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# Dynamic Relationship between Agriculture and Carbon Emissions in Indonesia: Evidence From Stirpat Model

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**ABSTRACT**

Over the past few decades, Indonesia's agricultural sector has become the backbone of the economy. However, the agricultural sector faces environmental challenges. Most agricultural activities are related to carbon emissions. This study aims to analyze the relationship between Indonesia's agricultural sector, renewable energy, and carbon emissions using STIRPAT model. The research data covers from 1990 to 2021. The analysis models used are ARDL, FMOLS, DOLS, and causality. The results of the study found that economic growth and population have a positive and significant effect in the long term. The findings show a negative and significant impact on the agricultural and renewable energy sectors. In the short-term estimate, only the agricultural sector, renewable energy, and population have a significant effect. The results of FMOLS and DOLS found that the long-term estimate is valid and reliable. In addition, some findings support the causality of the agricultural sector with renewable energy, which can affect economic growth and the relationship between population and carbon emissions. This study is expected to help policymakers mitigate carbon emissions.

**Keywords:** Carbon Emissions, Agricultural Sector, Economic Growth, Renewable Energy, Population, STIRPAT
**JEL Classifications:** O13, Q15, Q501

## INTRODUCTION

Over the past few decades, the agricultural sector has become the backbone of the Indonesian economy. The Central Bureau of Statistics of Indonesia noted that the agricultural sector contributes to GDP, reaching more than 30% yearly. This impact has a real effect on Indonesia because it stimulates the growth of other sectors (such as industry and food) and absorbs jobs. The emergence of this effect cannot be separated from the development of agriculture, which has undergone significant changes due to investment and infrastructure improvisation (Nor and Mohamad, 2024), thus transforming traditional agriculture into modern agriculture.

Amid rapid development, the agricultural sector faces challenges from all countries in increasing production without causing environmental problems. However, this effort is still very difficult due to technological limitations (Aluwani, 2023). Agricultural technology investments tend to be in developed countries compared to developing countries (Al-mulali et al., 2016). The Food and Agriculture Organization (FAO, 2016) stated that the agricultural sector plays a large role in environmental degradation (carbon emissions). Appiah et al. (2018) gave an example of greenhouse gas emissions arising from the rice processing process, which produces methane gas, reaching 10% of its contribution. Next, opening new land in forest areas is one way to increase production. However, deforestation, at least, contributes 25-30% to carbon emissions (Owusu and Asumadu-Sarkodie, 2017). In addition, there is also the massive use of fertilizers and pesticides to accelerate production targets (Matysek et al., 2019) but damages the agricultural ecosystem (Asumadu-Sarkodie and Owusu, 2016) to the mechanization of fossil-fueled agriculture (Qiao et al., 2019). This shows that most agricultural activities are related to carbon emissions.

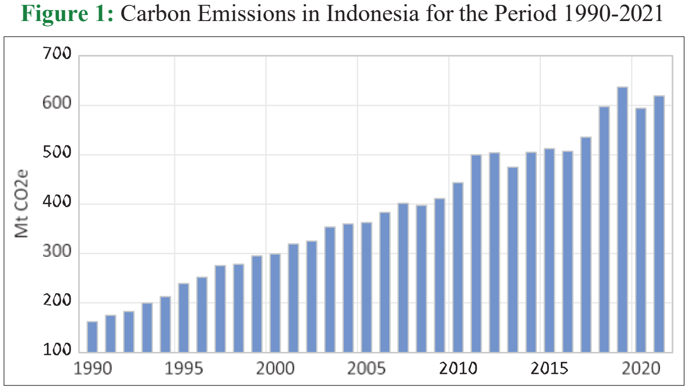
Carbon emissions have received serious attention and are highlighted by policymakers and researchers. Carbon emissions affect climate change (Balogh, 2022) and the environment. Climate change drives the frequency of natural disasters to occur more often such as air cycles, rain, floods, and heat (Czyżewski and Michałowska, 2022) and will have an impact on agricultural productivity (Hassan and Mohamed, 2024) and cause food insecurity (Ayyildiz and Erdal, 2020). In the case of Indonesia, carbon emissions have increased significantly (Figure 1). The World Bank Indicator (2024) recorded Indonesia's carbon emissions at 161.77 million tons (Mt) in 1990. In 2010, carbon emissions increased by more than 300% or 443.70 Mt. Carbon emissions peaked in 2019 at 637.31 Mt when, helping Indonesia experience economic growth of over 5%, accompanied by an increase. The following year, there was a decrease in carbon emissions, but in 2021, emissions increased again to 619.32 Mt. If this problem cannot be resolved, the SDG 13 (Climate Action) target will be hampered.

