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# Economic Growth, Agriculture, Capital Formation and Greenhouse Gas Emissions in Indonesia: FMOLS, DOLS and CCR Applications

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**Abstract**

Economic growth drives increased demand for resources, placing greater pressure on the agricultural sector. While the adoption of advanced technologies and increased capital investment can enhance productivity, they also have environmental consequences, contributing to greenhouse gas emissions. Based on this interconnected issue, this study aims to examine the long-term relationships between economic growth, agricultural productivity, gross fixed capital formation, and greenhouse gas emissions in Indonesia, utilizing data from the period 1965-2021. The study employs the Dynamic Ordinary Least Squares (DOLS) and Fully-Modified Ordinary Least Squares (FMOLS) methods, and includes robustness checks using the Canonical Cointegration Regressions (CCR) method. To provide a more comprehensive insight, the study also employs the pairwise Granger causality approach to detect the direction of the relationships. In concise terms, the results suggest that agricultural productivity, gross fixed capital formation, and greenhouse gas emissions have a positive long-term influence on economic growth. Additionally, gross fixed capital formation has a negative effect, while economic growth has a positive long-term impact on agricultural productivity. Furthermore, agricultural productivity has a negative impact, while economic growth indicates a positive long-term effect on gross fixed capital formation. Moreover, economic growth positively influences greenhouse gas emissions over the long term. Lastly, the study found three bidirectional causalities, with greenhouse gas emissions as the central figure. These important findings provide crucial information for policymakers, economists, and environmentalists, giving a nuanced understanding of the intricate relationships between economic activities and environmental consequences, as well as aiding in the formulation of sustainable strategies for green economic growth, especially in Indonesia.

## 1. Introduction

The nexus between economic growth, agricultural sector, capital formation, and greenhouse gas emissions underscores the intricate relationship between development in the economy, agricultural practices, investment in capital, and environmental impact. The expansion of the economy leads to a heightened need for resources such as food and energy, exerting more significant pressure on the agricultural sector. [1–3]. Although the adoption of advanced technologies and boosting capital investments can improve productivity, they come with environmental repercussions, adding to the emission of greenhouse gases [4–8].

In Indonesia, the relationship between them is particularly significant due to the country's status as a rapidly developing nation with a large agricultural sector. There also has been a push for agricultural intensification, with a focus on adopting advanced technologies and increasing capital investment, since economic growth has led to an increased demand for food, energy, and resources, putting pressure on the agricultural sector to meet these needs [9, 10]. However, This push for intensification has also raised environmental concerns, as Indonesia faces challenges related to deforestation, land degradation, and high greenhouse gas emissions that may have the potential to cause natural disasters [11–14]. Balancing the need for investment to increase agricultural output, fostering democracy, and ensuring a corruption-free environment to drive the national economy while also prioritizing the mitigation of environmental impacts is a crucial challenge for the country [15–19].

The Environmental Kuznets Curve (EKC) theory suggests an inverted U-shaped relationship between economic development and environmental degradation. It posits that as a country's income initially increases, so does its environmental degradation, but after a certain level of income is reached, environmental degradation starts to decrease [20, 21]. In developing agrarian economies like Indonesia, traditional farming methods may contribute to environmental harm. As income and capital formation increase, countries can transition towards more sustainable practices, thereby reducing environmental impact. Advanced economies with high-income levels tend to invest in cutting-edge technologies and enforce stringent regulations, further mitigating environmental harm [22–24].

An earlier study conducted in E7 countries indicates that there is a positive significant relationship between CO2 emissions, real GDP and agricultural value-added in the long term [25]. Furthermore, a study using the panel data of 89 economies shows empirical results that agricultural value-added is the major driver of agricultural emissions especially in the long term [26]. Similarly, a study in BRICS and BIMSTEC nations delved into the EKC hypothesis, taking into account agricultural activities. The empirical findings confirmed that agriculture has a detrimental impact on the environment, revealing a U-shaped relationship between agriculture and greenhouse gas emissions [27, 28].

