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ASSESSING THE IMPACT OF CLIMATE CHANGE ON AGRICULTURE IN INDONESIA: AN ARDL-ECM ANALYSIS

ABSTRACT

Agricultural production in Indonesia is threatened by climate change. Future climate predictions show a significant increase in temperature and erratic rainfall with high intensity. We examined long- and short-term effects of climate change on Indonesian agriculture. Our estimation results demonstrate that issues of climate change significantly impact Indonesia's agricultural output. Long-term climate change factors, such as temperature and rainfall, negatively impact Indonesian value-added agriculture, whereas primary factors, such as CO2 emissions, are unfavorable for crop yields. In the short run, other parameters, such as total greenhouse gas emissions, agricultural land area, and rural population, positively and significantly affect value-added agriculture. Moreover, fertilizer consumption has long-term beneficial effects on value-added agriculture in Indonesia. Our assessment shows that agriculture in Indonesia is quite vulnerable to climate change. These findings emphasize the importance of the government of Indonesia implementing concrete steps for climate change mitigation and adaptation, particularly in the agricultural sector.

Keywords: Indonesia, Climate Risk, Agricultural Output, Cointegration Approach
JEL Classification: O13, Q54

INTRODUCTION

Food insecurity is currently a challenge for countries worldwide. The (FAO, 2020) reports that approximately 8.9% of the world's population (i.e., 690 million people) suffers from hunger. This number has increased by 10 million per year or nearly 60 million people in 5 years. Food insecurity has become increasingly problematic due to the high vulnerability of the agricultural sector to climate change. The negative impacts of climate change are already being felt in the form of increasing temperatures, weather variability, and frequent extreme weather events (World Bank, 2021). The (IPCC, 2021) reported that the world's average temperature increased by 1.10 °C from 2011 to 2020. By the end of this century, the temperature is projected to increase by approximately 1.30–5.70 °C under both low- and extremely high-emission scenarios. This phenomenon will significantly affect the agricultural sector and is expected to have further significant impacts in the future. (Anh, Anh and Chandio, 2023) reported that in most of the Asia Pacific region, a considerable decline in agricultural production has been recently noted, accompanied by severe socioeconomic inequality, due to erratic weather, high temperatures and heavy rains.

The negative impacts of climate change tend to be more strongly felt in developing than in developed countries (Abeysekara, Siriwardana and Meng, 2023). The main reason is that the economic structure of many developing countries is mainly agricultural (29% of the gross domestic product (GDP), and most of their populations derive their livelihood from agriculture (CBD, 2016). (FAO, 2015) reported that at least 70% of impoverished people in developing countries live in rural areas and work as small farmers, producing food for consumption by nearly 2 billion people. Indonesia is a developing country whose economy relies on agriculture because it contributes approximately 14% of the country's GDP; thus, one-third of Indonesia's labor force is employed in the agricultural sector (Goh and Wu, 2021). As a result, the country is facing severe challenges from the climate change phenomenon.

During the period of 1990–2021, Indonesia experienced an increase in temperature with varying magnitudes of approximately 0.01 °C each year (World Bank, 2021). The USAID report (USAID, 2017) projects that in 2050, Indonesia will experience a temperature increase of 0.8–2.0 ℃ with significant warming on the islands of Sumatra, Java, and Kalimantan. The USAID also projects an increase in the frequency and intensity of high-intensity rain events of 3–23% and 2–7%, respectively, and a slight increase in the duration of rain breaks (+2 days). The World Bank and the Asian Development Bank (World Bank and Asian Development Bank, 2021) reported that Indonesia is one of the top three countries with the highest exposure to all types of flooding and extreme heat and that the intensity of these climate risks is expected to continue to increase, particularly in the agricultural sector, in line with climate change.