Related to our empirical study, many studies link agriculture with carbon emissions. Most papers use panel data models to see the relationship between agriculture and carbon emissions (Appiah et al., 2018; Czyżewski and Michałowska, 2022; Nwaka et al., 2020; Qiao et al., 2020; Pata, 2021; Adekoya et al., 2022). While the time series data approach is still limited. Both panel data and time series findings are often found to be inconsistent where the relationship between agriculture and emissions is found to have a positive effect, such as Asumadu-Sarkodie and Owusu (2016), Rafiq et al. (2015) and Ghosh (2018) but some have a negative effect such as Liu et al. (2017). In addition, the findings obtained are dominated by India, Pakistan, Ghana, the United States, and China. This basis is our motivation to test the relationship in Indonesia.

This study contributes to several pieces of literature on carbon emissions. First, the study enriches knowledge by involving the agricultural sector in the dynamic analysis. This will provide a deeper understanding of variables related to carbon emissions, especially in Indonesia. Second, the study adds knowledge to the debate on the agricultural sector's impact on carbon emissions. Finally, the study provides policies that are appropriate for Indonesia regarding the challenges of the agricultural sector in mitigating carbon emissions.

The article structure is formed as follows. Section 2 contains a literature review relevant to the research study, Section 3 explains the data and methods, and Section 4 reviews the empirical findings and discussion. Conclusions and policy suggestions are presented in Section 5.

**Figure 1:** Carbon Emissions in Indonesia for the Period 1990-2021




Source: World Bank Indicator (2024)

## 2. LITERATURE REVIEW

Previous studies have given attention to the importance of carbon emission issues. Earlier studies used various approaches to the agricultural sector, such as the added value of the agricultural sector, types of agricultural production, mechanization of agricultural machinery, and the agricultural sector's contribution. For example, Rafiq et al. (2015) discussed the problem of the agricultural sector on carbon emissions in high and low-middle-income countries. The analysis method of this study used dynamic mean groups linearly and non-linearly. The estimation results showed that the agricultural sector drives carbon emissions in high and low-income countries. Other variables, such as renewable energy, were only found to be significantly negative in high-income countries, and the increase in the industrial and service sectors could reduce carbon emissions.

Asumadu-Sarkodie and Owusu (2016) examined the relationship between the agricultural sector and carbon emissions with variable expansion in fertilizer and machinery use, type of production, and residue burning in Ghana. The research method used the VECM approach and Granger causality. The study found that variable expansion did not have an effect in the short term. Rice production, use of machinery in agriculture, and residue burning were found to be positive and significant in the long term. Meanwhile, the added value of the agricultural sector, livestock production, and emissions produced by the agricultural sector had no effect. The causality results of this study found that carbon emissions have a one-way impact on agricultural production (cereals and rice), and carbon emissions also had a one-way effect on agricultural added value and agricultural machinery.

Liu et al. (2017) analyzed the added value of the agricultural sector to carbon emissions using the environmental Kuznet curve approach in four ASEAN countries. The methods used were FMOLS, DOLS, and the Granger causality panel VECM. This study found that the added value of the agricultural sector had a negative effect and the same sign on renewable energy. In comparison, non-renewable energy has a positive impact. In the causality study, no causal relationship was found between the added value of the agricultural sector and carbon emissions. A two-way causal relationship occurs between renewable energy and the added value of the agricultural sector.

Ghosh (2018) linked the agricultural sector and carbon emissions by including the element of energy consumption in India. The analysis used is VECM and Granger causality. In the long term, the value added by the agricultural sector, energy consumption, trade, and financial development have a positive and significant effect. However, in the short term, only the value added and energy consumption have a positive and significant impact. Based on the Granger causality of VECM, a reciprocal relationship was found between the value added to the agricultural sector and carbon emissions, as well as energy consumption and carbon emissions.

A one-way relationship exists between the value added to the agricultural sector, energy consumption, and trade on energy consumption.

Appiah et al. (2018) re-examined the relationship with different methods, namely FMOLS, DMOLS, and Pooled Mean Group causality in selected emerging countries. FMOLS and DOLS estimates found that economic growth, food crops, and livestock had a significant positive effect, while the population was found to have a significant negative impact. The results of the causality test found that most of the research variables had a bidirectional relationship in the long term. Meanwhile, a one-way relationship was found between economic growth and food, livestock and energy consumption, energy consumption to population, and population to food.

Ali et al. (2019) examined the relationship between carbon emissions, economic growth, and agricultural production in Pakistan using the ARDL method and causality. The results of their study found that economic growth had a positive effect. Meanwhile, agricultural production such as cotton, milled rice, and wheat had a negative impact in the long term. Similar findings were also found in short-term estimates. The results of the Granger causality found that carbon emissions had a one-way relationship with agricultural production (cotton, milled rice, and sorghum). Only barley agricultural production had a one-way effect on carbon emissions.

