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, 2024, 14(6), 665-674.

Agriculture Productivity and Environmental Degradation in Indonesia: A Time Series Analysis

Rita Ariani[1]*, Kamal Fachrurrozi[2], Adhiana Adhiana[1], Akhmad Baihaqi[3]

[1]Faculty of Agriculture, Universitas Malikussaleh, Indonesia, [2]Faculty of Economics and Business, Universitas Syiah Kuala, Indonesia, [3]Faculty of Agriculture, Universitas Syiah Kuala, Indonesia. *Email: rita.ariani@unimal.ac.id

Received: 27 July 2024 **Accepted:** 23 October 2024 **DOI:** https://doi.org/10.32479/ijeep.17284

ABSTRACT

High carbon emissions pose a challenge in achieving sustainability. The agricultural sector is one of the contributors. This study aims to examine the relationship between the agricultural sector's contribution, agricultural productivity, economic growth, fossil energy consumption, and carbon emissions in Indonesia. The research data covers the time period from 1990 to 2021. The analytical methods used include autoregressive distributed lag (ARDL) and cointegration testing with Bayer and Hanck. Additionally, causality testing is applied using the Toda-Yamamoto (TY) approach. The results indicate the existence of cointegration in all five models. Furthermore, the contributions of the agricultural sector, economic growth, and fossil energy consumption drive an increase in carbon emissions in both the short and long term. Meanwhile, agricultural productivity effectively reduces carbon emissions in both time horizons. Finally, each variable exhibits a two-way causal relationship.

Keywords: Agriculture productivity, CO_2, Cointegration, Non-Causality
JEL Classifications: Q15, Q53

1. INTRODUCTION

In recent decades, issues regarding environmental degradation have become increasingly evident. Environmental degradation is a tangible problem witnessed firsthand, bringing disasters and threatening human survival both now and in the future. These include rising global temperatures, floods, storms, and forest fires. Environmental degradation is often associated with greenhouse gas emissions, which have increased significantly, leading to a decline in environmental quality (Appiah et al., 2018; Appiah et al., 2019). Among various greenhouse gases, carbon emissions constitute the largest share in both developing and developed countries.

Indonesia is one of the developing countries that contribute to carbon emissions. According to the EIA report (Energy International Agency, 2022), carbon emissions in Indonesia reached 685 million metric tons in 2022, with an average annual increase of 5.59%. Indonesia's contribution to global carbon emissions is projected to be 1.96% in 2023. These emissions are primarily from combustion, cement production, and gas (Global Carbon Budget, 2023). Although high carbon emissions can harm Indonesia's image, in reflect economic activity, indicating that the economy is functioning and growing.

Many scholars have identified economic growth (Abdullah, 2015; Alhassan, 2021) and the extensive use of fossil fuels (Hafeez et al., 2020; Adekoya et al., 2022) as primary contributors to carbon emissions. Consequently, carbon emissions are often seen as an inevitable byproduct. Economic growth indicates the level of activity within a region, and all countries strive for high growth as it signals increased production of goods and services, job creation, and higher incomes, leading to greater societal prosperity. However, this prosperity also drives up carbon emissions due to increased demand for daily necessities. Additionally, most countries recognize the crucial role of energy in sustaining economic and social activities, with fossil fuels being the most commonly available resources. Despite the volatile market price of crude oil, which sometimes exceeds $100/barrel, countries continue to rely on oil. Even oil-importing nations like Indonesia prioritize securing crude oil supplies over investing in environmentally friendly technologies. Since 1995, Indonesia has relied on fossil fuels for more than 60% of its energy consumption (WDI, 2024).

Apart from economic growth and fossil fuel use, the agricultural sector also contributes to rising carbon emissions. Indonesia is not only a developing country but is also recognized for its agricultural potential due to its fertile land. The term "agrarian" highlights the abundance of agricultural commodities and the dominance of farming as a livelihood for much of the population. The agricultural sector is crucial for food security (Edoja et al., 2016; Zhou et al., 2022), industrial development (Adem et al., 2020; Khurshid et al., 2022), and overall economic expansion (Appiah et al., 2018). However, as food production increases, so do carbon emissions (Nkawa et al., 2020). Currently, agriculture accounts for 21% of global greenhouse gas emissions (Hafeez et al., 2020).

