Jurnal Ilmu Pertanian Indonesia (JIPI), Juli 2025
(Indonesian Journal of Agricultural Sciences)
ISSN 0853-4217 EISSN 2443-3462

Vol. 30 (3): 490–499
http://journal.ipb.ac.id/index.php/JIPI
DOI: 10.18343/jipi.30.3.490

Factors Determining the Performance of the Indonesian Agricultural Sector in the Era of Climate Change

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(Received August 2024/Accepted Apryl 2025)

ABSTRACT

The agricultural sector plays a crucial role in Indonesia, serving as both a provider of food and a key driver of economic growth. This study aims to analyze the factors influencing Indonesia's agricultural sector from 1981 to 2021, focusing on agricultural production and its economic value. Climate change has emerged as a critical issue affecting agriculture, with greenhouse gas emissions serving as proxies for measuring its impact. This study employs the Autoregressive Distributed Lag (ARDL) model to examine both short- and long-term relationships. The findings indicate that, in the long run, agricultural land area and economic growth significantly affect the agricultural sector. In the short term, agricultural land area, economic growth, and fertilizer usage are the key factors. However, climate change did not have a significant negative impact on agricultural decline. In contrast, fertilizer usage was positively correlated with agricultural production. These findings highlight the essential role of government policy in fostering agricultural sector development in Indonesia. Strategic initiatives should focus on ensuring an adequate fertilizer supply, expanding agricultural land, and promoting key economic sectors that drive growth and support agricultural sustainability.

Keywords: agricultural sector, ARDL model, climate change, Indonesia

INTRODUCTION

Climate change poses a major challenge to Indonesia's agricultural sector owing to its significant impact on productivity and overall performance. The rapid growth of the global population necessitates a 60% increase in agricultural production by 2050 to meet the global food demand (FAO 2015). As one of the world's most populous countries, with an average population growth rate of approximately 1% over the past decade, Indonesia must ensure a sufficient food supply for its entire population (FAO 2023). Indonesia is globally recognized as a leading producer of palm oil, rubber, cocoa, copra, and coffee, and is one of the largest marine fishery producers in the world. Approximately 15% of Indonesia's agricultural land is allocated to cultivating these export-oriented commodities (World Bank 2021). Meanwhile, the agricultural sector contributed an average of 13.34% to the national GDP from 2010 to 2021 (FAO 2023).

In addition to its economic contribution, agriculture serves as a crucial source of employment. Between 2008 and 2022, the sector accounted for approximately 31.8% of the total workforce (Putra *et al.* 2023). The critical role of agriculture became even more evident during the COVID-19 pandemic. In the second quarter of 2020, when Indonesia's economic growth contracted by –5.32%, the agricultural sector remained resilient, recording a growth rate of 2.19% (Moeis *et al.* 2020). Any disruption in the agricultural sector could have far-reaching economic consequences, potentially slowing the overall economic growth.

At the macroeconomic level, a country's agricultural performance can be assessed using two key indicators: the Agricultural Gross Product Index and the Agricultural Gross Production Value (Anh *et al.* 2023). The Agricultural Gross Production Value reflects the economic growth of the agricultural sector, whereas the Agricultural Gross Product Index measures agricultural production, encompassing 173 agricultural commodities based on cultivated area, production volume, and productivity (Anh *et al.* 2023). Between 1992 and 2020, Indonesia's Agricultural Gross Product Index grew at an average annual rate of 2.9%, outpacing the country's population growth rate of 1.3% during the same period. This suggests that, in principle, Indonesia's agricultural sector can meet domestic food demands. However, this does not indicate a secure future for the agricultural sector. According to the World Bank (2021), Indonesia's agricultural sector is highly vulnerable to climate change. For instance, the average crop failure per district increased from 100,000 tons in 1981–1990 to 300,000 tons in 1991–2000. The

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Asian Development Bank (ADB) estimates that by 2100, climate change could impose economic costs equivalent to 2.5–7% of Indonesia's GDP (World Bank 2021). Therefore, continuous agricultural development is crucial for ensuring national and global food security.

Recognizing the urgency of climate change, the Indonesian government committed in 2009 at the G20 summit to reducing greenhouse gas emissions by 26% through domestic funding or 41% with international assistance within a ten-year period. This commitment was reinforced by Presidential Regulation (Perpres) No. 61 of 2011, which introduced the National Action Plan for Greenhouse Gas Reduction (RAN-GRK) as a programmatic framework (Meehan *et al.* 2019). Climate change itself is primarily driven by anthropogenic activities, which, in fulfilling human needs, have led to increased greenhouse gas emissions in the atmosphere.