Several previous studies have examined the impact of climate change on agricultural production in various countries such as Nepal (Dawadi *et al.*, 2022), Vietnam (Anh, Anh and Chandio, 2023), China (Chandio, Rehman and Rauf, 2020; Song *et al.*, 2022), Pakistan (Ahsan, Chandio and Fang, 2020), Sri Lanka (Abeysekara, Siriwardana and Meng, 2023), Thailand (Jatuporn and Takeuchi, 2023), Cameroon (Kodji, Tchobsala and Ibrahima, 2021), Gambia (Belford *et al.*, 2022), and Ghana (Kwakwa, Alhassan and Adzawla, 2022) and in Sub-Saharan Africa (Emediegwu, Wossink and Hall, 2022). These studies show the negative impact of climate change on agricultural production. Changes in temperature, rainfall, number of rainy days, air pressure, CO2 emissions, floods, and dry seasons are the causes of the decreases in short- and long-term agricultural production. The control variables used in the various studies include fertilizers, seeds, large land areas, machine technology, technology adoption, intensive capital, land accompanied by irrigation, human capital, and urbanization. Additionally, various methods were applied, including ordinary least squares, autoregressive distribution lag (ARDL), spatial panel data approach, computable general equilibrium, multi-regional input–output (MRIO) framework, key informant interviews (KIIs) and focus group discussions.

Various previous studies have also examined the relationship between climate change and agricultural production in the Indonesian context. For example, (Saptutyningsih, Endah and Setyawati Dewanti, Diah, 2021) revealed the impacts of climate change, such as floods, droughts, and pest attacks, on the failure of agricultural production in Yogyakarta Province. (Naylor *et al.*, 2007) noted the need for adaptation strategies for the rice farming sector in Indonesia, including increased investment in water storage, drought-tolerant crops, crop diversification, and early warning systems. Research by (Takama, Setyani and Aldrian, 2014) revealed a 20% decrease in lowland rice production on the island of Bali in the last 20 years due to climate change. Using a feasible generalized least squares estimation technique, (Massagony, Tam Ho and Shimada, 2022) reported that rising temperatures and rainfall negatively affect rice production in 14 provinces in Indonesia.

Despite evidence on the significant impacts of climate change on Indonesia's agricultural production, quantitative research on the short- and long-term impacts of climate change on agriculture is scarce and inadequate. This study is the first to assess the short- and long-term effects of climate change (including temperature, rainfall and CO2 emissions) on agricultural production. This research provides an up-to-date assessment of the impact of climate change on the agricultural sector in Indonesia and thus enriches the literature and references regarding the impact of climate change on the country's agricultural sector. It also serves as a good reference point for policy-makers in developing policies to mitigate the negative impacts of climate change on the agricultural sector in Indonesia.

RESEARCH METHODOLOGY

This study used annual time series data from value-added agriculture, climate change factors, and other control variables for Indonesia during the 1990–2019 period. The data were obtained from the World Development Indicators (WDI) and the Climate Change Knowledge Portal (CCKP). Table 7 presents the details of the research variables.

Table 1. Description of variables and data

Variable	Abbreviation	Unit	Source
Value added-agriculture	AGR	constant LCU	WDI
CO_2 emissions	CO_2	metric tons per capita	WDI
Total greenhouse gas emissions	GH	kt of CO_2 equivalent	WDI
Average annual temperature	TEMP	°C	CCKP
Average annual rainfall	RAIN	mm	CCKP
Agricultural land	LAND	km^2	WDI
Rural population size	POP	people	WDI
Fertilizer consumption	FER	kilograms per hectare of arable land	WDI

The estimation of time series data was based on the assumption of stationarity. Therefore, the estimation procedure adopted in this study was performed by first checking the stationarity of the variables using the augmented Dicky–Fuller (ADF) unit root test, the Phillips–Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. We used these three unit root tests to examine the stationarity of variables at level I(0) and at the first difference I(1). Then, we selected the appropriate lag length using several selection criteria, namely, the Akaike information criterion (AIC), the Schwarz information criterion and the Hanna–Quinn information criterion. Furthermore, after examining the stationarity of the data and the optimal lag length, we estimated the ARDL–error correction model (ECM) to examine the short- and long-term relationships between climate change factors and the output of the agricultural sector in Indonesia. Finally, we conducted several diagnostic tests to check the validity of the model.