The relationship between the agricultural sector and carbon emissions is often debated both theoretically and empirically. Theoretically, agriculture is transitioning from traditional practices to mechanized processes to enhance production efficiency (Otim et al., 2023). This transition encourages farmers, fishermen, and plantation workers to increase productivity (Wang et al., 2023), highlighting the importance of technological availability. However, technology distribution is uneven, with developed countries possessing superior, albeit sometimes environmentally unfriendly, technologies compared to developing countries (Chowdhury et al., 2022). Empirical studies confirm the link between agriculture and carbon emissions, as demonstrated by Aydoğan and Vandar (2019) in E7 countries, Adem et al. (2020) in Ethiopia, Adekoya et al. (2022) in affluent African nations, Balogh (2022) in Europe, and Zhou et al. (2022) in China. Their findings consistently show that agricultural expansion leads to increased carbon emissions.

This research focuses on the agricultural sector and carbon oxide gas emissions in Indonesia. The motivation behind this study is the goal of sustainable development to address climate change. This research contributes to the literature on agriculture and carbon emissions. To the best of the researchers' knowledge, this is the first study to investigate the impact of the agricultural sector and agricultural productivity on carbon gas emissions in Indonesia. Additionally, this research employs a dynamic econometric approach, specifically the Autoregressive Distributed Lag (ARDL) model, to analyze both short-term and long-term impacts, a method that is rarely applied. Previous studies have predominantly used panel data, such as those by Al-Mulali (2015), Al-Mulali et al. (2016), Uddin (2020), Nwaka et al. (2020), and Balogh (2022). Furthermore, the researchers utilized Toda-Yamamoto's (1995) non-causality approach to explore relationships between variables. It is hoped that this research will serve as a reference for policymakers to address carbon emission issues and promote sustainable development.

Climate change is a compelling subject for researchers because it pertains to the goals of sustainable development and the future survival of humanity. While the agricultural sector is crucial to the economy, it also contributes to carbon emissions. Additionally, economic growth and energy consumption are significant economic variables that greatly impact carbon emissions. Based on the aforementioned description, the research questions are: How do the agricultural sector, agricultural productivity, energy consumption, and economic growth affect carbon emissions in Indonesia? Do the variables studied have a causal relationship?

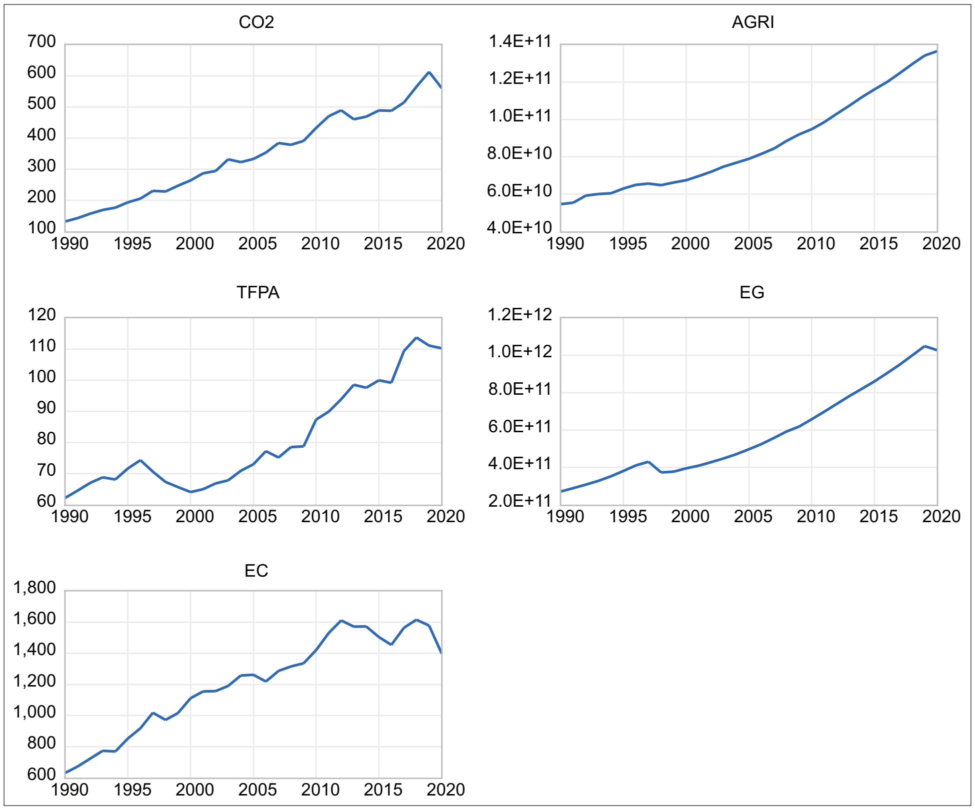
The structure of this study is as follows. Section 2 reviews previous research. Section 3 describes the data and research methods. Section 4 presents the empirical results and discussion. Finally, Section 5 provides the conclusions and suggestions