Czyżewski & Michałowska (2022) reviewed the problem of the agricultural sector with greenhouse gas emissions in the Visegrad group of countries after the 2008 economic crisis. The four countries included were the Czech Republic, Hungary, Poland, and Slovakia from 2008-2019. The analysis method used was the Fixed Effect Model. The results of the study explain that in 2008-2014, the added value of the agricultural sector drove an increase in greenhouse gas emissions but not in other sectors. Meanwhile, in 2015-2019, it was found that the agricultural and other sectors had no relationship to greenhouse gas emissions.

The latest study by Raihan et al. (2024), in which the study of carbon emissions involved several variables such as economic growth, energy, innovation, agriculture, and forests. The study used the FMOLS, DOLS, and CCR analysis methods in Vietnam. The results show that economic growth and energy use have a positive effect. Innovation technology, the agricultural sector, and forestry have a negative impact. The estimates are consistent across the three methods. Nor and Mohamad (2024) linked carbon emissions and agricultural productivity in Somalia with the ARDL approach. The results of their study explain that agricultural productivity, economic growth, and energy consumption have a negative effect on carbon emissions in Somalia.

## 3. DATA AND METHODS

### 3.1 Data

This study uses complete time series data sourced from the World Development Indicator (WDI) to test the relationship between the agricultural sector and $CO_2$ carbon emissions. Researchers also use other variables, namely economic growth, renewable energy, and population. Based on data availability, the research period covers 1990-2021 in Indonesia. Details of the data are presented in Table 1.

### 3.2 Model and Econometric Test

In some available literature, the model for analyzing environmental degradation is the Environmental Kuznets Curve (EKC) method approach. This method uses per capita income as an independent variable. However, there is a weakness in that the impact of per capita income has unitary elasticity. That applies to developing and developed countries (Shahbaz et al., 2016). Therefore, an alternative carbon emission model other than EKC is the Stochastic Impacts by Regression on Population Affluence and Technology (STIRPAT). Shahbaz et al. (2016) explain that population is an important factor because populations in different regions tend to influence environmental quality differently. Affluence is a variable that intersects with economic activity (Usman and Hammar, 2021). The availability of technology is also an important key in controlling environmental damage (Lin and Li, 2020).

STIRPAT is a derivative of IPAT (I = PAT) discovered by Holdren & Ehrlich (1983). Dietz and Rosa (1997) reformulated IPAT into STIRPAT so that this model can be applied in checking hypotheses (Usman et al., 2022). The STIRPAT model equation is explained below:

$$I_t = \gamma_t + P_t^{\theta 1} + A_t^{\theta 2} + T_t^{\theta 3} + \varepsilon_t \qquad (3.1)$$

Equation (3.1) explains that $I$ is environmental pollution, $P$ is population, $A$ is affluence, and $T$ is technology.$\theta_1$ to $\theta_3$ are parameter estimates and ε is residual. In this study, $I$ is described by carbon emissions ($CO_2$), $A$ by economic growth (GDP), and $T$ is technology (REN). The STIRPAT model can be further developed by including elements of the agricultural sector (AGRI). Following the concept by Rafiq et al. (2015), we re-modify equation (3.1) with the logarithm of both sides so that:

$$lnCO_{2t} = \gamma_t + \delta_1 lnGDP_t + \delta_2 lnAGRI_t + \delta_3 lnPOP_t + \delta_4 lnREN_t + \varepsilon_t \qquad (3.2)$$

To analyze equation (3.2), we use the Autoregressive Distributed Lag (ARDL) econometric model. This model aims to analyze the relationship in dynamic form (short and long run), which is very popular. One of its advantages is that it can be used on small samples and can be applied at different integration levels I(0) and I(1) or all integration I(1) (Effendi et al., 2024; Aliasuddin et al., 2024), accommodates different lags between variables and is free

**Table 1: Data and source**

| Variable | Symbol | Operational Variables | Source |
|---|---|---|---|
| Emission carbon | $CO_2$ | Carbon dioxide emissions (total) in Mt CO2e | WDI |
| Economic growth | GDP | GDP per capita real (2015 US$) | WDI |
| Agriculture | AGRI | Agriculture, forestry, and fishing, value added (constant 2015 US$) | WDI |
| Renewable energy | REN | Renewable energy consumption (% of total final energy consumption) | WDI |
| Population | POP | Population (total) | WDI |

from autocorrelation issues (Nor and Mohamad, 2024). However, the model is invalid when there is an integration level in I(2) (Ghosh, 2018). Based on equation (3.2), we can set the equation into the ARDL model so that:

$$\Delta lnCo2_t = \beta_0 + \sum_{i=1}^{p}\pi_{1i}\Delta lnCo2_{t-i} + \sum_{i=0}^{q}\pi_{2i}\Delta lnGDP_{t-i} + \sum_{i=0}^{q}\pi_{3i}\Delta lnAGRI_{t-i} + \sum_{i=0}^{q}\pi_{4i}\Delta lnREN_{t-i} + \sum_{i=0}^{q}\pi_{5i}\Delta lnPOP_{t-i} + \varphi_1 lnCO_{2t-1} + \varphi_2 lnGDP_{t-1} + \varphi_3 lnAGRI_{t-1} + \varphi_4 lnREN_{t-1} + \varphi_5 lnPOP_{t-1} + \varepsilon_t \quad (3.3)$$

Where the short-term estimate is denoted by the symbol Δ of $\pi_{1\text{-}5i}$ and $\varphi_2 - \varphi_5$ is the long-term parameter estimate. t is the time series from 1990-2021, p and q are the dependent and independent lag variables. The optimal lag in the model uses the Akaike Information Criterion, where the best lag number is calculated based on the smallest value. To confirm the long-term relationship in the model, we use the Bound F-test. The decision to reject the null hypothesis (no cointegration) if the F-stat value exceeds the lower and upper critical values. Conversely, if the F-stat is below the critical value or between the critical values, the decision is to accept the null hypothesis (Pesaran et al., 2001).

If the long-term relationship has been confirmed, equation (3.3) can be derived into an ECM model for short-term estimation. In this model, the ECT condition must be negative and significant. The ideal ECT condition is in the range of 0-1. This ECM model is presented in equation (3.4) as follows:

$$\Delta lnCO_{2t} = \phi_0 + \sum_{i=1}^{n}\chi_{1i}\Delta lnCO_{2t-i} + \sum_{i=1}^{n}\chi_{2i}\Delta lnGDP_{t-i} + \sum_{i=1}^{n}\chi_{3i}\Delta lnAGRI_{t-i} + \sum_{i=1}^{n}\chi_{4i}\Delta lnREN_{t-i} + \sum_{i=1}^{n}\chi^{5i}\Delta lnPOP_{t-i} + \upsilon_1 ECT_{t-1} + \varepsilon_t \quad (3.4)$$

After conducting ARDL estimation, we added Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) to test the consistency and reliability of the long-run coefficients. This test has been widely used by Nathaniel et al. (2019), Raihan and Tuspekova (2022), Ikhsan and Amri (2023), and Hassan and Mohamed (2024). Finally, we included the Granger causality analysis to determine the causal relationship. The causal relationship looks at the influence of X on Y and vice versa (Ikhsan et al., 2022).

## 4. EMPIRICAL FINDINGS

### 4.1. Summary Statistics

Descriptive statistics in Table 2 provide an overview of the five variables in the form of average, maximum, minimum, standard deviation, and data distribution. The average $CO_2$ is 5.88, GDP is 7.76, AGRI is 25.15, REN is 35.65, and POP is 19.25. Standard deviation measures dispersion around the average. The highest standard deviation is known in REN at 11.75, and the lowest in POP is 0.12. Data distribution shows that all variables have a normal distribution (Prob is greater than 0.05).

### 4.2. Stationarity Test Results

The results of the stationarity test are summarized in Table 3. This method is the most frequently used, and it was tested using Augmented Dicky-Fuller (ADF). The results show that all variables were found to be non-stationary in the initial stage of stationarity testing at the level level. In the next stage, at the first difference, all variables were found to be stationary with a significance level of 1%. This stationarity finding indicates that the ARDL model is suitable for use.

### 4.3. Cointegration Test Results

After conducting the stationary test, the next stage is to conduct a cointegration test. Cointegration aims to see the relationship between the estimated variables studied that have a long-term relationship. The long-term estimate cannot be interpreted if this cointegration fails to be met. We use the critical value of Narayan (2005) because the research sample is categorized as small. The results of the cointegration test are presented in Table 4. The table has five models where each variable is used as a dependent. The results show that the F-bound of these five models exceeds the lower and upper critical values at the 1% and 5% significance levels, so the null hypothesis is rejected. Thus, a long-term relationship occurs in the research variables.