Given the strong interconnection between agriculture and climate change in Indonesia, this study aims to identify the key determinants of agricultural sector performance by analyzing the economic and production-related impacts from 1981 to 2021. Specifically, this study examines the short- and long-term effects of various factors on agricultural production and the sector's economic value in the context of climate change. In addition to assessing these short- and long-term effects, this study explored the causal relationship between climate-related and agricultural factors affecting the sector. These insights are essential for developing strategic policies to enhance agricultural production during climate change.

METHODS

Methodology and Data

The Augmented Autoregressive Distributed Lag (ARDL) technique was employed to explore the determinants of Indonesia's agricultural sector performance in the era of climate change, both in the short and long terms. The ARDL model offers several advantages (Pesaran and Shin 1998; Anh *et al.* 2023). First, the stationarity condition for the variables in the model allows them to be integrated at order zero [I(0)], order one [I(1)], or a combination of both orders. Second, the ARDL model is well-suited for small-sample sizes. Third, it enables simultaneous analysis of both short- and long-term effects. Fourth, it allows for the possibility of endogeneity among the model variables. Fifth, the ARDL model effectively addresses endogeneity and serial correlation issues.

The climate factor used in this study was total greenhouse gas emissions (Sarkodie *et al.* 2019). Meanwhile, agricultural factors include agricultural land area (Raihan and Tuspekova 2022) and fertilizer use (Anh *et al.* 2023; Chandio *et al.* 2021). This selection allowed for the identification of the dominant variables influencing other factors within the model. Therefore, this study constructs a single-equation model incorporating both common and distinct independent variables, namely the Agricultural Gross Product Index (AGPII) and Agricultural Gross Production Value (AGPVI). The models are specified as follows.

Model I

$$AGPII = f(FRTZQ, GHGEM, ALAND, GDPII)$$

Model II

$$AGPVI = f(FRTZQ, GHGEM, ALAND, GDPII)$$

AGPII represents the Agricultural Gross Product Index, which reflects Indonesia's agricultural production performance by encompassing 173 agricultural products in the study. AGPVI refers to the Agricultural Gross Production Value, representing the economic performance of Indonesia's agricultural sector. Both variables are key evaluation metrics in this study, aligning with the research objectives and linked to climate change, represented by GHGEM (greenhouse gas emissions). GHGEM consists of multiple greenhouse gases, including CO_2 (carbon dioxide, the most dominant contributor to the greenhouse effect), CH_4 (methane), N_2O (nitrous oxide), HFCs (hydrofluorocarbons), PFCs (perfluorocarbons), SF_6 (sulfur hexafluoride), and NF_3 (nitrogen trifluoride) (EPA 2023).

This study utilizes annual time-series data from 1981 to 2021, resulting in 41 observations ($N = 41$). The definitions of the variables and their data sources for Models 1 (MI) and 2 (MII) are presented in Table 1. Before estimation, stationarity tests were conducted using the Augmented Dickey-Fuller (ADF) (Dickey and Fuller 1979) and Phillips-Perron (PP) tests (Phillips and Perron 1988). In applying the ARDL method, all variables were transformed using the natural logarithm to ensure that all variables remained non-negative.

Following the stationarity tests, a cointegration test was performed to determine the existence of long-run relationships among the variables in the model. The bound test for ARDL was applied to capture both short- and long-term effects. The linear form of the ARDL model is as follows:

$$\begin{aligned}\Delta AGPII_t = {} & \alpha_0 + \alpha_1 AGPII_{t-1} + \alpha_2 FRTZQ_{t-1} + \alpha_3 GHGEM_{t-1} \\ & + \alpha_4 ALAND_{t-1} + \alpha_5 GDPII_{t-1} \\ & + \sum_{i=1}^{p} \alpha_{6i} \Delta AGPII_{t-i} \\ & + \sum_{i=0}^{q} \alpha_{7i} \Delta FRTZQ_{t-i} \\ & + \sum_{i=0}^{r} \alpha_{8i} \Delta GHGEM_{t-i} \\ & + \sum_{i=0}^{s} \alpha_{9i} \Delta ALAND_{t-i} \\ & + \sum_{i=0}^{t} \alpha_{10i} \Delta GDPII_{t-i} + u_t\end{aligned}$$

Table 1 Definition and data sources of research variables

Notation	Description	Unit	Data source
AGPII	Gross Agricultural Production Index. The index represents statistical records of crops for 173 agricultural products. It includes data on harvested areas, production quantity, and yield.	2014–2016 = 100.	FAOSTAT (2024)
AGPVI	Gross Agricultural Production Value	*Constant 2014–2016 thousand US$*	FAOSTAT (2024)
FRTZQ	Total nutrient use of N, P_2O_5, K_2O from inorganic fertilizers and N nutrient from organic fertilizers	*in 1000 metric tons*	USA, Economic Research Service (2024)
GHGEM	Greenhouse gas emissions	*CO_2 equivalents*	https://ourworldindata.org/ (2024)
GDPII	Economic growth	*Current US$*	World Development Indicators (2024)
ALAND	Agricultural land area	m^2 per 1000 ha	FAOSTAT (2024)