2. LITERATURE REVIEW

Indonesia is one of the developing countries in Southeast Asia and is also recognized as an agricultural nation due to its significant agricultural workforce. Figure 1 illustrates the positive trend in the agricultural sector's contribution to the economy. In 1990, the agricultural sector contributed $54.7 billion to the economy, a figure that increased to $136 billion by 2020. This growth in agricultural production can be attributed, in part, to the rise in population over the same period. Examining productivity, we note fluctuations in the agricultural sector's performance during the early 1990s. Productivity dropped to 64.05%, nearly matching the 1990 level of 62.17%. However, in subsequent years, agricultural productivity saw a significant increase, reaching 113.76% in 2018. Economic growth in Indonesia has also been remarkable. In 1990, the GDP stood at $270 billion, and by 2020, it is projected to reach $1,027 billion, representing an average annual growth rate of 5%. Despite these achievements, Indonesia remains heavily dependent on crude oil as its primary energy source to fuel its economy. Oil consumption has seen a significant rise from 631 thousand barrels per day in 1990 to 1,398 thousand barrels per day in 2020, marking a staggering increase of 221% over the period.

The relationship between the agricultural sector and carbon emissions is explained by Appiah et al. (2018). One of the causes of the increase in carbon emissions is due to increasing population, energy demand, economic growth and the growth of the agricultural sector in maintaining food stocks. For each country, increasing the agricultural sector provides different carbon emission values, especially countries that are members of emerging markets and BRICS countries (Brazil, Russia, India, China and South Africa). Waheed et al. (2018) examined the relationship between the two in Pakistan using the ARDL approach. The results of his research explain that the agricultural sector (production) has a positive impact in the short and long term. Aydoğan and Vardar (2019) examined the agricultural sector with carbon emissions in E7 countries. Findings from FMOLS and DOLS explain that the agricultural sector has a positive influence of around 0.098%-0.105%. Hafeez et al. (2020) tested the relationship between the two in OBORI using the FMOLS approach and found that the agricultural sector had a positive effect on carbon emissions. In a study with the same method, Alhassan (2022) found a similar thing that the agricultural sector drives carbon emissions. Selvanathan et al. (2022) revealed that the agricultural sector has a

Figure 1: Trend of carbon dioxide, agricultural output, agriculture productivity, economic growth, and energy consumption in the period 1990-2020



positive influence in OECD countries through a fixed effect panel approach. However, there are findings that contrast with Liu et al. (2017) in four ASEAN and Chowdhury et al. (2022) in Bangladesh where the agricultural sector reduces carbon emissions. Ben Jebli and Ben Youssef (2019) use the agricultural sector as a proxy for agricultural value added in Brazil. The estimation results found that the agricultural sector only had a negative impact in the long term. Adekoya et al. (2022) tested in rich African countries the ARDL Panel approach and found negative signs of the agricultural sector in the long run. So the research hypothesis is:

H1: The agricultural sector has a positive effect on carbon emissions.

H1a: The agricultural sector has a positive effect on carbon emissions

H1b: The agricultural sector has a negative effect on carbon emissions.

Productivity is described as the ability of labor to produce goods. The higher the productivity, the higher the production. One role that can encourage productivity is technology. The latest technology has an impact on work efficiency and increases production capabilities under the same conditions. Regarding technology, generally countries with low productivity result in low use of technology so that impacts on the environment cannot be avoided. Zhou et al. (2022) with the non-linear ARDL approach in China to shift the conventional economy to a green economy. Agricultural productivity reduces carbon emissions in the long term. Recent research by Wang et al. (2023), from the ARDL method, explains that high productivity in the agricultural sector will reduce carbon emissions. Raihan et al. (2022) and Raihan et al. (2023) in two different places, namely Bangladesh and Egypt. Both findings conclude that agricultural sector productivity has a negative effect. However, the findings of Alhassan (2022) explain that if productivity is increased higher (based on the quadratic method) it will give rise to a paradox, namely a positive effect on emissions. So the productivity hypothesis is formed as follows:

H2a: Agricultural sector productivity has a negative effect on carbon emissions

H2b: Agricultural sector productivity has a positive effect on carbon emissions.