The ARDL–ECM approach was developed by Pesaran et al. (2001) and Pesaran and Shin (1999). This approach became popular because it overcomes the traditional restriction of integration tests in that the tested variables must be nonstationary and all variables must be integrated in the same order (Sam et al. 2019). Moreover, this contemporary method allows users to select the appropriate number of lags for the empirical model. Referring to Chandio et al. (2020), the functional form of the model used in this study is as follows:

$$AGR_t = f(CO2_t, GH_t TEMP_t, RAIN_t, LAND_t, POP_t, FER_t) \dots\dots\dots\dots (1)$$

The functional model in Equation (1) is then represented in an econometric equation as follows:

$$AGR_t = \alpha_0 + \alpha_1 CO2_t + \alpha_2 GH_t + \alpha_3 TEMP_t + \alpha_4 RAIN_t + \alpha_5 LAND_t + \alpha_6 POP_t + \alpha_7 FER_t + \mu_t \quad (2)$$

We apply natural logarithms to all variables to reduce the multicollinearity and volatility of the data. The log-linear equation of the model is as follows :

$$LNAGR_t = \alpha_0 + \alpha_1 LNCO2_t + \alpha_2 LNGH_t + \alpha_3 LNTEMP_t + \alpha_4 LNRAIN_t + \alpha_5 LNLAND_t + \alpha_6 LNPOP_t + \alpha_7 LNFER_t + \mu_t \quad (3)$$

Furthermore, the first step for the ARDL model is to test the existence of a long-term relationship between variables. The ARDL long-term model specification can be represented by the following equation:

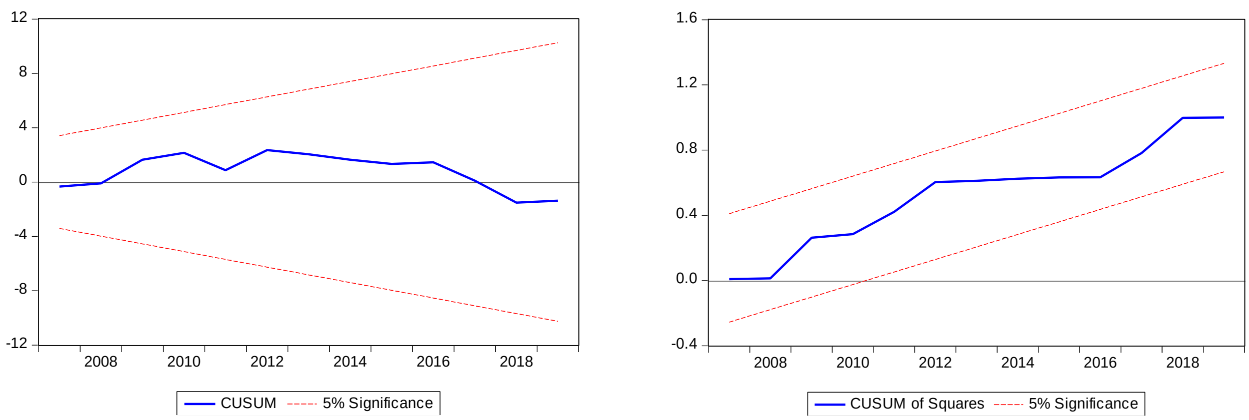
$$\begin{aligned}\Delta LNAGR_t = {} & \beta_0 + \sum_{i=1}^{D} \beta_{1i} \Delta LNAGR_{t-i} + \sum_{i=0}^{D} \beta_{2i} \Delta LNCO2_{t-i} + \sum_{i=0}^{D} \beta_{3i} LNGH_{t-i} + \sum_{i=0}^{D} \beta_{4i} LNTEMP_{t-i} \\ & + \sum_{i=0}^{D} \beta_{5i} LNRAIN_{t-i} + \sum_{i=0}^{D} \beta_{6i} LNLAND_{t-i} + \sum_{i=0}^{D} \beta_{7i} LNPOP_{t-i} \\ & + \sum_{i=0}^{D} \beta_{8i} LNFER_{t-i} + \delta_1 LNAGR_{t-1} + \delta_2 LNCO2_{t-1} + \delta_3 LNGH_{t-1} + \delta_4 LNTEMP_{t-1} \\ & + \delta_5 LNRAIN_{t-1} + \delta_6 LNLAND_{t-1} + \delta_7 LNPOP_{t-1} + \delta_8 LNFER_{t-1} + \mu_t\end{aligned} \quad (4)$$