Moreover, a previous investigation in Malaysia delved into the links between CO2 emissions, economic growth, and agriculture. The findings demonstrated a noteworthy increase in CO2 emissions attributed to economic growth, with the agricultural sector playing a substantial role in emission reduction [29]. In Brazil, a research endeavor scrutinized the dynamic interaction between added value in agriculture, CO2 emissions, and real GDP, uncovering a reciprocal cause-and-effect correlation in the extended period involving these variables [30]. Additionally, a study conducted in Pakistan disclosed that there exists both a short-term and long-term connection between agriculture, economic growth, capital, and CO2 emissions [31].

Despite numerous previous studies conducted specifically in Indonesia related to these four indicators, a gap still exists where there has yet to be a study that employs them in the same modeling and conducts a complete dynamic impact between them. While studies such as those by Nugraha & Usman [32], Bashir et al. [33], Shahbaz et al. [34], Prasetyani et al. [35], and Bimanatya & Widodo [36] have examined the relationship between economic growth and greenhouse gas emissions, they did not include the agricultural sector. Similarly, studies like those by Bashir & Susetyo [37], Bashir et al. [38], and Medyawati & Yunanto [39] have analyzed the connection between agriculture and economic growth but did not consider greenhouse gas emissions. Meanwhile, the study by Prastiyo et al. [40] explored the relationship between agriculture and emissions but did not address economic growth. Additionally, the study by Adebayo et al. [41] looked at the interplay between economic growth, emissions, and agriculture, but omitted capital formation. Furthermore, it focused solely on CO2 emissions, which represent a subset of greenhouse gas emissions.

Based on the theoretical concept explained and the gap that still exists in the literature, this study aims to examine the long-term relationship between economic growth, agricultural productivity, gross fixed capital formation, and greenhouse gas emissions in Indonesia for the period 1965-2021, utilizing various dynamic approaches. The important findings from this study will provide crucial information for policymakers,

**Table 1.** Variable synopsis.

| Variable | Description | Logarithmic Form | Unit | Sources |
|---|---|---|---|---|
| GDP | Gross Domestic Product | lnGDP | GDP (constant local currency unit) | WDI |
| AP | Agricultural Productivity | lnAP | AP (constant local currency unit) | WDI |
| GFCF | Gross Fixed Capital Formation | lnGFCF | GFCF (constant local currency unit) | WDI |
| GHG | Greenhouse Gas Emissions | lnGHG | Total GHG in ton | OWID |

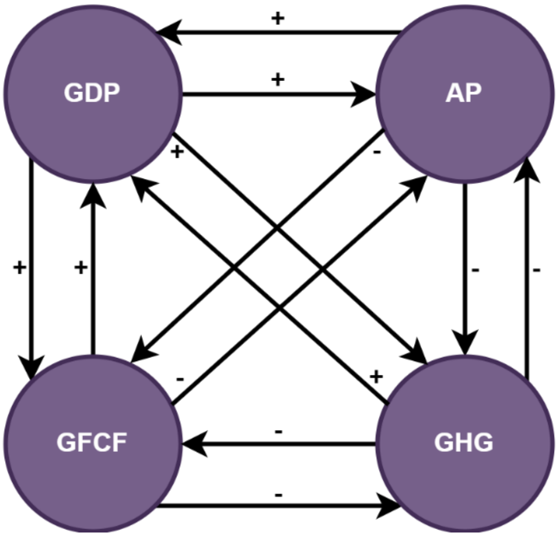


**Figure 1**. Conceptual framework of the study.

economists, and environmentalists, aiding in the formulation of sustainable strategies for economic growth in Indonesia, while also taking into consideration the environmental consequences.

## 2. Materials and Methods

### *2.1. Data*

This study utilizes annual data from Indonesia spanning 1965 to 2021. Economic growth (GDP), agricultural productivity (AP), and gross fixed capital formation (GFCF) were quantified in constant local currency units (LCU). Total greenhouse gas (GHG) emissions were assessed as the aggregate GHG present in the atmosphere, measured in tons. GDP, AGI, and GFCF data were obtained from the World Bank's World Development Indicators (WDI), while GHG emissions data were retrieved from the Our World In Data (OWID) website. To mitigate potential heteroscedasticity, the datasets were log-transformed prior to analysis.