### 4.4. ARDL Estimation Results

After validating the cointegration between variables, the next step is to investigate the short-term and long-term relationships of equation (3.3). The estimates are shown in Table 5. Assuming other variables are constant, long-term economic growth is positive and significant at 10%. It indicates that a 1% increase in economic growth will increase carbon emissions by 0.324% in the long term. However, the short-term economic growth

**Table 2: Descriptive Statistics**

| Variables | $CO_2$ | GDP | AGRI | REN | POP |
|---|---|---|---|---|---|
| Mean | 5.88 | 7.76 | 25.15 | 35.65 | 19.25 |
| Max | 6.45 | 8.25 | 25.65 | 59.20 | 19.43 |
| Min | 5.08 | 7.29 | 24.72 | 19.80 | 19.02 |
| Std. Dev. | 0.39 | 0.29 | 0.29 | 11.75 | 0.12 |
| Skenewss | −0.41 | 0.26 | 0.27 | −0.10 | −0.21 |
| Kurtosis | 2.16 | 1.76 | 1.75 | 1.98 | 1.84 |
| JB | 1.85 | 2.41 | 2.47 | 1.44 | 2.01 |
| Prob JB | 0.395 | 0.299 | 0.290 | 0.484 | 0.366 |

**Table 3: Unit root test**

| Variables | Level | First difference | Conclusion |
|---|---|---|---|
| $CO_2$ | −2.257 | −4.240*** | I (1) |
| GDP | −0.278 | −4.150*** | I (1) |
| AGRI | 0.618 | −4.462*** | I (1) |
| REN | −0.373 | −6.216*** | I (1) |
| POP | −0.908 | −5.142*** | I (1) |

*** indicates 1% significance level

coefficient was not found to have an effect. Next, the agricultural sector in the long term has a negative sign and is significant at 1% and in the short term at the 10% level. It explains that a 1% increase in the agricultural sector will reduce carbon emissions by 0.679-1.172%.

Furthermore, REN was found to have a negative and significant effect in both short-term and long-term conditions. An increase in REN use by 1% will reduce carbon emissions by 0.020% in the short term and 0.015% in the long term. The REN coefficient has the least effect compared to others. What is of concern is that in the long term, renewable energy experiences a decrease in effect. For POP, this variable was found to have a positive and significant effect on carbon emissions. An increase in POP by 1% will increase carbon emissions by 2,083% in the short term and 3,540% in the long term. Finally, ECT has a negative and significant sign, meaning there is a short-term to long-term convergence (Alola et al., 2019). It indicates that the deviation in the direction of equilibrium will be corrected by 58% annually based on the explanatory variables.

**Table 4: Cointegration test**

| Model | Optimal Lag | F-Bound | Conclusion |
|---|---|---|---|
| $CO_2$ = [GDP, AGRI, REN, POP] | 1,0,0,1,0 | 4.917** | Exist |
| GDP = [$CO_2$, AGRI, REN, POP] | 2,0,0,1,1 | 4.450** | Exist |
| AGRI = [GDP, $CO_2$, REN, POP] | 1,1,0,0,0 | 13.920*** | Exist |
| REN = [GDP, AGRI, $CO_2$, POP] | 3,2,1,0,3 | 11.029*** | Exist |
| POP = [GDP, AGRI, REN, $CO_2$] | 3,3,0,0,2 | 5.269** | Exist |
| Critical value | | I (0) | I (1) |
| 5% | | 2.947 | 4.088 |
| 1% | | 4.093 | 5.532 |

Critical value used small sample by Narayan (2005). ***, ** indicate the significance level of 1%, and 5%, respectively.

**Table 5: Short- and long-term estimates**

| Variables | Coefficient | Std. error | t-stat | Prob |
|---|---|---|---|---|
| Short-run | | | | |
| ΔGDP | 0.184 | 0.159 | 1.15 | 0.261 |
| ΔAGRI | −0.679* | 0.344 | −1.97 | 0.062 |
| ΔREN | −0.020*** | 0.003 | −5.26 | 0.000 |
| ΔPOP | 2.083** | 0.798 | 2.61 | 0.016 |
| ECT(−1) | −0.585*** | 0.098 | −5.970 | 0.000 |
| Long-run | | | | |
| GDP | 0.324* | 0.1608 | 2.104 | 0.055 |
| AGRI | −1.172*** | 0.186 | −6.273 | 0.000 |
| REN | −0.015*** | 0.004 | −3.484 | 0.001 |
| POP | 3.540*** | 0.392 | 9.029 | 0.000 |
| Cons | −34.685*** | 7.284 | −4.761 | 0.000 |
| Testing | Chi-stat | Prob. | | |
| Normality | 0.701 | 0.704 | | |
| Serial correlation | 0.980 | 0.612 | | |
| Heteroskedasticity | 5.169 | 0.522 | | |
| Ramsey RESET | 0212 | 0.649 | | |
| Cusum | Stable | | | |
| CusumSQ | Stable | | | |

***, **, * indicate 1%, 5%, and 10% significance levels

## 4.5. Diagnose Model

Table 5 shows the results of the model diagnostic test. The purpose of this diagnosis is to confirm efficient and reliable estimates. Model tests include normality, serial correlation, heteroscedasticity, and model misspecification. In addition, we also include long-term model stability testing. The normality, serial correlation, heteroscedasticity, and RESET test results found no violations because the probability was > 0.05. The model stability test in Figures 2 and 3 explains that the coefficient line is between the red lines so that the model is concluded to be stable in the long term.