where β_0 is the intercept, D is the lag order, Δ is the first difference operator, and μ_t is the error term. To examine the long-term relationship between variables, this study uses the F test with the following hypotheses:

- Null hypothesis: $H0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = 0$ (cointegration does not exist between variables)
- Alternative hypothesis: $H1: \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq \delta_6 \neq \delta_7 \neq \delta_8 \neq 0$ (cointegration exists between variables).

If the calculated F test value is greater than I(1), then cointegration exists. In contrast, if the calculated F test value is less than I(0), then cointegration does not exist. If the calculated F test value is between I(0) and I(1), then the existence of cointegration cannot be ruled out. To check the consistency of the cointegration, we used the CUSUM and CUSUMSQ tests (see Fig. 1). The second step is to assess the short-term relationships among CO_2 emissions, total greenhouse gas emissions, temperature, rainfall, agricultural land area, rural population, and value-added fertilizers in Indonesia. The ECM is formed in the ARDL model as follows:

Fig 1. CUSUM and CUSUMQ plots



$$\Delta LNAGR_t = \beta_0 + \sum_{i=1}^{D} \beta_{1i} \Delta LNAGR_{t-i} + \sum_{i=0}^{D} \beta_{2i} \Delta LNCO2_{t-i} + \sum_{i=0}^{D} \beta_{3i} LNGH_{t-i} + \sum_{i=0}^{D} \beta_{4i} LNTEMP_{t-i} + \sum_{i=0}^{D} \beta_{5i} LNRAIN_{t-i} + \sum_{i=0}^{D} \beta_{6i} LNLAND_{t-i} + \sum_{i=0}^{D} \beta_{7i} LNPOP_{t-i} + \sum_{i=0}^{D} \beta_{8i} LNFER_{t-i} + \theta ECM_{t-1} + \mu_t \quad (5)$$

RESULTS AND DISCUSSION

Table 2 shows the results of the descriptive statistics. The Jarque–Bera statistics show that all variables are normally distributed with constant and zero covariances. Table 2 summarizes the correlations between variables, here CO2 emissions, temperature, total greenhouse gas emissions, agricultural land area, rainfall, and fertilizer consumption are positively correlated with value-added agriculture. In comparison, rural population size is negatively correlated with value-added agriculture

Table 2. Descriptive Statistics

	LN_AGR	LN_CO2	LN_GH	LN_TEMP	LN_RAIN	LN_LAND	LN_POP	LN_FER
Mean	34.344	0.373	13.461	3.256	7.924	16.531	18.633	5.117
Median	34.298	0.408	13.470	3.255	7.948	16.542	18.634	5.001
Maximum	34.842	0.833	13.818	3.267	8.098	16.652	18.659	5.574
Minimum	33.943	-0.204	13.074	3.247	7.730	16.395	18.592	4.791
Std. Dev.	0.274	0.274	0.191	0.005	0.077	0.053	0.020	0.272
Skewness	0.324	-0.461	-0.261	0.441	-0.313	-0.493	-0.280	0.455
Kurtosis	1.839	2.393	2.443	2.231	3.056	3.834	2.125	1.694
Jarque–Bera	2.209	1.522	0.730	1.710	0.495	2.084	1.347	3.167
Probability	0.331	0.467	0.694	0.425	0.781	0.353	0.510	0.205
Sum	1030.332	11.187	403.838	97.667	237.705	495.935	558.976	153.520
Sum Sq. Dev.	2.176	2.179	1.062	0.001	0.172	0.081	0.011	2.138
Observations	30	30	30	30	30	30	30	30