### *2.2. The Framework of the Study*

The conceptual framework guiding this study is illustrated in Figure 1. The framework visually depicts the connections between the dependent and independent variables under investigation. It outlines the hypothesized relationships, with positive signs denoting expected positive associations and negative signs denoting expected negative associations. Specifically, the framework puts forth testable hypotheses regarding the impacts of GDP, AGI, GFCF and GHG emissions on one another. By mapping these variables and their predicted interrelationships, the framework provides a clear overview of the logic underlying the study and informs the statistical analyses used to empirically assess the postulated effects. In summary, Figure 1 summarizes the conceptual model, showing the variables of interest and their hypothesized causal relationships that will be tested through this research.

### *2.3. Model Specification*

This study employs an econometric model to examine the reciprocal impacts between GDP, AGI, GFCF, and GHG emissions in Indonesia. Advanced statistical techniques are utilized to quantify the magnitude and directionality of influence between these key variables, providing nuanced insights into their complex interrelationships. Rigorous specification testing and diagnostic analyses lend credibility to the model and ensure that the estimated linkages are statistically and economically meaningful.

The modeling framework enables the precise estimation of the impacts these factors exert on each other, revealing intricate patterns of mutual influence that shape the country's economic development and environmental outcomes. By analyzing these dynamics, this research deepens understanding of the interconnected drivers of economic growth, agriculture, capital, and greenhouse gas emissions. The mathematical function is presented in the Equations 1-4.

$$GDP = f(AP, GFCF, GHG) \quad (1)$$
$$AP = f(GDP, GFCF, GHG) \quad (2)$$
$$GFCF = f(GDP, AP, GHG) \quad (3)$$
$$GHG = f(GDP, AP, GFCF) \quad (4)$$

Each variable is detailed in Table 1. Consequently, Equations 5-8 represents the econometric model outlining the relationship between variables.

$$GDP_t = \pi_0 + \pi_1 AP_t + \pi_2 GFCF_t + \pi_3 GHG_t + \varepsilon_t \quad (5)$$
$$AP_t = \pi_0 + \pi_1 GDP_t + \pi_2 GFCF_t + \pi_3 GHG_t + \varepsilon_t \quad (6)$$
$$GFCF_t = \pi_0 + \pi_1 GDP_t + \pi_2 AP_t + \pi_3 GHG_t + \varepsilon_t \quad (7)$$
$$GHG_t = \pi_0 + \pi_1 GDP_t + \pi_2 AP_t + \pi_3 GFCF_t + \varepsilon_t \quad (8)$$

**Table 2.** Descriptive statistics.

| Statistical Measures | GDP | AP | GFCF | GHG |
|---|---|---|---|---|
| Mean | 35.6224 | 33.9889 | 34.1896 | 20.8731 |
| Median | 35.7669 | 34.0376 | 34.5116 | 21.0567 |
| Maximum | 36.9475 | 34.8782 | 35.8191 | 21.9505 |
| Minimum | 34.0391 | 33.0669 | 31.4436 | 20.0738 |
| Std. Dev. | 0.8674 | 0.5238 | 1.2353 | 0.5259 |
| Skewness | -0.2311 | -0.0413 | -0.6885 | -0.2582 |
| Kurtosis | 1.9384 | 1.9484 | 2.5305 | 1.7857 |
| Jarque-Bera | 3.1841 | 2.6426 | 5.0268 | 4.1352 |
| Probability | 0.2035 | 0.2668 | 0.0809 | 0.1265 |
| Sum | 2030.4750 | 1937.3720 | 1948.8080 | 1189.7650 |
| Sum Sq. Dev. | 42.1362 | 15.3618 | 85.4519 | 15.4882 |
| Observations | 57 | 57 | 57 | 57 |

