IJEEP

INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY

EJ EconJournals ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2026, 16(2), 323-332.

EJ EconJournals

Does Carbon Dioxide Have a Significant Dynamic Effect on Agricultural Productivity in Indonesia?

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Received: 02 September 2025 **Accepted:** 29 December 2025 **DOI:** https://doi.org/10.32479/ijeep.22400

ABSTRACT

This study investigates the dynamic influence of carbon dioxide (CO_2) emissions, labor, and capital formation on agricultural productivity in Indonesia, utilizing annual data from 2000 to 2023 and employing an Autoregressive Distributed Lag (ARDL) model. The coefficient of carbon dioxide has no significant dynamic effect on the agricultural productivity in Indonesia in the short run. Meanwhile, labor and capital have dynamic and significant effects on agricultural productivity in the short run. However, carbon dioxide, labor, and capital have no significant long-term effects on agricultural productivity. Furthermore, labor exhibits cyclical and inconsistent effects, reflecting seasonal employment patterns and skill limitations, whereas capital consistently has a positive impact on productivity through mechanization and technological advancements.

Keywords: Agricultural Productivity, Carbon Dioxide, Labor, Capital
JEL Classifications: Q12, Q52, J21, J24, G31

1. INTRODUCTION

The agricultural sector holds significant importance for Indonesia, serving as a major contributor to the nation's economy. It remains a fundamental pillar of Indonesia's economic framework. According to data from Statistics Indonesia (BPS) as of February 2024, the agricultural sector accounted for approximately 12.53% of the national Gross Domestic Product (GDP). This contribution highlights the vital role of agriculture in driving economic growth, particularly in rural regions. Moreover, the agricultural sector is among the sectors exhibiting positive growth, even amid economic contractions in other industries. Additionally, the agricultural sector plays an indispensable role in supplying raw materials for domestic processing industries, including the food, textile, and bioenergy sectors. By fulfilling its dual function as both a provider of food and a source of industrial raw materials, the agricultural sector enhances economic resilience. It helps maintain the stability of staple food prices.

The agricultural sector constitutes the foundation of the nation's food supply. Statistics Indonesia (BPS) has observed that the production of essential commodities, such as rice, corn, and soybeans, has demonstrated a positive trend from 2020 to 2024. Consistent rice production enables Indonesia to maintain its rice self-sufficiency, despite ongoing challenges related to climate change and land-use modifications. Data from BPS regarding the consumption of vital foodstuffs indicate that rice remains the primary dietary staple for the Indonesian population. Furthermore, the agricultural sector also contributes a variety of horticultural, plantation, and fishery products, thereby reinforcing the country's food security.

The agricultural sector also plays a key role in absorbing labor in Indonesia. According to Statistics Indonesia (BPS) data (August 2024), the agriculture, forestry, and fisheries sector employ about 28.18% of the total national workforce, roughly 40.75 million workers out of a total workforce of 144.64 million. In August 2023, employment in this sector was recorded at 36.46 million people

(26.07% of the total workforce). With 25.12 million agricultural households and 27.8 million land-using farmers (BPS, 2023), agriculture remains the leading sector in terms of employment in rural areas. The agricultural sector is vital not just for creating jobs but also for reducing poverty. Many rural households depend on agricultural work for their income, so boosting productivity and efficiency in this sector directly benefits community welfare.

Despite the critical role of the agricultural sector, it faces complex challenges. Agricultural labor productivity remains relatively low compared to the industrial and service sectors. The added value of agriculture per worker stays below the national average. Additionally, pressures from climate change, urbanization, and land conversion threaten the country's food production sustainability. To overcome these issues, future agricultural development strategies should focus on modernization, incorporating digital technology and precision agriculture, and promoting sustainable agricultural systems. This approach can help transform the agricultural sector into a key driver of Indonesia's green economy while supporting the achievement of the Sustainable Development Goals (SDGs).

Agriculture remains the cornerstone of Indonesia's economic framework, making substantial contributions to employment, food security, and rural development. Despite the country's swift structural transformation and industrialization, the agricultural sector remains a significant employer, employing over 25% of Indonesia's workforce and sustaining the livelihoods of around 40% of the population. Nevertheless, this vital sector encounters a paradox: while economic growth and capital accumulation have fostered enhanced productivity, environmental deterioration—particularly through an increase in carbon dioxide (CO_2) emissions—poses a substantial threat to sustainable agricultural development.

Globally, the relationship between carbon dioxide (CO_2) emissions and agricultural productivity has emerged as a subject of increasing scholarly debate. The carbon fertilization hypothesis posits that elevated atmospheric CO_2 levels can enhance photosynthetic efficiency and crop yields, particularly for C_3 crops such as rice, wheat, and soybeans (Liu and Lu, 2024). Correspondingly, Otim et al. (2023) observed that within East African Community countries, CO_2 emissions, renewable energy consumption, and labor availability exert a positive influence on agricultural yields in the long term. These findings highlight the potential of CO_2 to function as a short-term growth catalyst under controlled conditions.