## 4.6. Robustness Check

We use the FMOLS and DOLS estimators to check the consistency of the long-term estimates. Table 6 shows that both estimators are very reliable. The FMOLS estimation results show that economic growth and population have a significant positive effect, while the agricultural sector and renewable energy have a significant negative effect. Meanwhile, the DOLS estimation results indicate that economic growth has a significant effect at the 5% level. Based on this test, it can be concluded that the FMOLS and DOLS estimators are consistent with the long-term estimates made using the ARDL method.

**Figure 2:** Plot of CUSUM

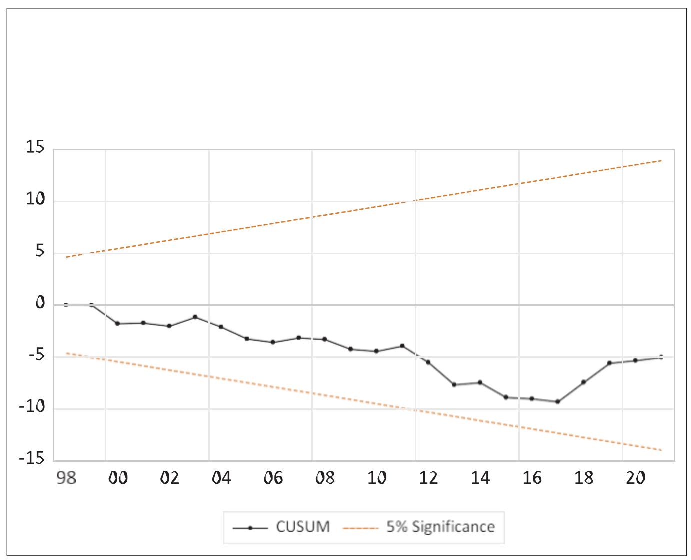



**Figure 3:** Plot of CUSUMSQ

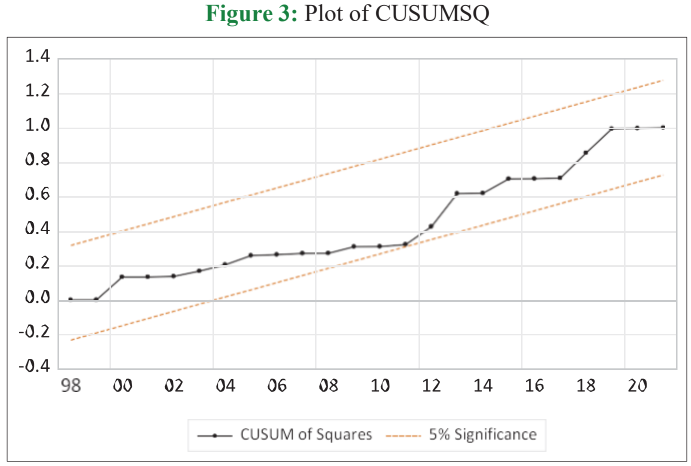


**Table 6: FMOLS and DOLS estimation results**

| Variables | FMOLS | DOLS |
|---|---|---|
| GDP | 0.285* | 0.623** |
| AGRI | −1.192*** | −1.458*** |
| REN | −0.015*** | −0.011** |
| POP | 3.746*** | 3.287*** |
| C | −37.833*** | −24.726*** |

***, **, * indicate 1%, 5%, and 10% significance levels.

## 4.7. Granger Causality Test Results

Regression estimation provides a picture of the one-way influence between the independent and dependent variables, but often fails to capture the complexity of the two-way relationships that may occur between these variables. Occasionally, the connection between variables can be reciprocal or complexly interrelated. This phenomenon can support the interpretation of the analysis results. The results of the Granger causality test in Table 7 show that POP affects $CO_2$ at the 5% significance level, AGRI affects GDP at the 5% significance level, GDP affects REN at the 10% significance level, AGRI affects REN at the 5% significance level, and there is a bidirectional between POP and REN at the 10% significance level. There is no relationship between GDP and $CO_2$, AGRI and $CO_2$, REN and $CO_2$, and POP and GDP.

