of Regression | 0.155 | | 0.108 | | 0.421 | |
| RMSE | 9208.727 | | 2027.018 | | 3441.499 | |
| MAPE | 12.119 | | 8.733 | | 36.470 | |

* and ** are the statistical significance levels of 0.05 and 0.01, respectively.

**Table 7** The estimated variance of the yield equation

| Variable | Sugarcane | | Cassava | | Oil Palm | |
|---|---|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S.E. | Coefficient | S.E |
| constant | -0.541* | 0.219 | -0.043 | 0.075 | -3.254 | 3.016 |
| A | 0.000 | 0.001 | <0.001 | <0.001 | -0.046** | 0.010 |
| averT | 0.163 | 0.110 | 0.070 | 0.036 | 0.821 | 1.444 |
| minT | 0.011 | 0.044 | -0.018 | 0.017 | -0.187 | 0.651 |
| maxT | -0.008 | 0.082 | -0.037 | 0.029 | 0.203 | 1.142 |
| Rf | 0.004 | 0.004 | 0.001 | 0.002 | 0.148* | 0.075 |
| Rfd | -0.009 | 0.005 | 0.003 | 0.002 | -0.007 | 0.075 |
| averVT | -0.004 | 0.007 | 0.002 | 0.002 | 0.041 | 0.059 |
| minVT | -0.004 | 0.006 | 0.001 | 0.002 | 0.038 | 0.031 |
| maxVT | 0.012** | 0.004 | -0.002 | 0.002 | 0.023 | 0.049 |
| Trend | 0.001** | <0.001 | <0.001 | <0.001 | -0.013** | 0.003 |
| Adjusted R-squared | 0.071 | | 0.003 | | 0.064 | |
| S.E. of Regression | 0.040 | | 0.016 | | 0.572 | |

* and ** are the statistical significance levels of 0.05 and 0.01, respectively.

**Table 8** The estimated potential impacts of climatic variables on energy crop productivity

| Temperature | Rainfall | | | | | | |
|---|---|---|---|---|---|---|---|
| | 300 mm. | 200 mm. | 100 mm. | 0 mm. | -100 mm. | -200 mm. | -300 mm. |
| Sugarcane | | | | | | | |
| 0°C | -0.842 | -0.585 | -0.305 | 0.000 | 0.337 | 0.715 | 1.142 |
| 1°C | -4.490 | -4.242 | -3.973 | -3.679 | -3.354 | -2.991 | -2.579 |
| 2°C | -7.892 | -7.654 | -7.394 | -7.111 | -6.797 | -6.447 | -6.049 |
| 3°C | -11.073 | -10.842 | -10.592 | -10.318 | -10.015 | -9.677 | -9.293 |
| Cassava | | | | | | | |
| 0°C | 0.973 | 0.673 | 0.350 | 0.000 | -0.384 | -0.808 | -1.335 |
| 1°C | 2.597 | 2.293 | 1.965 | 1.609 | 1.219 | 0.787 | 0.252 |
| 2°C | 4.204 | 3.895 | 3.562 | 3.201 | 2.805 | 2.367 | 1.823 |
| 3°C | 5.795 | 5.482 | 5.143 | 4.776 | 4.374 | 3.930 | 3.378 |
| Oil Palm | | | | | | | |
| 0°C | -0.176 | -0.121 | -0.063 | 0.000 | 0.068 | 0.141 | 0.222 |
| 1°C | 3.452 | 3.508 | 3.569 | 3.634 | 3.704 | 3.780 | 3.864 |
| 2°C | 7.042 | 7.101 | 7.164 | 7.231 | 7.304 | 7.383 | 7.469 |
| 3°C | 10.597 | 10.658 | 10.723 | 10.792 | 10.867 | 10.949 | 11.038 |

Note: The climatic scenarios are based on the changes in temperature and total rainfall from the average level.