Nonetheless, these advantageous effects are not uniformly assured. Excessive emissions of greenhouse gases (GHG) contribute to the acceleration of global warming, thereby modifying temperature, precipitation patterns, and soil moisture equilibrium—elements vital for agricultural productivity. Elevated temperatures and unpredictable rainfall diminish crop yield stability, impair soil fertility, and initiate pest infestations, particularly in tropical nations such as Indonesia. Evidence derived from an experimental investigation on peanuts by Ramana et al. (2025) indicates that although elevated CO_2 concentrations may alleviate yield reductions caused by thermal stress, they concurrently decrease the protein content and nutritional quality of the crop, suggesting that long-term nutritional outcomes could deteriorate despite an increase in biomass.

The interaction between capital formation and labor force dynamics introduces additional complexity. Capital investment—gauged by gross fixed capital formation—propels mechanization, irrigation, fertilizer application, and technological adoption, thereby enhancing land productivity. Concurrently, labor remains an essential input; however, its efficiency is contingent upon the quality of human capital and the rural employment structure (Yang et al., 2024). As agricultural modernization progresses, a dual challenge arises: to ensure the effective utilization of labor amidst urban migration and to allocate sufficient capital for climate-resilient agricultural systems.

For Indonesia, which has committed to achieving net-zero emissions by 2060, the stakes are high. Agriculture not only contributes to CO_2 emissions through land conversion, residue burning, and fertilizer use, but also serves as a potential carbon sink through reforestation, agroforestry, and soil carbon sequestration. Therefore, understanding how CO_2 emissions, capital, and labor interact to shape agricultural productivity is crucial for aligning economic development goals with environmental sustainability targets. Therefore, this study aims to empirically examine the dynamic relationship between carbon dioxide emissions, capital formation, and the labor force as determinants of agricultural productivity in Indonesia from 1990 to 2023. Using an Autoregressive Distributed Lag (ARDL) approach, this study investigates the short- and long-term relationships between these variables. It explores the extent to which CO_2 acts as a stimulant or inhibitor of agricultural growth.

2. LITERATURE REVIEW

Productivity—defined as the efficiency with which inputs are converted into output is a key factor in long-term economic growth and structural change. The relationship between labor and capital is the main driver of productivity growth, influencing sector performance, competitiveness, and living standards. Historically, classical economists such as Adam Smith and David Ricardo highlighted capital accumulation and labor specialization as the foundation of economic progress. In contrast, the neoclassical growth models of Solow and Swan later formalized the importance of technological change and factor accumulation in determining output per worker.

Contemporary empirical studies corroborate that productivity is contingent not solely on the quantity of capital and labor but also on their quality, composition, and complementarity. The interplay between these elements is dynamic and reciprocal: capital accumulation enhances the marginal productivity of labor through mechanization, technological adoption, and infrastructural investment, while a skilled and adaptable workforce amplifies the returns on capital and promotes the dissemination of innovation.

The relationship between agricultural productivity and its determinants—capital, labor, and the environment—has long been based on production theory and growth models. The Cobb–

Douglas production function expresses output as a function of capital (K), labor (L), and technology (A), where total factor productivity includes ecological and climatic influences such as CO_2. Empirical studies have shown that CO_2 emissions have a dual impact. The positive side, known as the CO_2 fertilization effect, increases photosynthesis in C_3 crops, thereby increasing crop yields (Liu and Lu, 2024). Furthermore, estimation results demonstrate the causal effect of CO_2 on crop yields, finding that a one-standard-deviation increase in CO_2 increases the yields of rice, wheat, and maize. The study also shows a shift in crop area toward C_3 crops when carbon fertilization improves their comparative advantage. However, in a carbon-neutral scenario, peak production is projected to occur around 2040-2041 and then decline, as rising temperatures partially counteract the benefits of CO_2 and the dynamic response of land allocation. These findings confirm that the benefits of carbon fertilization are heterogeneous across crop types ($C_{3\text{ vs.}}$ C_4) and are not linear with respect to long-term climate dynamics (Long et al., 2004).

Meanwhile, Otim et al. (2023) reported analogous findings within East African Community nations, where CO_2, renewable energy, and labor exerted a positive influence on agricultural output. Conversely, research conducted by Ramana et al. (2025) has indicated that prolonged exposure to CO_2 diminishes the nutritional quality of crops. Raihan (2023) emphasized that renewable energy and sustainable agricultural practices can mitigate emissions while maintaining productivity.

Experimental evidence on groundnut (*Arachis hypogaea*) reveals a more complex nuance: rising temperatures reduce biomass and haulm yield, and higher CO_2 only partially compensates for the heat-induced decline. Forage nutritional quality (decreased protein, increased NDF) also deteriorates, with negative implications for livestock. This indicates that although CO_2 temporarily enhances yield, alterations in quality and heat stress can diminish nutritional value and digestibility—constituting a significant trade-off for rural crop-livestock systems (Ramana et al., 2025). From a plant physiological standpoint, exposure to temperatures above the optimal level decreases net photosynthesis (via increased photorespiration and reduced Rubisco activity). It elicits a series of morpho-physiological responses that suppress growth. In hot tropical environments, rising CO_2 does not automatically lead to increased productivity; rather, it necessitates adaptation to temperature and drought stress (Ainsworth and Long, 2021).