## 4.8. Discussion

The study analyzed the relationship between agriculture and carbon emissions and elements of Indonesia's economic growth, renewable energy, and population. The results of the analysis found that economic growth positively and significantly affects carbon emissions. The findings conclude that when the economy grows, this finding is in line with Rafiq et al. (2015), Owusu and Asumadu-Sarkodie (2017), Appiah et al. (2018), and Ali et al. (2019). The production of goods and services is closely related to industrial activities, which require a large energy supply at an affordable cost (Rani and Kumar, 2018). Most developing countries rely more on fossil fuels (Touitou, 2021) than renewable energy because renewable energy development is still relatively expensive and not easily accessible. In addition, developing countries are often faced with technological limitations, policy challenges (Wang et al., 2018) and weak infrastructure (Wood, 2019), which hinder the industry from developing towards high technology. As a result, problems related to carbon emissions become difficult to overcome. From a causal perspective, there is potential for Indonesia's economic growth to drive demand for renewable energy. However, renewable energy has not yet provided significant feedback on increasing economic growth. In other words, Indonesia's achievement towards a green economy is still not optimal.

The next finding is that agriculture negatively and significantly affects carbon emissions. This finding is in line with Khan et al. (2022), Ariani et al. (2024), Zhou et al. (2022), Raihan et al. (2024), and Nor and Mohamad (2024), but contradicts Ghost (2018), Appiah et al. (2018), Ayyildiz and Erdal (2020), and Czyżewski and Michałowska (2022). So far, agriculture has been quite closely related to carbon emissions. Forms of agricultural activities will produce carbon emissions (Khan et al., 2022). However, agriculture does not always have a positive effect. Technological developments in agriculture are underway, and alternative

**Table 7: Results of pairwise granger causality testing**

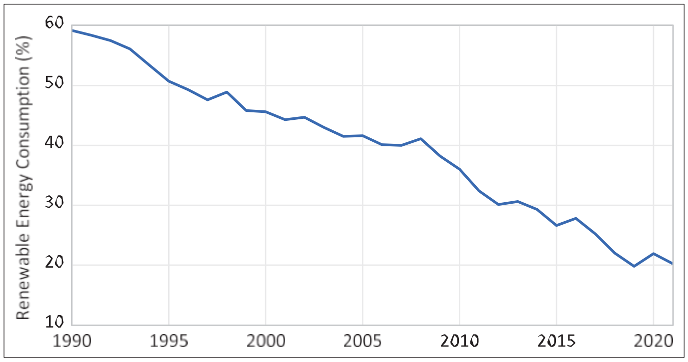
| Null hypothesis | F-statistic | Decision | Causality direction |
|---|---|---|---|
| GDP does not Granger Cause $CO_2$ | 1.508 | Accept | GDP≠$CO_2$ |
| $CO_2$ does not Granger Cause GDP | 0.022 | Accept | |
| AGRI does not Granger Cause $CO_2$ | 2.010 | Accept | AGRI≠$CO_2$ |
| $CO_2$ does not Granger Cause AGRI | 0.269 | Accept | |
| REN does not Granger Cause $CO_2$ | 0.116 | Accept | REN≠$CO_2$ |
| $CO_2$ does not Granger Cause REN | 0.188 | Accept | |
| POP does not Granger Cause $CO_2$ | 7.281** | Reject | POP→$CO_2$ |
| $CO_2$ does not Granger Cause POP | 0.380 | Accept | |
| AGRI does not Granger Cause GDP | 6.493** | Reject | AGRI→GDP |
| GDP does not Granger Cause AGRI | 2.178 | Accept | |
| REN does not Granger Cause GDP | 0.032 | Accept | GDP→REN |
| GDP does not Granger Cause REN | 3.153* | Reject | |
| POP does not Granger Cause GDP | 1.299 | Accept | POP≠GDP |
| GDP does not Granger Cause POP | 0.133 | Accept | |
| REN does not Granger Cause AGRI | 0.241 | Accept | AGRI→REN |
| AGRI does not Granger Cause REN | 7.495** | Reject | |
| POP does not Granger Cause AGRI | 1.876 | Accept | POP≠AGRI |
| AGRI does not Granger Cause POP | 1.034 | Accept | |
| POP does not Granger Cause REN | 4.003* | Reject | POP↔REN |
| REN does not Granger Cause POP | 3.096* | Reject | |

**, * indicate 5%, and 10% significance levels. ↔ is bidirectional, → is unidirectional, ≠ is no causality

energy sources are being used. Raihan et al. (2024) explain that renewable energy in agriculture is a promising solution. With the availability of sustainable renewable energy, the agricultural sector can increase productivity and direct more sustainable agricultural practices (Nor and Mohamad, 2024). According to Wang et al. (2023), one factor contributing to carbon emission reduction in the agricultural sector is changes in management and harvesting processes. The agricultural sector is increasingly adopting modern technologies and the latest techniques that enable greater efficiency from the initial to the final stages of production. The implementation of these innovations not only increases productivity but also reduces resource use and emissions generated during the agricultural process.