$$\Delta AGPVI_t = \beta_0 + \beta_1 AGPVI_{t-1} + \beta_2 FRTZQ_{t-1} + \beta_3 GHGEM_{t-1} + \beta_4 ALAND_{t-1} + \beta_5 GDPII_{t-1} + \sum_{i=1}^{p} \beta_{6i} \Delta AGPII_{t-i} + \sum_{i=0}^{q} \beta_{7i} \Delta FRTZQ_{t-i} + \sum_{i=0}^{r} \beta_{8i} \Delta GHGEM_{t-i} + \sum_{i=0}^{s} \beta_{9i} \Delta ALAND_{t-i} + \sum_{i=0}^{t} \beta_{10i} \Delta GDPII_{t-i} + u_t$$

where Δ represents the change in the variable, and *p*, *q*, *r*, *s*, and *t* denote the optimal lag values for each variable, determined using the Akaike Information Criterion (AIC). According to Firdaus *et al.* (2020), the ARDL model was first introduced by Pesaran and Shin (1998) as an approach for cointegration testing (long-term relationships among variables). This approach applies the Bound Test for Cointegration, where the *F*-statistics is compared with the *F*-table values developed by Pesaran *et al.* (2001). In the ARDL bounds test, the null hypothesis states that there is no cointegration (H_0: $\alpha h = 0$ ($\forall\ h = 1, 2, \ldots, 7$)). The decision to reject or accept the null hypothesis is based on an *F*-statistics. If the F-statistics exceeds the upper-bound critical value, the null hypothesis is rejected, indicating the presence of a long-term relationship among the variables.

Furthermore, the short-term function of the ARDL model can be expressed as follows:

$$\Delta AGPII_t = \alpha_{11} + \sum_{i=1}^{p} \alpha_{12i} \Delta AGPII_{t-i} + \sum_{i=0}^{q} \alpha_{13i} \Delta FRTZQ_{t-i} + \sum_{i=0}^{r} \alpha_{14i} \Delta GHGEM_{t-i} + \sum_{i=0}^{s} \alpha_{15i} \Delta ALAND_{t-i} + \sum_{i=0}^{t} \alpha_{16i} \Delta GDPII_{t-i} + \lambda ECM_{t-1} + u_t$$

$$\Delta AGPVI_t = \beta_{11} + \sum_{i=1}^{p} \beta_{12i} \Delta AGPII_{t-i} + \sum_{i=0}^{q} \beta_{13i} \Delta FRTZQ_{t-i} + \sum_{i=0}^{r} \beta_{14i} \Delta GHGEM_{t-i} + \sum_{i=0}^{s} \beta_{15i} \Delta ALAND_{t-i} + \sum_{i=0}^{t} \beta_{116i} \Delta GDPII_{t-i} + \lambda ECM_{t-1} + u_t$$

Based on the equation above, the coefficient of ECM_{t-1} (λ), which is negative and statistically significant, indicates cointegration in the model. This suggests the speed at which any temporary deviation in the relationship between the dependent and independent variables returns to the long-term equilibrium. This study employed EViews version 9 for data analysis.

RESULTS AND DISCUSSION

Descriptive Statistics

Indonesia, a Southeast Asian country located along the equator, is significantly affected by climate change (Zhang *et al.* 2023). According to Hasibuan *et al.* (2020), a study involving 500 small-scale citrus farmers in Indonesia in 2017 found that climate change severely impacted farmers in the country. In Indonesia, where approximately 60% of the population depends on agriculture for their livelihood, climate change has led to increased annual average temperatures, changes in rainfall patterns, rising sea levels, and more frequent and intense extreme weather events (Ruminta and Handoko 2016). These factors contribute to a decline in agricultural production and limit the sector’s role in providing long-term employment opportunities. Notably, during the COVID-19 pandemic, the agricultural sector absorbed a significant number of workers affected by job layoffs (Malahayati *et al.* 2021).

From 1981 to 2021, Indonesia's highest agricultural production and gross value were recorded in 2018, with an Agricultural Gross Production Index (AGPII) of 119.16 and an economic value of USD 139 billion. In

2018, the combined contribution of food crops, plantations, livestock, horticulture, and fisheries to Indonesia's Gross Domestic Product (GDP) was 11.97% (BPS 2019). Achievements in that year included rice, corn production of 30.06 million tons, and soybean productions of 83.03, 30.06, and 0.98 million tons, respectively. Consequently, Indonesia has received international recognition for its agricultural performance. For example, in 2017, the Economist Intelligence Unit (EIU) ranked Indonesia 69th out of 113 countries in the Global Food Security Index (GFSI), with an improvement in its food availability ranking from 76th in 2014 to 64th in 2017 (Kementan 2019). Conversely, Indonesia's lowest agricultural production and gross value were recorded in 1982, with an agricultural index value of 32.43 and an economic value of USD 39 billion. This downturn was attributed to the global recession in 1982, caused by events such as conflicts in the Middle East, issues in Indochina, and the Soviet invasion of Afghanistan, which impacted Indonesia's economy significantly. Table 2 presents a summary of the key descriptive statistics for the variables used in this study.