Agricultural productivity is not solely determined by carbon dioxide; capital and labor are also important factors in production and labor productivity. A qualified workforce plays a key role in increasing production. This workforce role is a crucial variable in enhancing productivity. A panel study conducted in East African Community countries by Otim et al. (2023) found that, in the long run, CO_2, labor, renewable energy, and land exhibit a positive relationship with the agricultural production index. The econometric approaches employed—Pooled Mean Group (PMG), ARDL, and Dumitrescu-Hurlin causality—illustrate the significance of classical factor inputs (labor and land) and energy transitions in elucidating agricultural productivity. Furthermore, Raihan (2023) demonstrates that renewable energy and agricultural productivity reduce CO_2 emissions by 1.50% and 0.20%, respectively, for each 1% increase. Conversely, economic growth, urbanization, and industrialization contribute to increased emissions. These findings affirm that enhancing environmentally sustainable agricultural productivity can facilitate emission reductions within the Southeast Asian region.

From a technological perspective, the energy-engineering literature highlights low-carbon mechanization—examples include ammonia-diesel dual-fuel agricultural machinery—which can reduce carbon emissions compared to solely fossil-fueled machinery. A study by Ji et al. (2025) demonstrated that utilizing ammonia as an alternative fuel in agricultural machinery can decrease CO_2 emissions by up to 60%, while maintaining combustion stability. In the medium term, green ammonia—produced using renewable energy—is regarded as a potential zero-carbon hydrogen carrier for future agricultural mechanization.

Another factor that cannot be disregarded is capital, which plays a pivotal role in enhancing productivity across both the agricultural sector and other industries. Capital formation catalyzes modernization, infrastructure development, and the adoption of advanced technologies within the agricultural domain. Ji et al. (2025) demonstrated that green technologies, such as ammonia-diesel dual-fuel engines, effectively reduce agricultural emissions while maintaining efficiency. The dynamics of the labor force are also critically important, as a skilled human capital base augments productivity and facilitates the implementation of sustainable practices (Raihan, 2023). Nevertheless, the existing empirical literature lacks a comprehensive analysis that integrates CO_2 emissions, capital formation, and labor within the context of Indonesian agriculture. This research addresses this gap by employing the ARDL approach to model both short-term fluctuations and long-term equilibrium relationships among these variables. The significance of this study lies in its potential to contribute to academic literature and to serve as a policy foundation for enhancing agricultural productivity in Indonesia.

Nevertheless, as Jat and Ramaswami (2025) observe in their analysis of India's productivity disparity, the non-agricultural sector is far from homogeneous. A substantial proportion of non-agricultural laborers are employed in low-productivity informal enterprises, which diminishes the sector's overall productivity advantage. Consequently, the quality of labor mobility—specifically, whether workers transition to the capital-intensive formal sector or remain within the informal sector—determines whether reallocation leads to genuine productivity improvements. Accordingly, the agricultural productivity gap (APG) not only reflects sectoral differences but also encapsulates the structural dualism between the formal and informal economies.

Human capital enhances labor productivity, expedites the adoption of technology, and encourages innovation. Lu et al. (2025) illustrated an inverted U-shaped relationship between rural human capital and agricultural carbon emissions, indicating that initial human capital development can elevate output and emissions; however, beyond a certain threshold, more educated workers tend to implement cleaner and more efficient technologies. This observation aligns with endogenous growth theory, which posits that human capital drives learning, adaptation, and continuous productivity growth.

Similarly, Saha et al. (2025) established that in Bangladesh, human capital—symbolized by education and health—substantially enhances agricultural labor productivity. Additionally, remittance inflows further augment this influence by providing investment funding for education, health services, and agricultural technology. These findings exemplify the synergistic relationship between financial and human capital: remittances serve as a conduit for capital accumulation, while education influences the efficiency of capital utilization.

Chen and Hu (2025) expand upon this reasoning through the concept of financial inclusion, demonstrating that access to rural credit fosters human capital development, which in turn elevates agricultural gross domestic product (GDP). This mechanism exemplifies how institutional capital, facilitated by financial inclusion, supports human development and productivity enhancement, particularly in rural nations with limited access to financial services.

The interaction between physical and human capital is characterized by capital-skill complementarity, which indicates that technological advancements elevate the relative demand for skilled labor. Lei et al. (2025) corroborate this mechanism at the corporate level in China: the implementation of artificial intelligence (AI) enhances a company's Total Factor Productivity (TFP) by improving production efficiency and managerial decision-making, while human capital serves as a mediating factor that enables workers to leverage AI technology effectively. In this context, capital no longer merely replaces labor but also enhances its efficiency and capacity for innovation.

Capital investment in agricultural machinery, irrigation, and infrastructure also enhances labor productivity by diminishing workloads and boosting efficiency. The agricultural mechanization observed by Li et al. (2024) demonstrates that capital investment not only elevates output but also transforms the employment structure, fostering labor migration and industrial diversification. However, returns on capital are contingent upon labor absorption—economies characterized by low educational levels or fragile institutions may encounter diminishing marginal returns from capital accumulation.

Synthesizing these insights, productivity growth emerges because of intricate synergies among labor, capital, and institutional quality. Labor contributes via education, skill development, and efficient allocation; capital participates through investment, technological advancement, and innovation; and institutions enhance their interaction by improving financial access, securing property rights, and fostering social cohesion. The reviewed studies collectively challenge the conventional linear perspective of growth as solely dependent on capital accumulation, advocating for a multidimensional framework wherein human agency, institutional inclusiveness, and technological adaptation collectively influence productivity trajectories.