Economic growth is defined as the total of goods and services in one period. In macroeconomics, increasing economic growth is due to the push from demand. From the supply side, producers will produce more goods. Then carbon gas emissions will increase. Zhang et al. (2019) found a positive relationship between economic growth and carbon emissions. Qiao et al. (2019) found a positive relationship and the contribution was greater in developed countries compared to developing countries. The two variables are reciprocally related. Meanwhile, Ben Jebli and Ben Youssef (2019) both short and long term economic growth have a positive impact on carbon emissions. Rehman et al. (2019) used the ARDL method in Pakistan. The estimation results explain that positive economic growth increases carbon emissions in the long term. The economic growth hypothesis is formed as follows:

H3: Economic growth has a positive effect on carbon emissions.

Energy has an important role in the economy and agricultural sector. Energy can encourage a sector to use machine mechanisms. Many countries still use fossil energy. One of the reasons is that this energy is still easy to find and cheap. However, this energy is non-renewable energy and causes emissions. Empirical studies such as Raihan et al. (2022) tries to relate this to the ARDL method. His research found energy contributed greatly to increasing emissions in Bangladesh. The same findings were also found by Appiah et al. (2019) in emerging countries. Pata and Caglar (2021) found a positive impact in China based on Augmented ARDL. The hypotheses regarding fossil energy are:

H4: Fossil energy has a positive effect on carbon emissions.

After summarizing relevant studies, this research gap literature includes (1) the literature between the agricultural sector and agricultural sector productivity has different findings so it is inconsistent. Then, there is no research that combines the two in an analysis. (2) Most of the previous research studies discussed agricultural sector issues and productivity in certain countries such as China, Pakistan, Bangladesh or group countries such as ASEAN, OBORI, OECD. Studies in Indonesia, based on literature, have not yet been carried out. Based on this gap, researchers reviewed the relationship between the two using two approaches, namely ARDL and Toda-Yamamoto Non-Causality in Indonesia.

3. DATA AND METHODOLOGY

3.1. Models and Data

This paper encompasses Indonesian data spanning from 1990 to 2021, comprising a total of 32 observations. The dependent variable under study is carbon emissions (CO2), while the independent variables include agricultural sector output (AGRI), agricultural sector productivity (TPFA), economic growth (EG), and energy consumption (EC). Thus, the research model is constructed as follows:

$$CO2_t = (AGRI_t, TFPA_t, EG_t, EC_t) \quad (1)$$

Where CO_2 is measured as equivalent carbon emissions from energy, process emissions, methane, and combustion, expressed in millions of tons. AGRI is measured by the contribution of the agricultural sector to GDP in dollars, while TFPA is measured by productivity level in conjunction with land, labor, capital, and other materials, expressed in percentage units. EG is measured by GDP at constant prices in 2010, denoted in USD units, and EC is measured by oil consumption in thousands of barrels per day. We utilized various secondary data sources: AGRI and EG data are sourced from the World Development Indicator, TFPA data is obtained from the USDA Economic Research Service, and CO_2 and EC data are sourced from the Energy Institute. To address issues of normality, autocorrelation, multicollinearity, and heteroscedasticity, the data were transformed into natural logarithms (Ikhsan et al., 2022; Fachrurrozi et al., 2022). Additionally, logarithmic transformations facilitate interpretation in terms of percentage or elasticity. Thus, the transformation of equation (1) is as follows:

$$lnCo2_t = \alpha_0 + \alpha_1 lnAGRI_t + \alpha_2 lnTFPA_t + \alpha_3 lnEG_t + \alpha_4 lnEC_t + \varepsilon_t \quad (2)$$

3.2. Empirical Strategy

To achieve the research objectives, researchers employed two methodological approaches: autoregressive distributed lag (ARDL) and Toda-Yamamoto Non-Causality. Before proceeding with the selected model, stationarity testing is a crucial requirement. Stationarity testing determines whether a variable is stationary at integration I(0) or I(1). Researchers utilized the Augmented Dickey-Fuller (ADF) test (1981). The null hypothesis posits the existence of a unit root if the t-statistic value is lower than the critical value. Conversely, if the t-statistic exceeds the critical value, the null hypothesis is rejected. Additionally, structural break stationarity testing is conducted using the Zivot and Andrews (ZA) test (1992). A weakness of the ADF method is its holistic approach to data stationarity, disregarding specific data movements, potentially leading to decision-making errors. The potential for data to exhibit extreme changes at specific times due to known or unknown factors is considerable. The null hypothesis of the ZA test posits non-stationarity, while the alternative hypothesis assumes stationarity.