Stationarity Test

Stationarity testing is crucial in time-series data analysis. In this study, stationarity was tested using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Table 3 indicates that all variables in models MI and MII were stationary at the level (GHGEM) and at the first difference (AGPII, AGPVI, FRTZQ, GDPII, ALAND). None of the variables required differencing beyond the first order, confirming that the data were suitable for the ARDL model.

Cointegration Test

The ARDL bounds test was employed to assess the long-term cointegration relationships between the dependent and independent variables in models MI and MII. Table 4 shows that the ARDL bounds test F-statistics exceeds the upper bound at the 1% significance level, indicating the existence of long-term cointegration between the variables. Following Pesaran and Shin (1998), the Akaike Information Criterion (AIC) was used to select the optimal lag length.

After establishing cointegration, the next step involved estimating the long-term effects of the specific variables. Table 5 presents the short- and long-term ARDL estimations for model MI. The results indicate that agricultural land area (ALAND) and economic growth (GDPII) have significantly positive effects on Indonesia's agricultural gross production. A 1% increase in ALAND and GDPII is associated with a 0.52% and 0.56% increase in agricultural production, respectively.

Regarding agricultural land, BPS (2024) reported a decline in the rice harvested area and production from 2018 to 2023, despite an increase in rice productivity, as illustrated in Figure 1. Between 2018 and 2023, the average annual reduction in the rice harvested area was –2.21%, whereas rice production declined by

Table 2 Description of variables in Model MI and Model MII

	AGPII	AGPVI	FRTZQ	GHGEM	ALAND	GDPII
Average	70,58	82675945	4099949	1610000000	49603,15	509000000000
Median	61,65	72509766	3104334	1540000000	48675,00	428000000000
Maximum	119,16	139000000	8401532	3410000000	64600,00	1070000000000
Minimum	32,43	39125377	1639054	678000000	37052,00	171000000000
Std. Dev.	26,68	30134426	1951448	515000000	8419,23	276000000000

Table 3 Stationarity test

Variables	ADF-test		PP-test	
	Level	First-difference	Level	First-difference
AGPII	–1.1154	–6.5498***	–1.4099	–6.5847***
AGPVI	–1.0840	–.9439***	–1.4019	–7.0962***
FRTZQ	–0.2626	–.9860***	–0.5398	–9.2073***
GHGEM	–3.0772**	–6.3301***	–3.0772**	–11.3160***
GDPII	–0.6482	–4.7399***	–0.6482	–4.7263***
ALAND	–0.1783	–5.0486***	–0.1783	–5.0486***

Remaks: ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

Table 4 Results of cointegration bounds test

Estimated model	Maximum lag length	*F*-stat	Significance level (%)	Critical value	
				Lower bound	Upper bound
Model AGPII	4	7.3706***	10	2.45	3.52
			5	2.86	4.01
Model AGPVI	4	12.3038***	2.5	3.25	4.49
			1	3.74	5.06

Remaks: ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

Table 5 Short-term and long-term ARDL estimation for Model I (AGPII)

Variables	Coefficient	*t*-Statistics
Long-run form		
FRTZQ	–0.0234 (0.1141)	–0.2055
GHGEM	–0.0472 (0.0683)	–0.6909
ALAND	0.5289** (0.2370)	2.2315
GDPII	0.5654*** (0.1028)	5.4978
C	–15.3090 (1.3575)	–11.2767
ECM Regression (short-run form)		
Variables	Coefficient	*t*-Statistics
D(FRTZQ)	0.1455** (0.0708)	2.0551
D(GHGEM)	–0.0057 (0.0309)	–0.1846
D(ALAND)	0.2552** (0.1247)	2.0457
D(GDPII)	0.2728** (0.1101)	2.4771
CointEq(-1)	–0.4825*** (0.1689)	–2.8564
R-Squared	0.9950	
Adjusted R-Squared	0.9939	
Durbin-Watson	1.76	
Diagnostic test		
Breusch-Godfrey Serial Correlation LM Test	*F*-stat	0.5642
	p-value	0.2611
Breusch-Pagan-Godfrey Heteroskedasticity Test	*F*-stat	0.4747
	p-value	0.8396
Jarque-Bera Normality Test	Test-stat	0.5683
	p-value	0.7526
Ramsey Reset Test	*F*-stat	0.8538
	p-value	0.3701

Remaks: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Numbers in parentheses represent standard errors.