**Table 3.** Results of unit root test.

| Variable | Augmented Dickey-Fuller | | | | Phillips-Perron | | | | Im-Pesaran-Shin | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Individual Intercept | | Individual Intercept and trend | | Individual Intercept | | Individual Intercept and trend | | Individual Intercept | | Individual Intercept and trend | |
| | Level | 1st diff. | Level | 1st diff. | Level | 1st diff. | Level | 1st diff. | Level | 1st diff. | Level | 1st diff. |
| GDP | 0.2864 | 0.0000 | 0.6305 | 0.0001 | 0.2864 | 0.0000 | 0.8462 | 0.0001 | 0.2864 | 0.0000 | 0.6305 | 0.0001 |
| AP | 0.8696 | 0.0000 | 0.5970 | 0.0000 | 0.8573 | 0.0000 | 0.6273 | 0.0000 | 0.8696 | 0.0000 | 0.5970 | 0.0000 |
| GFCF | 0.0013 | 0.0001 | 0.5776 | 0.0000 | 0.0540 | 0.0001 | 0.7320 | 0.0002 | 0.0013 | 0.0001 | 0.5776 | 0.0000 |
| GHG | 0.6613 | 0.0000 | 0.4697 | 0.0000 | 0.6305 | 0.0000 | 0.0376 | 0.0000 | 0.6613 | 0.0000 | 0.4697 | 0.0000 |

Furthermore, this study has transformed equations 5-8 into logarithmic form for time-series analysis, as presented in Equations 9-12.

$$lnGDP_t = \pi_0 + \pi_1 lnAP_t + \pi_2 lnGFCF_t + \pi_3 lnGHG_t + \varepsilon_t \quad (9)$$
$$lnAP_t = \pi_0 + \pi_1 lnGDP_t + \pi_2 lnGFCF_t + \pi_3 lnGHG_t + \varepsilon_t \quad (10)$$
$$lnGFCF_t = \pi_0 + \pi_1 lnGDP_t + \pi_2 lnAP_t + \pi_3 lnGHG_t + \varepsilon_t \quad (11)$$
$$lnGHG_t = \pi_0 + \pi_1 lnGDP_t + \pi_2 lnAP_t + \pi_3 lnGFCF_t + \varepsilon_t \quad (12)$$

Where $ln$ denotes the natural logarithm, $\pi$ represents the coefficient estimates, $t$ indexes the time series from 1965 to 2021 (T = 57 years), and $\varepsilon$ is the stochastic error term.

*2.4. Methods*

In this study, we utilized both the Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) estimation techniques. FMOLS, originally proposed by Phillips and Perron for time-series modeling, is a regression approach designed for efficient parameter estimation in cointegrated systems [42]. As highlighted by Hamit-Haggar, it is particularly noted for its reliability in small sample sizes and its ability to address endogeneity and serial correlation [43]. On the other hand, the DOLS estimation method pioneered by Stock and Watson has been shown to outperform FMOLS in terms of estimation results, specifically by accounting for correlations among regressors, as demonstrated by Kao and Chiang [44, 45]. Additionally, we employed the Canonical Cointegrating Regression (CCR) as a robustness check to corroborate the findings obtained through FMOLS and DOLS [5, 12, 46].

Additionally, a unit root test was conducted to verify the stationarity of the data used in this research. Following this, a cointegration test was applied to ascertain if there was a long-term relationship among the variables. In the subsequent stage, FMOLS and DOLS tests were utilized to assess the impact of various determinants on each variable. Lastly, the pairwise Granger causality test was employed as a stringent method to explore the causal links between the variables.