The ARDL method includes the use of varying lags of the dependent variable and explanatory variables. The model discovered and developed by Pesaran et al. (2001) can see dynamic influences in the form of short and long terms. Several advantages of using the ARDL method are: First, this model can use a small number of samples. Second, the variables used may have different stationarity I(0) and I(1) in testing cointegration. Third, the lag used can be different or the same with various shapes. Fourth, the lag variable is free from endogeneity problems. So the form of the equation is as follows:

$$\begin{aligned}\Delta lnCo2_t &= \alpha_0 + \sum_{i=1}^{p}\gamma_{1i}\Delta lnCo2_{t-i} + \sum_{i=1}^{q}\gamma_{2i}\Delta lnAGRI_{t-i} \\ &+ \sum_{i=1}^{q}\gamma_{3i}\Delta lnTFPA_{t-i} + \sum_{i=1}^{q}\gamma_{4i}\Delta lnEG_{t-i} + \sum_{i=1}^{q}\gamma_{5i}\Delta lnEC_{t-i} \\ &+ \lambda_1 lnCO2_{t-1} + \lambda_2 lnAGRI_{t-1} + \lambda_3 lnTFPA_{t-1} \\ &+ \lambda_4 EG_{t-1} + \lambda_5 lnEC_{t-1} + \varepsilon_t \end{aligned} \quad (3)$$

Where Δ is a difference operator that indicates short-term values while λ_1-$\lambda_5$reflects long-term values, t is time, p and q are optimal lags, ε is the error term. In selecting the optimal lag, researchers used the Akaike Information Criterion (AIC). Testing the cointegration hypothesis via Bound F-test using Wald F-statistic restrictions and comparing the upper band and lower band critical values with the null hypothesis, namely H0: $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = 0$ which indicates there is no cointegration, while the alternative hypothesis is H1: $\lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq 0$. We use critical values by Narayan (2005). Apart from the Bound test, we implemented the Bayer and Hanck (2013) method. We apply this method as a supporting material for cointegration as has been done by Chowdhury et al. (2022), Ahmed et al. (2019), Shahbaz et al. (2017), and Nathaniel et al. (2019). Bayer and Hanck (2013) cointegration combines cointegration probability values from Boswijk (1994), Johannsen (1991), Engle and Granger (1987), and Banerjee et al. (1998). The advantage of the cointegration combination is that it can provide consistent, reliable results and prevent doubts in the results when cointegration tests are carried out separately. The decision to reject the null hypothesis (no cointegration) if the Fisher statistic value is greater than the Bayer and Hanck (2013) critical value. Fisher's formula is as follows:

$$EG-JOH = -2[\ln(\rho_{EG})+(\rho_{JOH})] \quad (5)$$

$$\mathrm{EG-JOH-BO-BDM} = -2[\ln(\rho_{EG})+(\rho_{JOH})+(\rho_{BO})+(\rho_{BDM})] \quad (6)$$

Equation (3) can be reformulated into an ECM model. Short-term correction models are also used for the purpose of identifying short-term dynamic estimates. This correction term (ECM) is expected to have a negative and significant sign on the dependent variable. The specifications for the short-term correction model in this research are as follows:

$$\Delta lnCO2_t = \phi_0 + \sum_{i=1}^{n}\chi_{1i}\Delta lnCO2_{t-i} + \sum_{i=1}^{n}\chi_{2i}\Delta lnAGRI_{t-i} + \sum_{i=1}^{n}\chi_{3i}\Delta lnTFPA_{t-i} + \sum_{i=1}^{n}\chi_{4i}\Delta lnEG_{t-i} + \sum_{i=1}^{n}\chi_{5i}\Delta lnEC_{t-i} + \upsilon_1 ECT_{t\ 1} + \varepsilon_t \quad (6)$$

Equation (6) illustrates that the Error Correction Mechanism (ECM) represents the speed of adjustment. The ideal ECM condition ranges from 0 to 1, with a possibility of extending to 1-2. Values outside this range indicate potential long-term adjustments in subsequent periods. The expected coefficient υ_1 is negative as it converges towards the long run; a positive coefficient suggests divergence from the long term.