–1.92%. However, rice productivity increased by 0.31% during the same period. These findings align with those of Moeis *et al.* (2020), who highlighted that agricultural land remains a critical household asset for farmers.

Household expenditure data support this trend. Between 2000 and 2007, farmers' per capita expenditure fell from IDR 36,833 in 2000 to IDR 68,683 in 2007, indicating a decline in farmer welfare. The reduction in agricultural land is a pressing issue that requires government intervention to address it. One potential solution is agrarian reform, as seen in Central Kalimantan, where the government allocated 12% of the state land for distribution to farmers (Resosudarmo *et al.* 2019). Additionally, technological advancements are necessary to enhance agricultural productivity amid decreasing land availability (Aggarwal *et al.* 2019).

Economic growth (GDPII) also plays a critical role. Figure 2 illustrates that government spending on agriculture has generally increased over time. However, a distinction can be made between the periods 2007–2010, which saw an average increase of 23.14%, and 2018–2022, which experienced an average decline of –6.61%. This trend raises concerns regarding the government's commitment to agricultural development. According to FAO (2023), agriculture's contribution to Indonesia's GDP is substantial. Although its share has declined by an average of –2.01% annually from 1970 to 2021, its absolute value has increased by an average of 8.61% per year (Figure 3).

The agricultural sector is also a major employment provider, with an average of 31.82% of the workforce engaged in agriculture between 2008 and 2022 (Figure 4). Table 6 presents the ARDL estimations for model MII, which corroborate the findings in Table 5: ALAND and GDPII have significant positive effects, while greenhouse gas emissions (GHGEM) negatively impact agricultural production, though not significantly. The study also found that fertilizer use (FRTZQ), despite not having a statistically significant effect, was

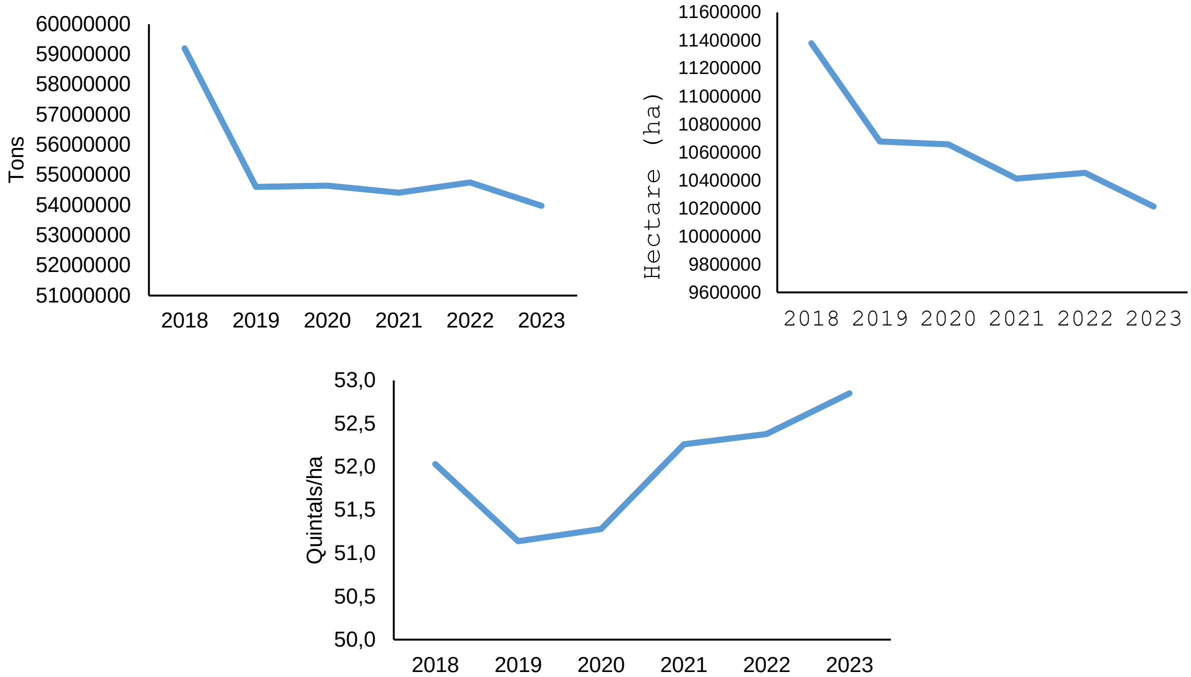

Figure 1 a) rice production (tons), b) harvested rice area (ha), c) rice productivity (quintals/ha) (BPS 2024).