## 3. Results and Discussion

Table 2 displays descriptive statistics for logarithmic values of economic indicators, with the mean indicating the average level of economic growth (35.62), agricultural productivity (33.99), gross fixed capital formation (34.19), and greenhouse gas emissions (20.87). The standard deviation suggests that gross fixed capital formation (1.23) has the highest variability, while greenhouse gas emissions are the most stable (0.53). Skewness and kurtosis values hint at non-normal distributions, particularly for gross fixed capital formation with a significant left skew (-0.69) and a peaked distribution (kurtosis of 2.53). The Jarque-Bera test shows no strong evidence against normality for any of the variables,

**Table 4.** Results of Johansen co-integration test.

| Null Hypothesis | Fisher Stat.* (from trace test) | Prob. | Fisher Stat.* (from max-eigen test) | Prob. |
|---|---|---|---|---|
| R = 0 | 56.8243* | 0.0058 | 32.8789* | 0.0095 |
| R ≤ 1 | 23.9454 | 0.2028 | 14.0212 | 0.3633 |
| R ≤ 2 | 9.9243 | 0.2866 | 8.4209 | 0.3375 |
| R ≤ 3 | 1.5034 | 0.2202 | 1.5034 | 0.2202 |

**Table 5**. FMOLS, DOLS and CCR results.

| Model | Method | | GDP | AP | GFCF | GHG | Constant | $R^2$ Adj. |
|---|---|---|---|---|---|---|---|---|
| GDP | FMOLS | Coeff. (t-stat.) | - | 1.1139 (16.6280)* | 0.1922 (6.4608)* | 0.1012 (2.4493)** | -10.920 (-8.3825)* | 0.9982 |
| | DOLS | | - | 1.1454 (16.7577)* | 0.1880 (6.3847)* | 0.0805 (1.9035)*** | -11.417 (-8.5657)* | 0.9983 |
| | CCR | | - | 1.1092 (16.2228)* | 0.1917 (6.6436)* | 0.1072 (2.3015)** | -10.8697 (-8.1488)* | 0.9982 |
| AP | FMOLS | Coeff. (t-stat.) | 0.8432 (17.3545)* | - | -0.1405 (-4.2777)* | -0.0726 (-2.0050)*** | 10.2720 (17.8478)* | 0.9964 |
| | DOLS | | 0.8209 (16.6617)* | - | -0.1335 (-4.1152)* | -0.0564 (-1.5167) | 10.4890 (17.8148)* | 0.9967 |
| | CCR | | 0.8471 (17.8148)* | - | -0.1409 (-4.4663)* | -0.0781 (-1.8857)* | 10.2651 (17.5207)* | 0.9964 |
| GFCF | FMOLS | Coeff. (t-stat.) | 3.6567 (6.6850)* | -3.5345 (-4.2440)* | - | -0.2234 (-1.1770) | 28.7246 (2.7231)* | 0.9832 |
| | DOLS | | 3.7012 (6.1423)* | -3.6691 (-3.9818)* | - | -0.1610 (-0.7655) | 30.4144 (2.5959)** | 0.9836 |
| | CCR | | 3.6635 (6.4847)* | -3.5303 (-4.1023)* | - | -0.2394 (-1.1250) | 28.6734 (2.5951)** | 0.9831 |
| GHG | FMOLS | Coeff. (t-stat.) | 2.0528 (2.1228)** | -1.9941 (-1.7081)*** | -0.2158 (-0.8940) | - | 22.9178 (1.8404)*** | 0.8739 |
| | DOLS | | 2.0966 (2.1577)** | -2.0476 (-1.7292)*** | -0.2129 (-0.9020) | - | 23.0607 (1.8182)*** | 0.8806 |
| | CCR | | 2.0167 (2.0284)** | -1.9620 (-1.6132) | -0.2017 (-0.8475) | - | 22.6294 (1.7269)*** | 0.8744 |

Note: *, ** and *** indicates 1%, 5%, and 10% significant level

supported by probabilities above 0.08, and all indicators are based on 57 data points, ensuring consistency across the measures.

*3.1. Diagnostic Tests*

*3.1.1. Unit Root Test*

A unit root signifies that a variable does not exhibit stationarity or stability, and displays a random pattern instead of converging to a consistent average over time. In contrast, stationary variables maintain a consistent average and variability, making them suitable for reliable dynamic estimation. Despite DOLS, FMOLS, and CCR methods not requiring a unit root test since they can be applied to stationary or non-stationary variables, this study uses pairwise Granger causality, so this test is a must. As shown in Table 3, various tests indicate that all variables are stationary at the first difference (I(1)) order. This implies that the data's average and variability remain consistently stable over time for dynamic and causal estimation.