Estimation of the ARDL model utilizes the Ordinary Least Squares (OLS) estimation technique, necessitating estimation diagnostics to ensure efficiency and reliability. Diagnostic tests include assessing normality, autocorrelation, heteroscedasticity, and model misspecification. Null hypothesis testing determines whether the statistical value is lower or higher than the critical value, guiding the acceptance or rejection of the null hypothesis. Additionally, assessing the stability of the research model is essential to evaluate the stability of estimated coefficients in the long term, which can be analyzed using CUSUM and CUSUMQ graphs.

Furthermore, we conducted Granger non-causality testing using the Toda-Yamamoto (TY) (1995) approach. Standard Vector Autoregression (VAR) is applied when all variables are at the same level or first difference. However, traditional regression methods only account for influence in one direction, potentially overlooking reciprocal influences. TY is an advancement of traditional Granger causality analysis, particularly suitable for variables with differing integration levels, thereby minimizing errors in identifying integration. This comprehensive approach ensures robust analysis and accurate inference (Mavrotas and Kelly, 2001). The econometric research process is presented in Figure 2 below:

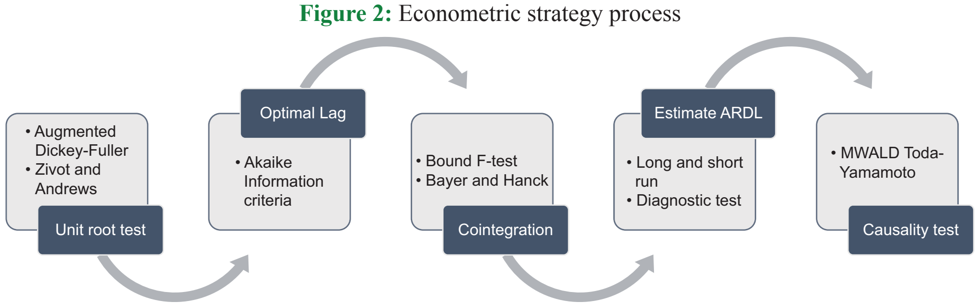
4. EMPIRICAL RESULTS AND DISCUSSION

Descriptive statistics for variables in Table 1 show that carbon emissions, agricultural sector contribution, agricultural sector productivity, economic growth and energy consumption are normally distributed. The standard deviation of carbon emissions is 0.44, the contribution of the agricultural sector is 0.28, the productivity of the agricultural sector is 0.19, economic growth is 0.28, and energy consumption is 0.40. Carbon emissions and energy consumption show frequent fluctuations compared to others. Jarque-Berra (JB) explained whether the data distribution was normal or not. JB test results show that all data is normally distributed (probability above 5%).

The first step in the time series model is to carry out stationarity testing. This is important for making decisions about stationary variables at level I(0) or I(1) and ensuring that variables are not stationary at I(2). Researchers used the Augmented Dickey-Fuller (ADF) approach by Dickey and Fuller (1981) as a stationarity test tool. Table 2 shows that all variables are not stationary at level level. Testing the first difference level or I(1) found that all variables were stationary. Thus, the stationarity of the research variables is at level I(1).

Even though variable stationarity has been found at level I(1), the stationarity needs to be tested again for consistency. ADF has a weakness in that the method does not see fluctuations in data. Data can change drastically due to policies or situations that cannot be controlled. This can be seen from the development of research data

Figure 2: Econometric strategy process



shown in Figure 1. Therefore, researchers applied the structural break stationarity test by Zivot and Andrew (1992). The detailed results of this test are shown in Table 3. The results show that all variables are not stationary at level I(0), which means they are still not stationary. Testing at the first difference level (I[1]) found all variables were significant at the 1% level where the decision taken was to reject the null hypothesis. Carbon emissions are estimated to have broken in 1999. That year, Indonesia's economic recovery began after experiencing the monetary crisis in 1997-1998.

After knowing the level of stationarity, the next stage is to test the cointegration of the variables. ARDL cointegration uses a bound test approach which requires a certain lag. The optimal lag is obtained using the Akaike Information Criteria (AIC). One of the differences between ARDL's optimal lag and VAR or VECM is that each variable lag has its own lag. The VAR and VECM methods use the same lag for all variables. The optimal lag of the research variables is presented in Table 4.