Table 3. Correlation results

	LN_AGR	**LN_CO2**	**LN_GH**	**LN_TEMP**	**LN_RAIN**	**LN_LAND**	**LN_POP**	**LN_FER**
LN_AGR	1.000							
LN_CO2	0.943***	1.000						
LN_GH	0.957***	0.995***	1.000					
LN_TEMP	0.676***	0.631***	0.660***	1.000				
LN_RAIN	0.238	0.297	0.283	0.063	1.000			
LN_LAND	0.655***	0.734***	0.730***	0.361**	0.614***	1.000		
LN_POP	-0.980***	-0.943***	-0.961***	-0.681***	-0.259	-0.647***	1.000	
LN_FER	0.916***	0.788***	0.805***	0.574***	0.231	0.577***	-0.850***	1.000

Note: ***, **, and * denote ***p < 0.01, **p < 0.05, and *p< 0.10, respectively.

Before implementing the unit root tests, we plotted the data to determine the integration status of the research variables (see Fig. 2). Fig. 2 provides an initial description of the behavior of the research variables throughout the observation period. Next, we conducted the ADF, PP, and KPSS unit root tests. Table 3 reports the results, indicating that all variables are stationary in combinations I(0) and I(1). Thus, stationary properties can display strong long-term relationships between the variables and support the application of the ARDL approach