*3.1.2. Cointegration Test*

In addition to the unit root test, the cointegration test is also crucial for dynamic and causality approaches, as it indicates a sustained connection between the variables over the long term. This study employs the Johansen cointegration test, widely regarded as one of the most trustworthy tests for detecting cointegration. Table 4 confirms that all the variables used demonstrate strong cointegration at a 5% probability level. This supports the conclusion that the estimation outcomes of all dynamic methods employed in this study are reliable, suggesting a stable long-term relationship.

*3.2. Econometric Results*

*3.2.1. Impact of GFCF, AP, and GHG on GDP*

As shown in Table 5, all independent variables in GDP Model, based on DOLS and FMOLS estimation, exhibit a significant impact on GDP in the long term. The CCR test confirms the robustness of the results. GFCF and AP show strong significance, reaching a 5% level of probability in

**Table 6.** Results of pairwise Granger causality test.

| Null Hypothesis | F-Statistic | Prob. |
|---|---|---|
| AP ≠ GDP | 1.5770 | 0.2147 |
| GDP ≠ AP | 0.1559 | 0.6945 |
| GFCF ≠ GDP | 0.0217 | 0.8835 |
| GDP ≠ GFCF | 0.8413 | 0.3632 |
| GHG ≠ GDP | 21.6478* | 0.0000 |
| GDP ≠ GHG | 15.5580* | 0.0002 |
| GFCF ≠ AP | 0.9520 | 0.3336 |
| AP ≠ GFCF | 1.3084 | 0.2578 |
| GHG ≠ AP | 7.5761* | 0.0081 |
| AP ≠ GHG | 12.3487* | 0.0009 |
| GHG ≠ GFCF | 6.2397** | 0.0156 |
| GFCF ≠ GHG | 16.0973* | 0.0002 |

Note: * and ** indicates 1% and 5% significant level

all methods, while GHG exhibits a weak, significant influence with a 10% level of probability in the DOLS results. However, since both FMOLS and CCR show a 5% significance level for GHG impact, we can conclude that all explanatory variables strongly and significantly impact GDP in the long term.

Estimation results of GDP Model demonstrate that all independent variables, including GFCF, AP, and GHG, exhibit a positive long-term impact on GDP. Specifically, a 1.0% increase in GFCF is associated with approximate GDP growth of 0.1880% according to the DOLS, 0.1922% based on FMOLS, and 0.1917% according to the CCR. Similarly, a 1.0% increase in AP leads to a substantial increase in GDP, with growth rates of approximately 1.1454%, 1.1139%, and 1.1092% according to the respective methods. Moreover, a 1.0% increase in GHG also demonstrates a positive impact on GDP, with growth rates of approximately 0.0805% (DOLS), 0.1012% (FMOLS), and 0.1072% (CCR).

*3.2.2. Impact of GDP, GFCF, and GHG on AP*

In AP Model, based on DOLS and FMOLS estimation, Table 5 indicates that the variables GDP and GFCF exhibit a significant impact, but GHG shows a weak significant effect on AP in the long term. Robustness checks with CCR also yield the same results. GDP and GFCF, reaching a 5% level of probability, indicate strong significance in all methods, but GHG produces a weaker significant influence with a 10% level of probability in the FMOLS and CCR results, and an insignificant influence in the DOLS results. Thus, this study concludes that GDP and GFCF variables are strongly significant, but GHG indicates a weak significant influence on AP in the long term.

The findings from AP Model indicate that the GDP variable has a positive effect, while GFCF and GHG have a negative effect on AP in the long term. A 1.0% increase in GDP is linked to an estimated increase of about 0.8209% in AP according to DOLS, 0.8432% according to FMOLS, and 0.8471% according to CCR. Conversely, a 1.0% rise in GFCF results in a decrease in AP of roughly 0.1335%, 0.1405%, and 0.1409% according to the respective methodologies. Similarly, a 1.0% increase in GHG also shows a negative impact on AP of about 0.0726% (FMOLS) and 0.0781% (CCR).