Next, renewable energy was found to have a negative and significant effect on carbon emissions. This finding is in line with research by Liu et al. (2017), Nwaka et al. (2020), Ridzuan et al. (2020), and Aluwani (2023). Renewable energy is a key element in

**Figure 4:** Development of renewable energy consumption for the period 1990-2021




Source: World Bank Indicator (2024)

carbon emission mitigation. Based on research, carbon emissions will decrease by 0.01% if renewable energy consumption increases by 1%. Although it can reduce emissions, the coefficient is smaller when compared to the findings of Liu et al. (2017), which was 0.07%; Ridzuan et al. (2020), which reached 0.1%, and Zaman et al. (2021), which was 0.99%. This relatively small figure reflects Indonesia's renewable energy consumption development, which has shown a significant downward trend recently (Figure 4). This condition can negatively impact the future, especially in efforts to mitigate carbon emissions.

Population has a significant influence on carbon emissions. This finding is in line with the research of Lin et al. (2017) and Abdullah Abbas Amer et al. (2024) but different from the research results of Appiah et al. (2018), Khan (2024), and Pea-Assounga et al. (2025). The relationship between population and carbon emissions can be studied through household consumption patterns. The greater the population growth, the higher the demand for production, especially in urban areas (Lin et al., 2017). Rapid population growth is unavoidable in developing countries (Aluwani, 2023). According to Abdullah Abbas Amer et al. (2024), population growth drives increased energy extraction and mass production in industry, ultimately contributing to increased carbon emissions. Not only in terms of utility, carbon emissions can grow due to a lack of education. Low levels of education can result in inefficiency in work and wasteful energy consumption (Pea-Assounga et al., 2025). Therefore, the population needs environmentally friendly energy to reduce carbon emissions while supporting sustainable development.

## 5. CONCLUSION AND POLICY IMPLICATIONS

This study aims to analyze the relationship between the economic growth, agricultural sector, renewable energy, population and carbon emissions in Indonesia from 1990 to 2021 and test the causality relationship between these variables. The results of long-term estimation using the ARDL model show that economic growth and population tend to drive an increase in carbon emissions, while renewable energy and the agricultural sector play a role in reducing carbon emissions. Meanwhile, short-term estimation shows similar results, except economic growth has no significant effect. Model reliability testing using the FMOLS and DOLS methods shows results consistent with the ARDL model. The analysis of the causality relationship reveals a two-way relationship between population and renewable energy, as well as a one-way relationship from population to carbon emissions, the agricultural sector to renewable energy, economic growth to renewable energy, and the agricultural sector to economic growth.

Based on the econometric analysis above, several important recommendations can be made. Economic growth, which is often associated with increased production of goods and services by industry, needs to be integrated with the concept of sustainability. This includes using environmentally friendly raw materials and alternative energy to support economic activities. In addition, providing incentives for industries that adopt environmentally friendly technology is also a strategic step. With this approach, economic growth can be directed towards sustainable and environmentally friendly development.

Policymakers need to work to improve the agricultural sector by integrating modern technology and more efficient methods. Currently, agriculture is still dominated by traditional methods, which often rely on fossil fuels due to limited access to environmentally friendly energy. To overcome this problem, increasing the added value of agricultural products can effectively mitigate carbon emissions. In addition, the growth of the agricultural sector can also be encouraged without having to open new land, thus supporting environmental conservation while improving productivity.

Policies that focus on the development and optimization of renewable energy are needed to take advantage of renewable energy's negative impact on carbon emissions. Although the impact of reducing emissions is still very small, environmental problems can be reduced slowly. Policymakers can encourage massive investment in environmentally friendly energy infrastructure. Utilizing environmentally friendly technology encourages and achieves the development target of SDG 13.

Finally, the population plays a significant role in carbon emissions because they consume goods and services daily. Therefore, the community must be educated and empowered about the importance of sustainable lifestyles, such as energy efficiency, recycling, and responsible consumption. These policies can include training programs to raise awareness about the use of environmentally friendly energy and campaigns that encourage waste reduction and resource reuse. With community empowerment focusing on sustainability, the population can become agents of change in carbon emission mitigation efforts.

This study has several limitations that need to be considered. The study was conducted using time series data with limited samples. However, there are opportunities for future research development. One is conducting a comparative analysis among ASEAN countries, adding patent variables as technology indicators and including agricultural sub-sector variables such as plantations, livestock, fisheries, and food. This approach can provide a more in-depth analysis of the relationship between the agricultural sector and carbon emissions.

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