Fig. 2 Time Plot Series of Study Variables

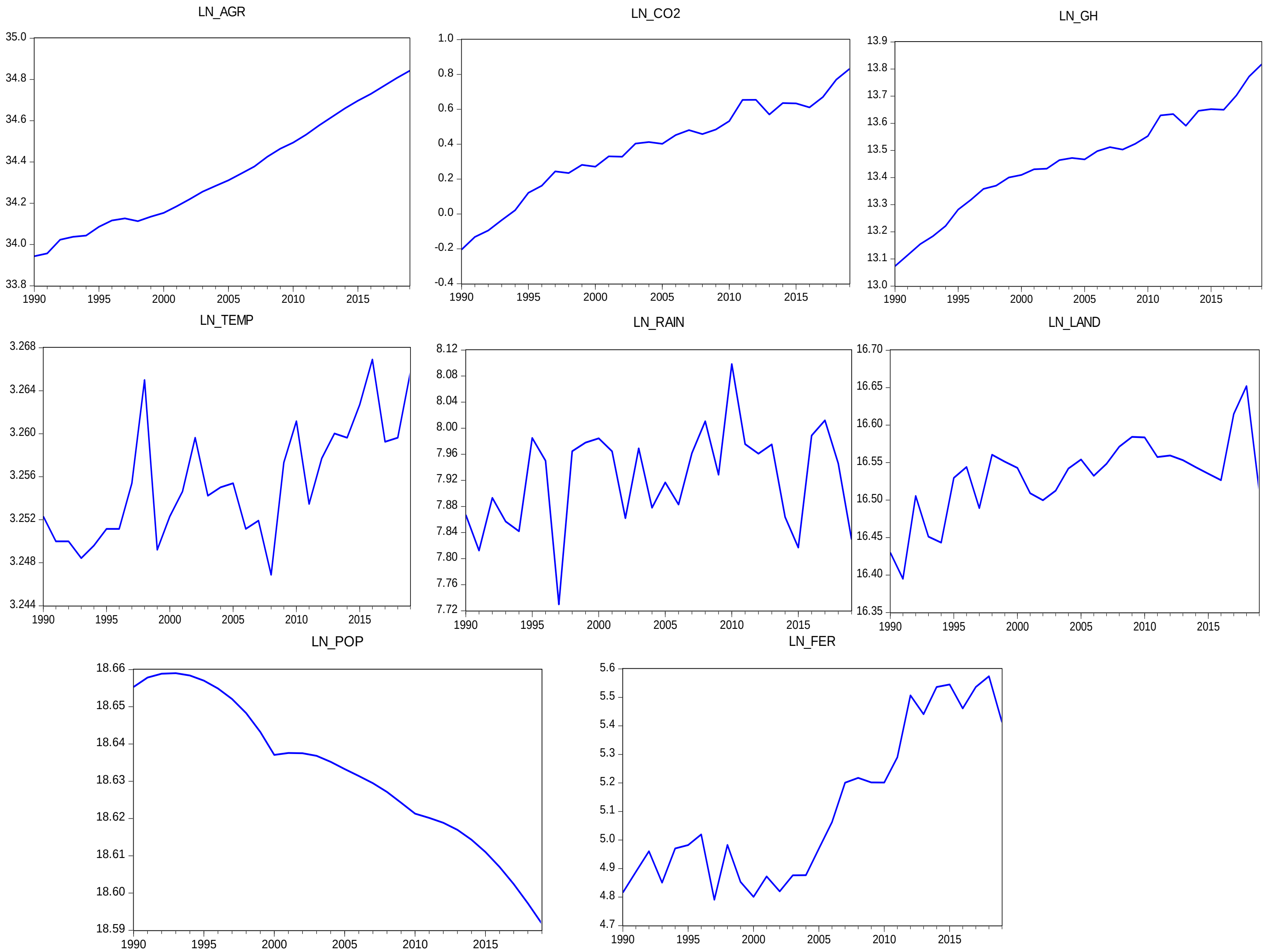


Table 4. Unit root test results

Variable	ADF		PP		KPSS	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LN_AGR	2.120	-0.833	2.259	-0.869	0.706**	0.179**
LN_CO2	-1.475	-2.759	-1.849	-2.823	0.709**	0.151**
LN_GH	-0.852	-2.339	-0.849	-2.339	0.715**	0.121*
LN_TEMP	-2.667*	-4.400***	-2.476	-4.400***	0.536**	0.102
LN_RAIN	-4.520***	-4.667***	-4.520***	-4.602***	0.314	0.112
LN_LAND	-3.177**	-4.403***	-3.177**	-4.028**	0.580**	0.134*
LN_POP	0.831	-1.620	2.092	-2.125	0.702**	0.122*
LN_FER	-1.011	-2.108	-0.862	-2.053	0.597**	0.143*
D(LN_AGR)	-4.404***	-4.858***	-4.431***	-4.847***	0.445*	0.081
D(LN_CO2)	-5.342***	-5.310***	-5.365***	-5.418***	0.196	0.155**
D(LN_GH)	-4.690***	-4.585***	-4.691***	-4.587***	0.177	0.142*
D(LN_TEMP)	-6.354***	-6.233***	-17.635***	-19.813***	0.500**	0.500***
D(LN_RAIN)	-6.203***	-6.158***	-13.227***	-22.448***	0.268	0.179**
D(LN_LAND)	-6.946***	-6.903***	-6.900***	-8.782***	0.358*	0.199**
D(LN_POP)	-2.568	-2.791	-2.511	-2.800	0.383*	0.093
D(LN_FER)	-7.070***	-6.949***	-7.104***	-7.006***	0.106	0.107

Note: ***, **, and * denote ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$, respectively.

The ARDL approach is used in this study to investigate the long-term relationships between climate change factors and other control variables and value-added agriculture in Indonesia. Before estimating the ARDL model, we applied a suitable lag length selection. Table 5 reports the results of several selection criteria, where the optimal sequence of lag lengths is determined based on the SIC. Furthermore, Table 6 shows the results of the ARDL bounds test. The test illustrates that the computed F values are 9.78 above the critical upper bound at the 1% level of significance. Therefore, the null hypothesis that cointegration does not exist is rejected. These results confirm that CO_2 emissions, total greenhouse gas emissions, temperature, rainfall, agricultural land area, rural population size, and fertilizer consumption have long-term relationships with value-added agriculture in Indonesia.