Li et al. (2024) present compelling evidence derived from China's Agricultural Tax Exemption (ATE) reforms, illustrating how institutional changes in taxation have precipitated a reallocation of labor from the agricultural sector to non-agricultural sectors. This reform led to a 46% increase in agricultural capital investment, improved total factor productivity (TFP), and facilitated the transfer of surplus agricultural labor to sectors with higher productivity. These findings support the 'labor push hypothesis' in development economics, which posits that increases in agricultural productivity free labor for expansion in the industrial sector, thereby contributing to overall economic efficiency.

3. RESEARCH METHODS

The data used in this study are secondary data obtained from various sources, including Statistics Indonesia (BPS) and the World Bank. More detailed data sources are listed in Table 1.

This study uses an Autoregressive Distributed Lag (ARDL) model to estimate the short- and long-term effects of CO_2 emissions, capital, and labor on agricultural productivity in Indonesia. Annual data from 1990 to 2022 were collected from the World Bank (WDI, 2023) and several publications from other official institutions. The estimation model states:

$$\Delta AP_t = \gamma_0 + \sum_{k=1}^{p} \beta_{1k} \Delta AP_{t-k} + \sum_{k=0}^{p} \beta_{2k} \Delta lnCO_{2t-k} + \sum_{k=0}^{p} \beta_{3k} \Delta K_t + \sum_{k=0}^{p} \beta_{4k} \Delta L_t + \theta_1 AP_{t-1} + \theta_2 lnCO_{2t-1} + \theta_3 K_{t-1} + \theta_4 L_{t-1} + \varepsilon_t \quad (1)$$

Where AP is agricultural productivity measured by the contribution of the agricultural sector to Gross Domestic Product (GDP) in percent, CO_2 is carbon dioxide in tons and transformed into its

Table 1: Data and their sources

Variable	Definition	Source
Carbon dioxide (CO_2)	Total carbon emissions in tons, converted to natural logarithm.	https://databank.worldbank.org/source/millennium-development-goals/Series/EN.ATM.CO2E.KT#
Agricultural productivity (AP)	Share of the agricultural sector of GDP (percent)	https://www.bps.go.id/en/statistics-table/2/MjI2OCMy/-2010-version--quarterly-gdrp-at-current-market-price-by-industrial-origin-in-province--billion-rupiahs-.html
Capital (K)	Share of Gross Domestic Capital Formation to GDP (percent)	https://www.bps.go.id/en/statistics-table/2/MTEwIzI=/-2010-version--3--distribution-of-gdp-at-current-market-prices-by-expenditure--percent-.html
Labor (L)	Percentage of nonformal workers in the agricultural sector (percent)	https://www.bps.go.id/en/statistics-table?subject=520

natural logarithm, K is capital measured by gross fixed capital formation to GDP in percent, and L is the percentage of the population employed in the agricultural sector, ϵ is the residual assumed to be normally distributed and constant variance. Furthermore, γ, β, and θ are the estimated coefficients for the constant, short-run coefficient, and long-run coefficient, respectively.

Productivity is measured by input capacity compared to production, and this aligns with the method developed by Bai et al. (2024), which measures resource efficiency/resource productivity as the ratio of natural resource use to economic output. Meanwhile, Aliasuddin et al. (2024) measure energy efficiency as the ratio of energy use to Gross Domestic Product (GDP).

Estimation begins with a stationarity test of the variables used in this study, employing the Ng and Perron (2001) approach as an improvement over the Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests. This test is used to determine whether a time series is stationary or contains a unit root, i.e., whether the variable exhibits a stochastic trend that could invalidate econometric estimation results.

The reasons for using this test are: (i) it is more efficient for small samples: it reduces bias in the ADF and PP when sample sizes are small; (ii) it addresses the problem of over-differencing: it is less likely to reject H_0 when the data is stationary after differentiation incorrectly; (iii) it handles autocorrelation and heteroscedasticity better: it uses an efficient long-run variance; (iv) it detects unit roots with high precision: it increases test power and lowers the probability of a type I error; and (v) it is consistent with modern time series theory: it is suitable for ARDL, VAR, and NARDL models.

After the stationarity test, the optimal lag is determined using the Akaike Information Criteria (AIC). According to the ARDL approach, the estimated model may have different lags for the variables used in the estimation. Next, the complete ARDL model is estimated, including a short-term to long-term test using the Bound Test, supplemented by testing several assumptions of classical linear regression. As a prerequisite, model stability is tested using the Cusum and Cusum Squares approaches.

4. FINDINGS AND DISCUSSION

4.1. Descriptive Statistics

Descriptive statistics provide helpful information about data distribution, so this descriptive statistical analysis is included in this paper. The descriptive statistics are presented in Table 2.

Table 2 illustrates an average agricultural productivity (AP) value of 13.84, accompanied by a median of 13.49. This indicates a slight rightward skewness (positive skewness) in the AP data distribution, as evidenced by a skewness coefficient of 0.91. Consequently, the majority of the data resides below the mean, although several elevated values raise the overall average. The maximum and minimum values of 16.32 and 12.40, respectively, denote a considerable range of approximately 3.9 points, signifying variations in productivity across different periods or regions. The standard deviation of 1.10 reflects moderate fluctuation, suggesting some variability in agricultural productivity over time. Furthermore, the kurtosis value of 2.75 implies a distribution approaching normality (mesokurtic), indicating that extreme values do not exert undue influence. In summary, the AP variable exhibits relative stability, yet it also demonstrates productivity increases during specific years, potentially attributable to factors such as agricultural modernization, improved fertilizer application, or government policies that impact the agricultural sector.