The next step is to test the existence of cointegration. The results in Table 4 show that for the carbon emissions model, the F-stat number is 14.23. The agricultural sector model found an F-stat figure of 8.53. The agricultural productivity model found an F-stat figure of 5.62. The economic growth model is 5.95 and the fossil energy consumption model is 9.17. Referring to Pesaran et al. (2001) that cointegration occurs if the statistical number is greater than the lower bound and upper bound. Based on this, it is concluded that the carbon emissions model rejects the null hypothesis, namely that cointegration occurs in the long term at the 1% significance level. Cointegration results were also found for the agricultural sector model, productivity, economic growth and energy consumption at a significance level of 1%.

Even though the bound test approach has found co-integration, other tests are needed to find the existence of the condition. Some of them were tested using Johansen cointegration. Researchers used the Bayer and Hanck (2013) approach because this method is more reliable than individual cointegration (Ahmed et al., 2019). The test results are shown in Table 5. All cointegration models were found to be significant at the 1% level. So the conclusion drawn is to reject the null hypothesis, namely cointegration. The Bound and Bayer and Hanck approaches have the same findings in that all five models have cointegration extensions.

The next stage is to look for the relationship between the independent variable and the dependent variable. The estimates shown in Table 6 include short-term and long-term estimates. The results show that the agricultural sector has a positive and almost elastic impact on carbon emissions. Statistical figures show that the agricultural sector has a significant impact. Indications from the agricultural sector explain that a 1% increase in the agricultural sector will increase carbon emissions by 0.998%. These results support hypothesis H1 and are in line with Liu et al. (2017), Chowdhury et al. (2022), Alhassan (2022) and Hafeez et al. (2022). Meanwhile, the productivity of the agricultural sector on carbon emissions was found to have a negative and more elastic influence. The relationship is statistically significant at the 1% level. The implication is that if the productivity of the agricultural sector increases by 1%, carbon emissions will be reduced to 1,657%. This finding supports hypothesis H2a and is in line with the study of Wang et al. (2023) and Riahan et al. (2022) and Raihan et al. (2023).

Next, the relationship between economic growth and carbon emissions is positive and significant at the 5% level of carbon emissions. If economic growth increases by 1%, carbon emissions will increase by 0.837%. This economic growth slope is almost elastic. These findings support hypothesis H3 where economic growth has a positive influence. Empirically, the study findings are in line with Zhang et al. (2019) and Rehman et al. (2019). Finally, long-term estimates for energy consumption were found to have a significant positive effect on carbon emissions. Carbon emissions

Table 1: Descriptive statistics and correlation matrix

Variables	$lnCO2_t$	$lnAgri_t$	$lnTFPA_t$	$lnEG_t$	$lnEC_t$
Mean	5.76	25.14	4.37	7.06	27
Max	6.41	25.64	4.73	7.38	27.67
Min	4.88	24.72	4.12	6.44	26.32
Std. Dev.	0.44	0.28	0.19	0.28	0.40
JB	2.15	2.33	3.34	1.97	3.08
Prob JB	0.341	0.310	0.188	0.371	0.213

Source: Author computation

Table 2: Unit root tests

Variables	Level (I[0])	First difference (I[1])	Conclusion
$lnCO2_t$	−2.229	−5.837***	I (1)
$lnAgri_t$	−1.226	−4.870***	I (1)
$lnTFPA_t$	−1.316	−4.775***	I (1)
$lnEG_t$	−1.716	−3.803***	I (1)
$lnEC_t$	−1.100	−4.860***	I (1)

Source: Author computation. *** mean significant level at 1%

Table 3: Zivot and Andrews unit root tests

Variables	Level	Break year	First difference	Break year
$lnCO2_t$	−4.228	2004	−5.254***	1999
$lnAgri_t$	−3.739	2001	−5.092***	2015
$lnTFPA_t$	−3.401	2001	−4.992***	1998
$lnEG_t$	−3.258	2003	−4.443**	1999
$lnEC_t$	−2.588	2013	−4.686***	2013

Source: Author computation. *** mean significant level at 1%

Table 4: Bound test cointegration

Estimated models	F-stat	Lower bound I (0)	Upper bound I (1)	Optimal Lag
$lnCO2_t$=f ($lnAgri_t$, $lnTFPA_t$, $lnEG_t$, $lnEC_t$)	14.23***	4.28	5.84	1, 3, 3, 0, 2
$lnAgri_t$=f ($lnCO2_t$, $lnTFPA_t$, $lnEG_t$, $lnEC_t$)	8.523***	4.28	5.84	1, 0, 0, 0, 1
$lnTFPA_t$=f ($lnAgri_t$, $lnCO2_t$, $lnEG_t$, $lnEC_t$)	5.626***	4.28	5.84	1, 0, 0, 2, 0
$lnEG_t$=f ($lnAgri_t$, $lnTFPA_t$, $lnCO2_t$, $lnEC_t$)	5.958***	4.28	5.84	2, 0, 0, 1, 2
$lnEC_t$=f ($lnAgri_t$, $lnTFPA_t$, $lnEG_t$, $lnCO2_t$)	9.178***	4.28	5.84	1, 0, 1, 0, 0