*3.2.3. Impact of GDP, AP, and GHG on GFCF*

Table 5 indicates that in GFCF Model, the independent variables GDP and AP have a notable effect, while GHG does not significantly influence GFCF over the long term. The results are supported by the robustness check using the CCR. Both GDP and AP demonstrate a strong level of significance, with a probability below 5% in all methods. Conversely, GHG exerts a non-substantial influence, with a probability exceeding 10% across all methods. This study concludes that GDP and AP variables exert a significant impact, whereas GHG does not significantly affect GFCF in the long term.

The results from GFCF Model show that GDP positively influences GFCF, while AP has a negative impact on it over the long term. More specifically, a 1.0% rise in GDP is linked to an estimated GFCF increase of about 3.7012% as per the DOLS approach, 3.6567% according to FMOLS, and 3.6636% based on the CCR method. Conversely, a 1.0% increase in AP results in a decrease in GFCF of approximately 3.6691%, 3.5345%, and 3.5303% respectively, according to the corresponding methods.

*3.2.4. Impact of GDP, AP, and GFCF on GHG*

Based on both DOLS and FMOLS estimations for GHG Model, Table 5 indicates that only the variable GDP has a strong and significant impact on GHG in the long term. AP demonstrates a weak but statistically significant effect, while GFCF shows no significant effect on GHG in both DOLS and FMOLS results. Robustness checks with CCR also confirm these findings. GDP, with a 5% probability level, indicates strong significance in all methods. AP exerts a weak but statistically significant influence with a 10% probability level in the DOLS and FMOLS results, whereas GFCF exerts no significant influence in all methods. Based on these results, this study concludes that GDP has a strong and significant impact, AP has a weak but significant impact, and GFCF does not have a significant impact on GHG in the long term.

The estimation results from GHG Model indicate that while GDP has a positive impact, AP has a detrimental effect on GHG over the long term. A 1.0% rise in GDP corresponds to a GHG increase of roughly 2.0966% as per DOLS, 2.0528% based on FMOLS, and 2.0167% according to the CCR method. Conversely, a 1.0% increase in AP results in a GHG decline of approximately 2.0476%,

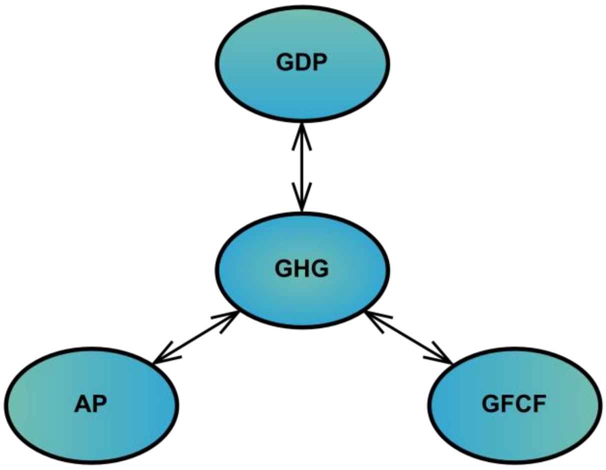


**Figure 2.** Overview of pairwise Granger causality test.

1.9941%, and 1.9620% according to the respective methodologies.

*3.2.5. GDP, AP, GFCF and GHG Causality Relationships*

The pairwise Granger causality estimation yields intriguing insights, revealing three bidirectional causal relationships with GHG at the core. As depicted in Table 6 and Figure 2, it is evident that GDP, AP, and GFCF variables all exhibit bidirectional causality with GHG. Furthermore, the results highlight the robustness of these relationships, with all three demonstrating a strong and statistically significant causality at the 1% probability level. This underscores the intricate interplay between these variables in the context of economic activities, productivity of the agricultural sector, investment in fixed capital, and environmental impact.