Table 2: Descriptive statistics of the variables

Statistics	AP	LCO_2	LABOR	Capital
Mean	13.84	8.66	40.05	28.12
Median	13.49	8.69	40.78	30.89
Maximum	16.32	8.87	66.48	32.81
Minimum	12.39	8.45	28.50	19.43
Standard Deviation	1.10	0.12	8.19	4.961
Skewness	0.91	−0.02	1.28	-0.74
Kurtosis	2.75	1.80	5.63	1.95

Source: Estimated Results, 2025

Furthermore, the mean of carbon dioxide (CO_2) is 8.66, with a median of 8.69, signifying a balanced distribution of values above and below the central tendency. A skewness of −0.017 suggests an approximately symmetrical distribution, with negligible bias to either side. The range of LCO_2 values is relatively narrow, spanning from a maximum of 8.87 to a minimum of 8.45, with a minimal standard deviation of 0.12, indicating stable carbon emission levels over time. This pattern implies that CO_2 emissions per unit of production are relatively consistent, potentially due to the stable utilization of fossil fuels within the production process. A kurtosis of 1.80 reflects a platykurtic distribution, characterized by a flatter curve compared to a normal distribution, resulting in a more uniform spread of data. Consequently, there are no significant anomalies or extreme spikes in carbon emissions during the observation period. Overall, the stability of LCO_2 suggests that the contribution of the production sector to carbon emissions remains consistent, attributable to energy efficiency and the relatively stagnant adoption of low-carbon technologies.

The labor force variable exhibits a mean of 40.05 and a median of 40.78, accompanied by a notably high positive skewness of 1.28. This indicates that the distribution is asymmetrically skewed to the right and predominantly influenced by lower values, while specific periods or regions display exceptionally high levels of labor force. The maximum value recorded is 66.48, and the minimum is 28.50, reflecting substantial variation in labor absorption—an almost 38-unit range. The standard deviation stands at 8.19, the highest among all variables, signifying considerable fluctuations in the labor force area.

The kurtosis value of 5.63 significantly exceeds 3, indicating a leptokurtic distribution—specifically, most data points are concentrated around the mean, with identifiable extreme values. This occurrence may be attributed to seasonal labor fluctuations, such as during planting or harvesting periods, or alterations in employment policies. Generally, the LABOR variable exhibits considerable variability and is influenced by seasonal factors, as well as policies related to the development of the productive sector.

The capital exhibits a mean of 28.12 and a median of 30.90, suggesting that most data points lie above the mean—consistent with a negative skewness of -0.74. This left-skewed distribution signifies the presence of periods with comparatively low capital levels, which consequently depresses the overall mean. The value range is notably extensive, spanning from a maximum of 32.81 to a minimum of 19.43, with a standard deviation of 4.96, indicating considerable fluctuations in capital over time, which may be attributable to changes in investment or real-sector financing policies. The kurtosis value of 1.95 indicates a platykurtic distribution, characterized by a relatively even spread of data without pronounced peaks. This implies that variations in capital tend to progress gradually, with no extreme spikes observed in specific periods. Such a pattern may reflect capital's reliance on medium-term investment cycles and relatively stable fiscal policies.

Overall, these results suggest that the production sector experienced productivity increases in line with fluctuations in labor and capital, while carbon emissions remained relatively stable. This could indicate improved efficiency in the production process, although variations in labor and investment continue to play a significant role in determining economic output.

4.2. Testing for Stationarity and Estimation Process

The stationarity test was conducted using the Ng–Perron approach, as explained in the previous section, and the results are displayed in Table 3. Table 3 shows that the dependent variable is stationary after the first difference, while the other variables are stationary at level 1. Based on these results, the ARDL model is more suitable for application in this study.

After determining the appropriate ARDL model, the next step is to determine the optimal lag using the Akaike Information Criteria (AIC). Based on the results in Figure 1, the appropriate model in this study is 1, 4, 4, 4, as estimated in this study.

4.3. Estimated Results

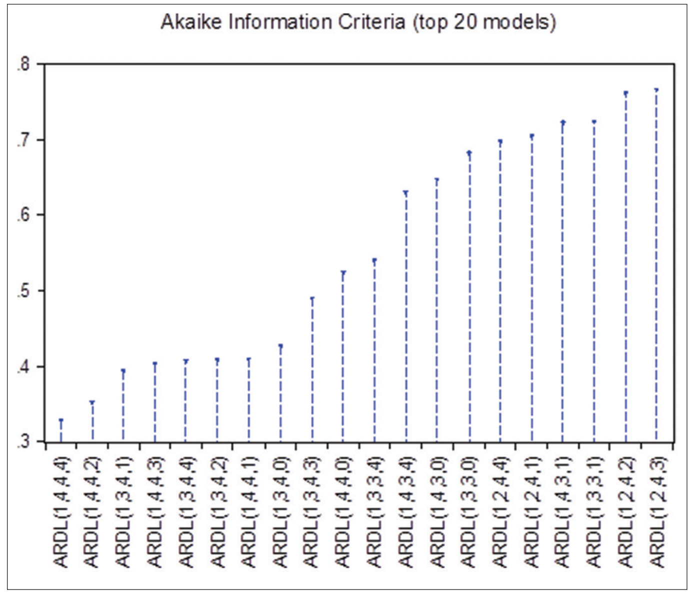
Estimations were conducted using the Autoregressive Distributed Lag (ARDL) model, yielding both short-term and long-term coefficients. The results of the short-term estimations are detailed in Table 4. The findings indicate that CO_2 emissions exert a statistically significant and immediate negative influence on agricultural productivity, with the coefficient D(LCO_2) = –26.37 (P = 0.0002). This implies that abrupt increases in carbon emissions tend to diminish productivity within the same period, likely due to adverse effects on temperature or rainfall that adversely affect crop performance. Conversely, a rebound effect is observed with a one-period lag (D(LCO_2(−1)) = 7.60; P = 0.0092), suggesting the operation of short-term adaptive mechanisms, such as improved water management or the recovery of photosynthetic activity. These contrasting signals illustrate the typical pattern of over-adaptation observed in tropical agroecological systems undergoing stress and recovery phases following environmental shocks.