Table 5. VAR lag length selection

Lag	AIC	SIC	HQC
0	-34.485	-34.104	-34.368
1	-45.440	-42.014	-44.393
2	-49.331*	-42.860*	-47.353*

Note: * indicates the lag order selected by the criterion

Table 6. ARDL bounds test for cointegration

Significant	I0 Bound	I1 Bound
1%	2.96	4.26
2.5%	2.6	3.84
5%	2.32	3.5
10%	2.03	3.13
F-statistic 9.78***		

Note: *** denotes $p < 0.01$.

Table 7 (Panel A) shows the results of the analysis of the long-term relationships of climate change factors and other control variables with value-added agriculture. The estimation results reveal that temperature rise plays a vital role in Indonesia's value-added agriculture. Temperature rise has a long-term negative impact on value-added agriculture at a significant level of 1%. A 1% increase in temperature can reduce value-added agriculture by 2.498%. This result is in line with those of various studies, such as (Chandio, Rehman and Rauf, 2020), (Jatuporn and Takeuchi, 2023), (Kodji, Tchobsala and Ibrahima, 2021; Song *et al.*, 2022). Similarly, the coefficient of the long-term estimation of rainfall shows a negative relationship with value-added agriculture. When rainfall increases by 1%, value-added agriculture decreases by 0.049%. The findings of this study are in line with those of (Chandio, Rehman and Rauf, 2020), (Jatuporn and Takeuchi, 2023), (Kodji, Tchobsala and Ibrahima, 2021; Song *et al.*, 2022). The results of the long-term estimation of CO_2 emissions and total greenhouse gas emissions are not statistically significant, with coefficients of 0.030 and 0.191 points, respectively. An increase in CO_2 emissions and total greenhouse gas emissions of 1% can increase value-added agriculture by 0.030–0.191% in the long term.

Table 7. Long- and short-term coefficients using the ARDL-ECM

Dependent variable: lnAGR; selected model: ARDL (1, 1, 1, 1, 1, 1, 1, 1)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Panel (A) long-run estimation				
LN_CO2 (-1)	0.030	0.109	0.275	0.787
LN_GH (-1)	0.191	0.192	0.995	0.337
LN_TEMP (-1)	-2.498***	0.705	-3.543	0.003
LN_RAIN (-1)	-0.049	0.048	-1.022	0.325
LN_LAND (-1)	-0.002	0.111	-0.013	0.989
LN_POP (-1)	-1.184	0.732	-1.618	0.129
LN_FER (-1)	0.062**	0.029	2.135	0.052
C	34.701**	16.556	2.096	0.056
Panel (B) short-run estimation				
D(LN_CO2)	-0.480**	0.213	-2.247	0.045
D(LN_GH)	1.127***	0.392	2.872	0.013
D(LN_TEMP)	-1.731***	0.548	-3.160	0.008
D(LN_RAIN)	0.031	0.030	1.042	0.316
D(LN_LAND)	0.123*	0.067	1.839	0.089
D(LN_POP)	8.131***	2.320	3.505	0.004
D(LN_FER)	-0.082***	0.029	-2.837	0.014
ECM (-1)	-0.202**	0.077	-2.640	0.020
Panel (C) residual diagnostic test				
Panel C: residual diagnostic test				
R-squared 0.879163				
F-statistic 6.305516***				
DW statistic 2.502318				
χ^2SERIAL 1.281760 (0.2797)				
χ^2NORMAL 0.884090 (0.642721)				
χ^2ARCH 1.629442 (0.2170)				
χ^2White 1.771592 (0.1535)				
χ^2RESET 1.588840 (0.2315)				
CUSUM stable				
CUSUM square stable				

Note: ***, **, and * denote ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$, respectively.