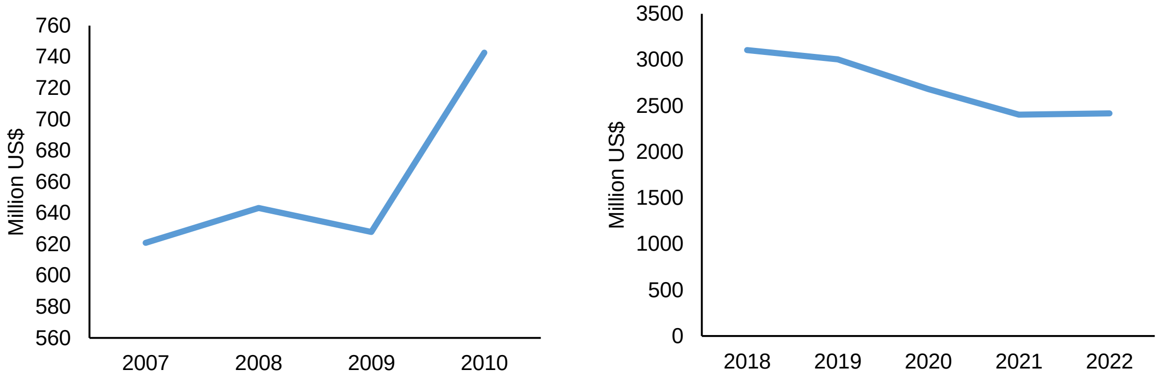

Figure 2 Government expenditure in the agricultural sector in 2007–2010 and 2018–2022 (million US$) (FAO 2024).

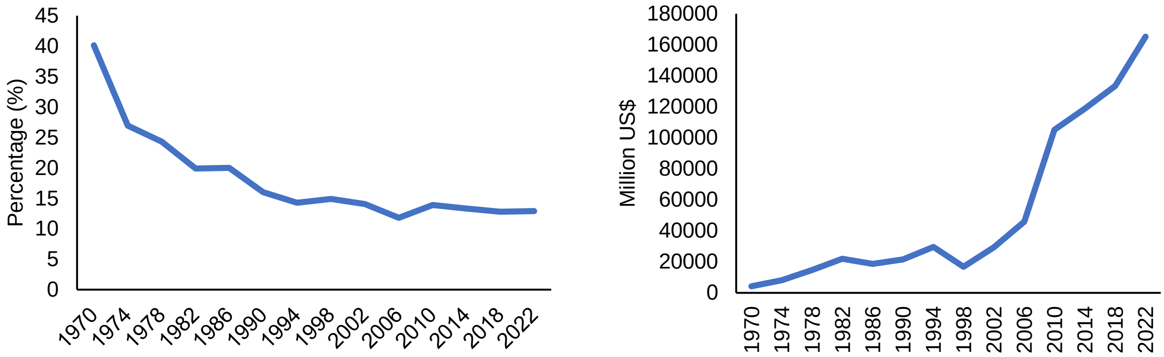

Figure 3 (a) Share of the agricultural sector in Indonesia's GDP (%), (b) Value of the agricultural sector's share in GDP (Million US$) (FAO 2023).

crucial for agricultural productivity. Expanding fertilizer crucial for agricultural productivity. Expanding fertilizer applications could help offset the declining availability of agricultural land.

Although the effects of climate change were not statistically significant in this study, they were evident for specific agricultural commodities. For example, Khairulbahri (2021) found that climate change reduces rice productivity in West Nusa Tenggara (NTB), a crop vital for employment and the economy of Indonesia. Similarly, Frimawaty *et al.* (2013) reported that rice farming in Jambi is unsustainable, with a sustainability index of 41.96. Yamamoto *et al.* (2019) estimated that rural agricultural productivity in Indonesia declined by 45% between 2001 and 2014, equating to a USD 2.63 billion loss in 2014. Climate change also threatens Indonesia's medicinal plant species, with projections indicating a 50–80% reduction in distribution areas by 2050–2080 (Cahyaningsih *et al.* 2021). Rising sea levels have already submerged 12 outer islands, with 83 more at high risk (Vinata *et al.* 2023), potentially altering Indonesia's maritime boundaries.

To address climate change challenges, the government must implement targeted policies, including low-carbon economic development, renewable energy promotion, technological innovation financing, and climate-smart agriculture (Raihan *et al.* 2022). The short-term estimation results of this study reveal the presence of an ECMt-1 value, represented by CointEq (–1), which has a negative and statistically significant coefficient at the 1% level, specifically –0.48 for Model I (AGPII) and –0.76 for Model II (AGPVI). This indicates that the adjustment rates between Models I and II are corrected by 48% and 76%, respectively, from the short term to the long term over the study period. In other words, this finding confirms the existence of a stable long-term relationship among the variables in the ARDL model.