Table 3: Testing for stationarity using Ng–Perron approach

Variable	At level	First difference	Critical VALUE (5%)	Conclusion
AP	3.8368	905.811	5.48	I (1)
CO_2	8.2479	-		I (0)
Labor	81.5908	-		I (0)
Capital	18.967	-		I (0)

Source: Estimated Results, 2025

Figure 1: Akaike information criteria



The labor variable exhibits alternating signs across lags: an initial adverse effect (−0.11; P = 0.0375) followed by two positive lags (0.52 and 0.39), and a subsequent reversal (−0.20). This cyclical behavior reflects the seasonality of agricultural activity and the temporary reallocation of labor across the cropping phase. This suggests that labor is a crucial factor in driving productivity growth in Indonesia.

These empirical findings align with international evidence, including studies by Liu and Lu (2024) and Long et al. (2004), which suggest that while moderate CO_2 increases can temporarily enhance C_3 photosynthesis in plants, prolonged exposure to tropical heat and humidity negates these benefits through soil stress and nutrient depletion. The current findings support this: the short-term positive lag is offset by an initial negative shock and ultimately becomes insignificant in the long term.

Furthermore, capital demonstrates a robust and persistent positive coefficient across lags (0.45-0.30), indicating that capital deepening—via mechanization, irrigation, and infrastructure—exerts a significant short-term influence on productivity. Capital constitutes an essential element of productivity enhancement, primarily through investments in agricultural infrastructure and the modernization of agricultural production.

Consistent with Ji et al. (2025) and Li et al. (2024), capital investment remains the most reliable driver of productivity through technological modernization, irrigation improvements, and

Table 4: The estimated coefficients of short–run model of ARDL

Variable	Coefficient	Standard error	t-statistic	Probability
Constant	142.3793	205.0589	0.6943	0.5374
D (LCO_2)	−26.3735	3.6770	−7.1725	0.0002
D (LCO_2(−1))	7.5972	2.1325	3.5626	0.0092
D (LCO_2(−2))	1.0841	2.3621	0.4589	0.6602
D (LCO_2(−3))	−5.2080	2.3054	−2.2590	0.0584
D (LABOR)	−0.1108	0.0433	−2.5606	0.0375
D (LABOR(−1))	0.5180	0.0855	6.0601	0.0005
D (LABOR(−2))	0.3919	0.0836	4.6857	0.0022
D (LABOR(−3))	−0.2016	0.0506	−3.9827	0.0053
D (CAPITAL)	0.4538	0.0589	7.7099	0.0001
D (CAPITAL(−1))	0.4132	0.0874	4.7273	0.0021
D (CAPITAL(−2))	0.2296	0.0594	3.8621	0.0062
D (CAPITAL(−3))	0.2990	0.0637	4.6967	0.0022
COINTEQ	−1.3092	0.1669	−7.8437	0.0001
R-squared	0.9624	Mean dependent var		−0.1328
Adjusted R-squared	0.8980	S.D. dependent var		0.6444
S.E. of regression	0.2058	Akaike info criterion		−0.0738
Sum squared resid	0.2964	Schwarz criterion		0.5734
Log likelihood	13.7385	Hannan-Quinn criterion		0.0525
F-statistic	14.9410	Durbin-Watson stat		3.4241
Prob (F-statistic)	0.0008			

Source: Estimated Results, 2025

efficient resource use. Meanwhile, the fluctuating labor coefficient aligns with the views of Otim et al. (2023) and Saha et al. (2025), who emphasize that the quality of human capital—not just the quantity of labor—determines sustainable productivity growth.

The correction term for errors (ECT = −1.309; $P < 0.001$) is negative and highly significant, confirming a swift adjustment towards the long-term equilibrium in response to short-term imbalances. The elevated R^2 value (0.962) and the statistical significance of the F-statistic further substantiate the model's robustness. The substantial magnitude of the ECT (−1.309) signifies a rapid correction rate—more than 100% of short-term imbalances are rectified within one year—indicating that the Indonesian agricultural sector responds dynamically to deviations from its equilibrium trajectory through adaptive resource reallocation and input adjustments. This also reflects an increase in agricultural productivity within Indonesia.