Furthermore, the relationships of agricultural land area and rural population size with value-added agriculture are statistically nonsignificant, with negative estimation coefficients of 0.002 and 1.184, respectively. These results revealed that a 1% increase in agricultural land area and rural population size decreased value-added agriculture by 0.002–1.184%. These results are in line with those of Mekuria (2018). In the long run, rural population growth and land degradation reduce agricultural production in Indonesia. The long-term analysis also revealed that fertilizer application is essential for determining agricultural production in Indonesia. Statistically, the relationship between fertilizer and value-added agriculture is significant, with a positive estimation coefficient of 0.062. A 1% increase in fertilizer consumption can increase value-added agriculture by 0.062%. This result is similar to those of (Janjua, Samad and Khan, 2013; Chandio, Rehman and Rauf, 2020; Anh, Anh and Chandio, 2023).

The short-term estimation results presented in Panel B of Table 6 reveal that the leading climate change factors, namely, CO2 emissions and temperature, are significantly negatively correlated with agricultural production. The short-term CO2 emissions and temperature coefficients are 0.480 and 1.731, respectively, indicating that a 1% increase in CO2 emissions and temperature will reduce value-added agriculture by 0.480–1.731%. The long- and short-term estimations show that some climate change factors, particularly temperature, have a significant negative impact on value-added agriculture in Indonesia. As a climate change factor, rainfall does not significantly affect value-added agriculture in the short term. This result is similar to that of (Janjua, Samad and Khan, 2013).

Furthermore, the control variables, such as agricultural land area and rural population size, show a positive and significant correlation with value-added agriculture. These variables are the primary inputs of agricultural production. According to the short-term estimates, a 1% increase in agricultural land area and rural population size will increase the value-added agriculture by 0.123–8.131%. In contrast to the results of the long-term analysis, these two variables negatively affect value-added agriculture.

The short-term analysis also revealed that total greenhouse gas emissions have a positive and significant relationship with value-added agriculture, with an estimated coefficient of 1.127. Thus, a 1% increase in total greenhouse gas emissions will increase value-added agriculture by 1.127%. These findings also confirm that the agricultural sector is the source of greenhouse gas emissions in Indonesia. Fertilizer consumption demonstrated long- and short-term significant relationships with value-added agriculture. However, the short-term estimation coefficient is -0.082. Thus, a 1% increase in fertilizer consumption will reduce value-added agriculture by 0.082%.

The estimated elasticity ECM_{t-1} result is negative and significant at the 5% level. ECM_{t-1} describes the speed of adjustment toward long-run equilibrium from short-term shocks to the regressor. The estimation results for the diagnostic test on the ARDL model shown in Panel C of Table 6 indicate that the model passed several diagnostic tests (χ^2SERIAL, χ^2NORMAL, χ^2ARCH, χ^2White, and χ^2RESET). Finally, we used the CUSUM and CUSUMSQ tests to check the stability of the ARDL model. The estimation results show that the plots of the two model stability tests are within the critical limits at the 5% significance level. Therefore, the estimated model parameters are stable during that period.

CONCLUSION

Agriculture in Indonesia is facing a severe threat from climate change. This research provides empirical evidence on the impact of climate change on value-added agriculture in Indonesia during the 1990–2019 period. The ARDL–ECM estimation results reveal long- and short-term relationships between value-added agriculture and temperature in Indonesia. Temperature increases in the long and short term have severe negative impacts on agricultural output. Although rainfall has a negative impact on value-added agriculture in the long term, it has a positive impact in the short term. These findings emphasize the importance of the government of Indonesia implementing concrete steps for climate change mitigation and adaptation, particularly in the agricultural sector. These steps can include using modern technologies for accurate weather forecasting, developing improved irrigation systems, adjusting planting times and cropping patterns, adopting environmentally friendly fertilizing technologies, implementing sustainable soil and water management, and using rice varieties that are adaptive to climate change. Finally, this study has limitations. The data used in this study are a national aggregate and thus cannot capture differences in climatic conditions in various regions of Indonesia. Thus, future research should consider regional characteristics, particularly the different climatic conditions. Aspects of the different types of food crops, horticulture, and plantations also need to be considered in further research.

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