Furthermore, diagnostic tests were conducted to assess the ARDL model's consistency. A summary of the diagnostic test results is presented in Table 7, which indicates no issues related to autocorrelation, heteroscedasticity, normality, or functional form misspecification in the ARDL model's results. Additionally, the study employed CUSUM and CUSUMSQ tests to validate the ARDL model's long-term estimates. The CUSUM and CUSUMSQ plots (Figure 5) for all ARDL models demonstrate satisfactory results at the 5% significance level, as the blue lines remain within the red boundary. This confirms that the ARDL model is stable, supporting the validity of the long-term agricultural production and value models used in this study.

CONCLUSION

The agricultural sector in Indonesia faces numerous challenges. This study finds that, in the long run, Indonesia's agricultural sector is influenced by the agricultural land area and economic growth. In the agricultural production model, a 1% increase in agricultural land area and economic growth was associated with a 0.52% and 0.56% increase in agricultural production, respectively. Meanwhile, in the agricultural value model, a 1% increase in agricultural land area and economic growth leads to a 0.37% and 0.47% rise in Indonesia's gross agricultural value, respectively. In the short run, the key influencing variables are agricultural land area, economic growth and fertilizer usage. Although climate change negatively affects the agricultural sector, its impact is not statistically significant. Similarly, fertilizer use has a positive but statistically insignificant effect on agricultural production. Given these findings, the government's role must be strengthened through increased fiscal spending in the agricultural sector. The government should enhance access to fertilizers, expand agricultural land, and support strategic sectors to mitigate the effects of climate change. Although the impact of climate change was not statistically significant, proactive measures are necessary to prevent greater losses in the future.

ACKNOWLEDGMENT

The author expresses gratitude to the Indonesia Endowment Fund for Education (LPDP) under the Ministry of Finance of the Republic of Indonesia for funding this research, which enabled the successful completion of this study.

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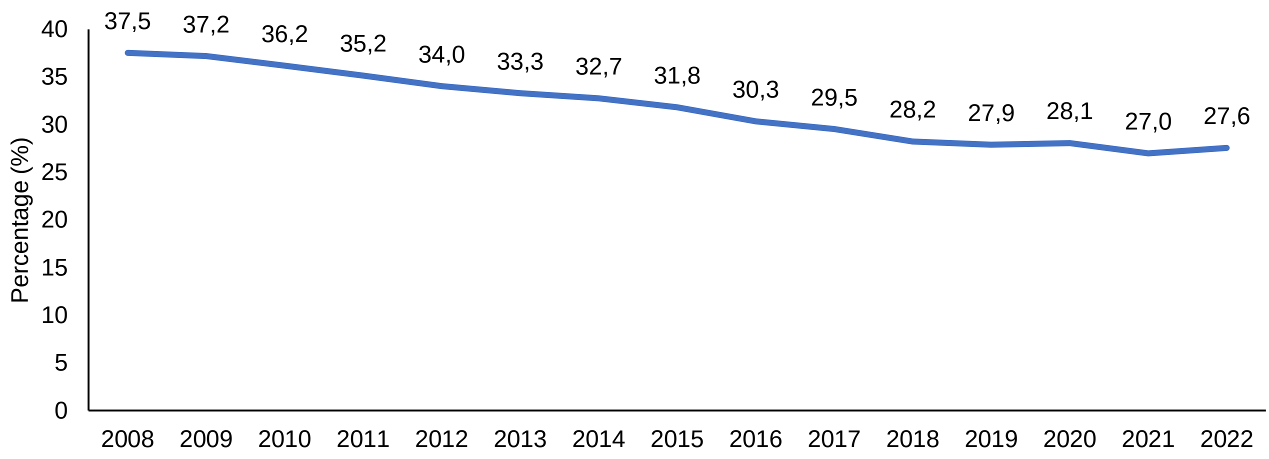

Figure 4 Percentage of the workforce employed in the agricultural sector (%) (FAO and BPS 2023)

Table 6 Estimation of Short-Term and Long-Term ARDL Model II (AGPVI)

Long-run form		
Variables	Coefficient	*t*-statistics
FRTZQ	0.1063 (0.0678)	1.5683
GHGEM	-0.0126 (0.0371)	-0.3397
ALAND	0.3737** (0.1430)	2.6118
GDPII	0.4686*** (0.0629)	7.4462
C	0.2358 (0.8404)	0.2806
ECM regression (short-run form)		
Variables	Coefficient	*t*-statistics
D(FRTZQ)	0.0809 (0.0497)	1.6263
D(GHGEM)	-0.0096 (0.0276)	-0.3465
D(ALAND)	0.2842** (0.1241)	2.2912
D(GDPII)	0.3564** (0.1032)	3.4531
CointEq(-1)	-0.7606*** (0.1728)	-4.4001
R-Squared	0.9943	
Adjusted *R*-Squared	0.9934	
Durbin-Watson	1.6823	
Diagnostic test		
Breusch-Godfrey Serial Correlation LM Test	*F*-stat	0.9234
	p-value	0.1714
Breusch-Pagan-Godfrey Heteroskedasticity Test	*F*-stat	1.0744
	p-value	0.3791
Jarque-Bera normality Test	Test-stat	0.2998
	p-value	0.8607
Ramsey Reset Test	*F*-stat	2.1685
	p-value	0.1581

Remaks ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Numbers in parentheses represent standard errors.