Table 5 indicates that, in the short term, there is no cumulative dynamic effect of carbon dioxide on agricultural productivity in Indonesia. This suggests that some of the carbon dioxide is absorbed by plants for photosynthesis, which subsequently serves as a source of food for them. Additionally, labor emerges as a critical factor influencing labor productivity in Indonesia in the short term, evidenced by its statistically significant coefficient for agricultural productivity. This is justified by the fact that the agricultural sector employs a substantial informal workforce, some of whom possess relatively low levels of education. Enhancing educational attainment will be vital in augmenting agricultural productivity in Indonesia. Moreover, capital does not exert a short-term cumulative dynamic effect within the Indonesian context.

Table 6 shows the long-term estimated coefficients, and none of the variables are statistically significant. This means that carbon dioxide, labor, and capital have no effect on agricultural productivity in Indonesia. This indicates that farmers are more focused on the short term than the long term.

Table 5: Dynamic short run coefficients of the variables

Variable	Chi-square statistics	P-value	Conclusion
CO_2	8.8329	0.1159	Accept Ho
Labor	15.3894	0.0088	Reject Ho
Capital	14.4485	0.1299	Accept Ho

Source: Estimated Results, 2025

Table 6: Estimated long-run coefficients

Variable	Coefficient	Standard Error	t-Statistic	Probability
LCO_2(−1)	−13.7047	22.3053	−0.6144	0.5824
LABOR(−1)	−0.2586	0.3447	−0.7503	0.5075
CAPITAL(−1)	0.1209	0.1988	0.6084	0.5859

Source: Estimated Results, 2025

Table 7: F-bound testing for long-run relationship

Asymptotic: n=30				
F-statistic	6.582841	10%	3.008	4.15
K	3	5%	3.71	5.018
		1%	5.333	7.063

Source: Estimated Results, 2025

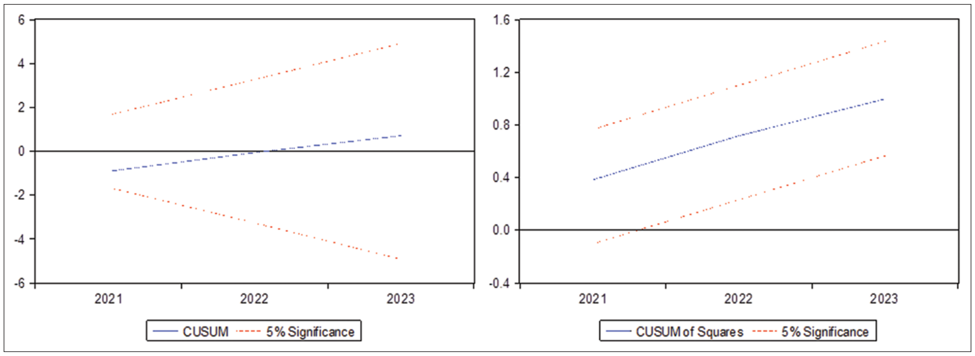
Table 7 shows the results of the short-run to long-run test using Bound Testing. The F-Bound test confirms the existence of a long-run cointegration relationship between agricultural productivity, CO_2 emissions, labor, and capital (F = 6.582 > upper bound at 5% = 5.018). However, according to the results in Table 6, the long-run coefficients for CO_2 (−13.70; P = 0.582), labor (−0.26; P = 0.508), and capital (0.12; P = 0.586) are individually insignificant. This finding implies that although a long-run equilibrium binds these variables, their isolated effects neutralize over time—likely due to structural adjustments, policy interventions, and technological shifts that collectively determine the long-run path of agricultural productivity.

Table 8: Testing for selected classical linear regression assumptions

Assumption	Approach	Statistics	P-value	Conclusion
Normality	Jarque-Bera	0.3396	0.8438	Residuals are normally distributed.
Heteroscedasticity	Breusch-Pagan-Godfrey	0.3513	0.9295	Homoscedasticity
Serial Correlation	LM Test	3.404	0.3579	No Serial Correlation Exists

Source: Estimated Results, 2025

Figure 2: Testing for model stability using Cusum and Cusum squares



4.4. Testing for Selected Classical Linear Regression Assumptions and Model Stability

Table 8 provides a summary of the outcomes of various classical linear regression diagnostics—namely, normality, heteroscedasticity, and serial correlation—conducted to verify that the ARDL model complies with the Gauss-Markov assumptions. The Jarque–Bera statistic (0.3396; P = 0.8438) indicates that the residuals follow a normal distribution, suggesting that the regression errors are symmetrically centered around zero and are free from extreme outliers. Ensuring normality is essential for the validity of hypothesis tests concerning the coefficients and the construction of confidence intervals, particularly in small-sample scenarios.

The Breusch–Pagan–Godfrey test (0.3513; P = 0.9295) confirms homoscedasticity, indicating that the residual variance remains constant across the estimated values. Homoscedasticity of errors implies the efficiency of the ordinary least squares estimator and the reliability of the standard error computation. The absence of heteroscedasticity indicates that the variance of productivity shocks is not systematically related to the magnitude of adjusted productivity, reflecting a stable production process throughout the observation period.