*3.3. Discussion*

This study's empirical results shed light on the dynamic and intricate web of relationships among economic growth, agricultural productivity, gross fixed capital formation, and greenhouse gas emissions in Indonesia. Notably, economic growth emerges as a pivotal factor with far-reaching impacts on the other variables. A rise in economic growth is associated with significant long-term increases in both gross fixed capital formation and agricultural productivity. This aligns with established economic theories, emphasizing the crucial role of investment and technological progress in fostering economic development [47–49]. These findings are consistent with prior studies that have underscored the positive correlation between economic growth and investment in fixed capital [50–52].

Surprisingly, the results reveal a somewhat counterintuitive dynamic between agricultural productivity and gross fixed capital formation. Contrary to conventional expectations, a long-term increase in agricultural productivity appears to be associated with a decrease in the need for fixed capital investment in the sector. This raises intriguing questions about the nature of technological advancements in Indonesia’s agricultural sector and their implications for capital-intensive practices. These findings prompt further exploration into the nuanced relationship between agricultural productivity and capital formation [53–55], offering fresh perspectives on the evolution of agricultural systems.

The study also uncovers a complex interaction between economic growth and greenhouse gas emissions. As Indonesia's economy grows in the long term, so do emissions, indicating a critical challenge for sustainable development efforts. This aligns with the EKC hypothesis, which posits an initial rise in emissions followed by an eventual decline as nations reach higher income levels [56–60]. The findings reinforce the urgency of adopting environmentally conscious policies and technologies to decouple economic growth from environmental degradation. This echoes the broader discourse in environmental economics and underscores the need for concerted efforts to mitigate the environmental impact of economic activities.

Furthermore, the results highlight the positive influence of agricultural productivity on reducing greenhouse gas emissions. This connection underscores the potential for advancements in Indonesia’s agricultural practices to contribute to long-term environmental sustainability. Enhanced productivity leads to more efficient resource utilization, thereby mitigating the sector's overall environmental footprint [61, 62]. These findings resonate with the growing interest in sustainable agriculture and resource-efficient practices [63, 64]. They provide empirical support for ongoing discussions on the role of agriculture in achieving broader environmental objectives, emphasizing the importance of innovation in shaping the future of the sector, especially in Indonesia.

## 4. Conclusions and Policy Recommendations

The empirical findings of this study provide valuable insights into the intricate and dynamic relationships between economic growth, agricultural productivity, gross fixed capital formation, and greenhouse gas emissions in Indonesia from the period 1965 to 2021, with the application of various methodologies. The results demonstrate that each of these factors exerts a significant, long-term influence on one another, highlighting the interconnectedness of these critical elements within the Indonesian economic landscape.

In concrete and concise conclusions, the results suggest that agricultural productivity, gross fixed capital formation, and greenhouse gas emissions have a positive long-term influence on economic growth. Additionally, gross fixed capital formation has a negative effect, while economic growth has a positive long-term impact on agricultural productivity. Furthermore, agricultural productivity has a negative impact, while economic growth indicates a positive long-term effect on gross fixed capital formation. Moreover, economic growth positively influences greenhouse gas emissions over the long term. Lastly, the study found three bidirectional causalities, with greenhouse gas emissions as the central figure.

A comprehensive policy framework is imperative to implement in order to address the interdependent relationships between these indicators. Priority should be given to strategies aimed at enhancing Indonesia's agricultural productivity through targeted investments and technological advancements. Concurrently, policies should be put in place to promote sustainable capital formation in the agricultural sector, with a focus on modernization and infrastructure development. Additionally, efforts should be made to foster Indonesia's economic growth in conjunction with sustainable agricultural practices, recognizing their mutually reinforcing effects. Finally, mitigating greenhouse gas emissions should be a central objective, with initiatives aimed at reducing emissions while promoting economic development. This policy approach should recognize the bidirectional causalities identified in the study, with particular attention given to addressing greenhouse gas emissions as a pivotal factor in shaping the long-term trajectory of economic growth, agricultural productivity, and capital formation in Indonesia.

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