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Table 7 Model evaluation results

Model	Residual assumption test			Stability	
	Autocorrelation	Heteroscedasticity	Normality	CUSUM	CUSUMSQ
MI	√	√	√	Stable	Stable
MII	√	√	√	Stable	Stable

Remaks: √ indicates that the model met the classical assumption tests.

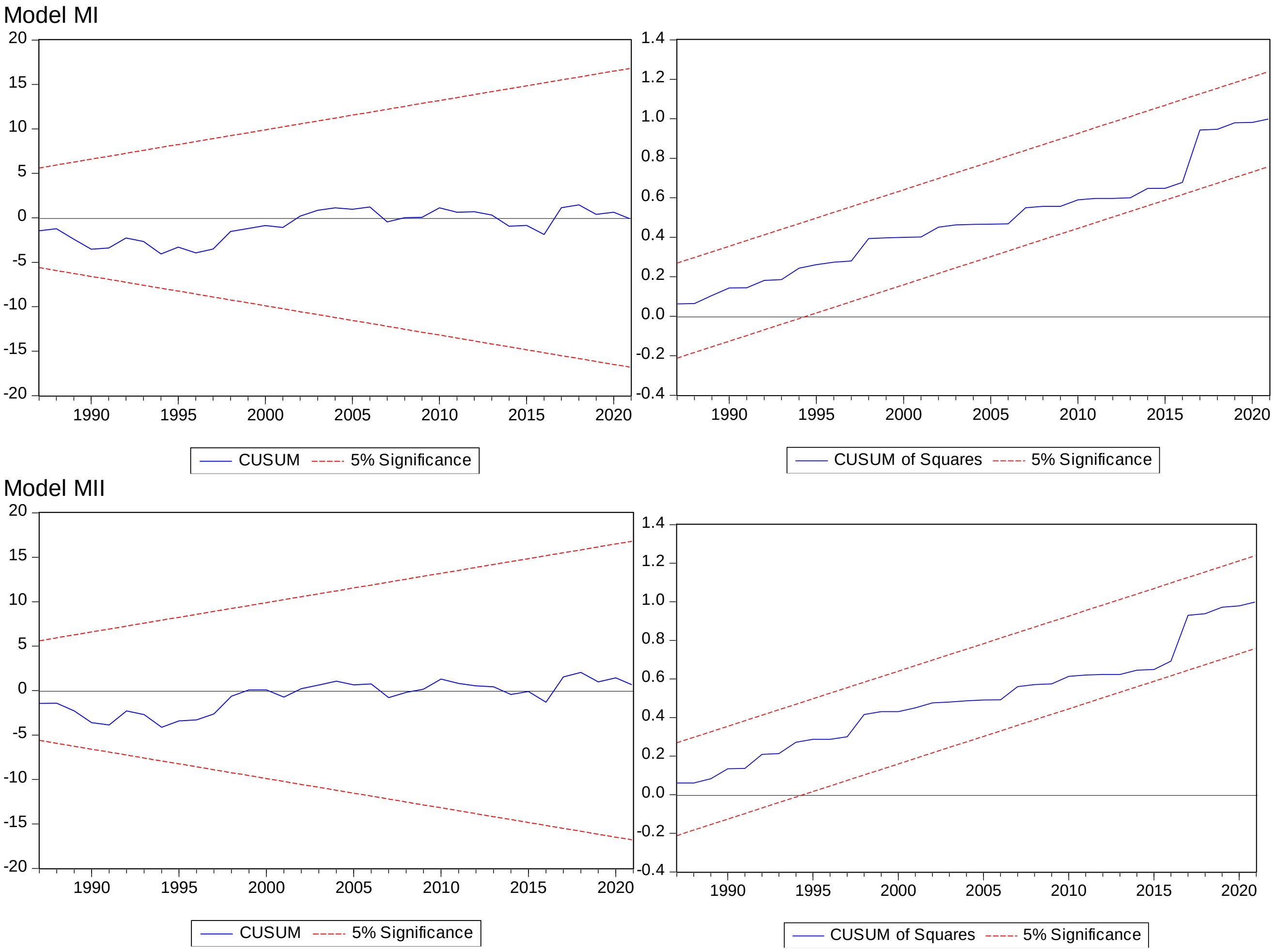

Figure 5 Plot of CUSUM and CUSUMSQ.

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