The LM test for serial correlation (3.404; P = 0.3579) further indicates the absence of autocorrelation in the residuals. This implies that the error term within a period is independent of the previous disturbance, validating the lag structure of ARDL and ensuring that the dynamic relationships between variables are correctly specified. Overall, the combination of normality, homoscedasticity, and independence confirms that the ARDL model meets the Best Linear Unbiased Estimators (BLUE) criteria, thus enhancing the credibility of short- and long-run parameter inferences.

Figure 2 presents the CUSUM and CUSUM Squares (CUSUMQ) plots, which assess the stability of the estimated ARDL model parameters. Both lines remain within the 5% significance level throughout the sample period, indicating that the estimated coefficients are structurally stable and that no significant parameter shifts or structural breaks have occurred in the model.

The stability demonstrated by these plots has two important implications. First, it confirms that the relationship between CO_2 emissions, capital, labor, and agricultural productivity remains consistent over the period 2000-2023, despite macroeconomic shocks such as fluctuations in commodity prices or climate anomalies. Second, it demonstrates the robustness of the chosen lag structure (1, 4, 4, 4) and the adequacy of the ARDL specification in capturing dynamic adjustments without producing unstable estimates.

Collectively, the diagnostic and stability results validate the model's econometric robustness: the residuals behave well, the specifications are dynamically consistent, and the parameters remain stable. Consequently, the empirical conclusions drawn from the ARDL estimation—particularly the asymmetric short-run response of productivity to CO_2 shocks and the dominant role of capital formation—are statistically reliable and robust for policy interpretation.

5. CONCLUSION AND POLICY RECOMMENDATIONS

This study investigates the dynamic relationship between carbon dioxide (CO_2) emissions, labor, and capital formation and their impact on agricultural productivity in Indonesia, employing an Autoregressive Distributed Lag (ARDL) approach with data spanning the period 2000-2023. The analysis reveals several important empirical insights. CO_2 emissions in the short run exhibit a negative and statistically significant impact on agricultural productivity, confirming that environmental degradation directly impairs crop performance and soil fertility. However, a temporary positive rebound effect emerges at subsequent lags, suggesting that

Indonesian agriculture has limited adaptive capacity—possibly through improved management, crop diversification, or short-term soil restoration. This pattern underscores that the productivity impacts of CO_2 are asymmetric and transient, depending on the balance between environmental pressures and adaptive practices.

Capital formation consistently exerts a strong positive effect across all short-run lags, confirming that investment in technology, mechanization, and irrigation remains a key driver of productivity growth. Meanwhile, labor exhibits a cyclical and inconsistent effect, reflecting the sector's reliance on seasonal work and limited skills development among rural workers.

The ARDL bounds test confirms a valid cointegration relationship among all variables, although the individual long-run coefficients are not statistically significant. This suggests that agricultural productivity in Indonesia is governed by a systemic equilibrium in which CO_2, labor, and capital interact over time, rather than exerting isolated effects. If a shock occurs, the model will rapidly and progressively shift towards equilibrium, indicating a trend towards increasing agricultural productivity in Indonesia.

The statistical reliability of the model, as evidenced by normal residuals, homoscedasticity, and the absence of serial correlation, combined with stable coefficients over time, as demonstrated by Cusum and Cusum Squares, ensures that the estimated relationships are robust and reliable for policy design. Overall, these results imply that agricultural productivity in Indonesia is highly dependent on technological investment, human resource quality, and environmental adaptability, which together shape the nation's long-term food security trajectory.

Based on empirical findings and consistent with previous literature, five main policy pathways are recommended to improve agricultural productivity, environmental sustainability, and food security in Indonesia. Promote Climate-Resilient Agricultural Investment. The consistent positive role of capital suggests that productivity gains depend on expanding climate-smart investments—such as efficient irrigation, renewable energy-based mechanization, and low-carbon fertilizer technologies. Fiscal incentives, green credit facilities, and public-private partnerships should be strengthened to accelerate the diffusion of these technologies, especially among smallholder farmers.

Improve human capital and labor productivity. The effects of fluctuating labor demand reflect inefficiencies arising from seasonal dependence and skills gaps. Strengthening rural education, vocational training, and extension services is crucial to enhancing farmers' technical capacity in precision agriculture, pest control, and post-harvest management. Integrating digital agricultural tools can improve labor coordination and reduce productivity losses during the transition.

Integrate climate mitigation and agricultural adaptation. Because CO_2 shocks negatively impact productivity, agricultural policies must integrate climate adaptation measures, such as sustainable soil management, agroforestry, carbon sequestration programs, and drought-resistant crop varieties. Strengthening the link between agricultural planning and Indonesia's net-zero target by 2060 will align productivity goals with climate resilience.

Implement a multidimensional agricultural strategy. Given the long-term systemic balance between variables, increasing productivity necessitates an integrated policy portfolio, rather than a single-factor approach. Combining financial inclusion, technological modernization, workforce improvement, and institutional capacity building will generate more resilient and inclusive growth in the agricultural sector.

Strengthen food security through the synergy of productivity and resilience. Empirical evidence shows that increasing agricultural productivity is the most direct path to strengthening national food security. Capital investment increases production capacity, while improvements in labor and technology ensure consistent food availability and stability across seasons. Therefore, policymakers must link productivity-oriented interventions with a food security framework—for example, by promoting regional food farming programs, improving storage and logistics infrastructure, and supporting local seed innovation. This synergy ensures that increased productivity leads to a reliable food supply, reduces dependence on imports, and increases resilience to global supply shocks.

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