Critical value collected from Narayan (2005) for small sample. Optimal lag base on AIC

Table 5: The result of Bayer and Hanck combined cointegration

Estimated models	EG-JOH	EG-JOH-BO-BDM	Cointegration
$lnCO2_t = f(lnAgri_t, lnTFPA_t, lnEG_t, lnEC_t)$	19.779***	80.816***	Exist
$lnAgri_t = f(lnCO2_t, lnTFPA_t, lnEG_t, lnEC_t)$	20.204***	24.432***	Exist
$lnTFPA_t = f(lnAgri_t, lnCO2_t, lnEG_t, lnEC_t)$	25.712***	35.512***	Exist
$lnEG_t = f(lnAgri_t, lnTFPA_t, lnCO2_t, lnEC_t)$	19.544***	30.445***	Exist
$lnEC_t = f(lnAgri_t, lnTFPA_t, lnEG_t, lnCO2_t)$	18.608***	24.675***	Exist

Source: Author computation. *** mean level of significance at 1%

Table 6: Long and short run analysis. Dependent variable=$lnCO_{2t}$

Variable	Coefficient	Std. error	T-stat
Long-run			
$lnAgri_t$	0.998***	0.267	3.74
$lnTFPA_t$	−1.657***	0.268	−6.17
$lnEG_t$	0.837**	0.296	2.83
$lnEC_t$	0.413***	0.127	3.25
C	−37.529***	3.245	−11.56
Short-run			
$lnAgri_t$	−0.129	0.523	−0.24
$lnTFPA_t$	−0.568**	0.198	−2.86
$lnEG_t$	0.385	0.227	1.69
$lnEC_t$	0.366**	0.125	2.91
ECT	−0.886***	0.123	−7.16
C	−33.259***	5.508	−6.037
Diagnostic tests	**F-statistic**	**Prob. value**	
χ_2 *NORMAL*	0.016	0.991	
χ_2 *SERIAL*	0.080	0.923	
χ_2 *ARCH*	1.584	0.218	
χ_2 *REMSEY*	0.011	0.916	

Source: Author computation. *, **, *** mean as level of significance at 10%, 5%, and 1%

Figure 3: CUSUM stability

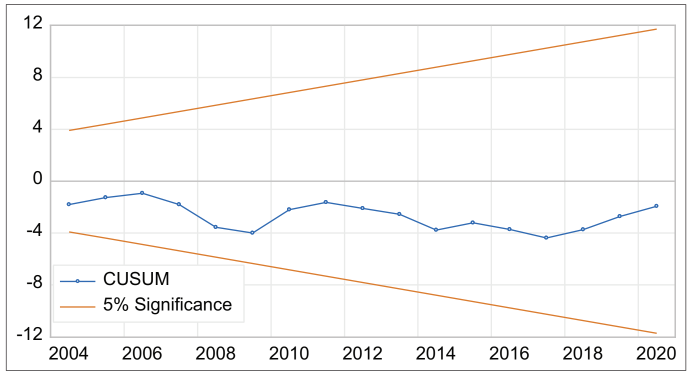
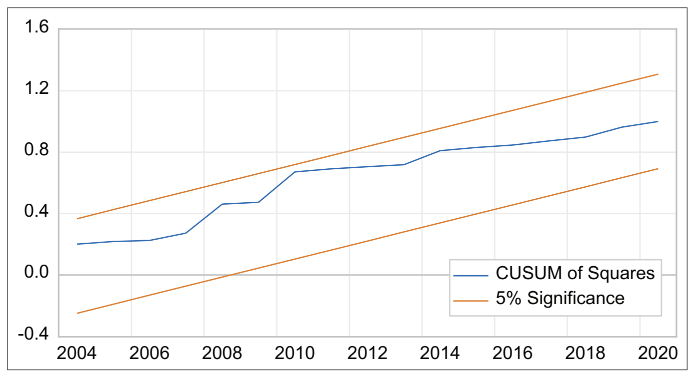


Figure 4: CUSUMQ stability



increase by 0.413% if there is an increase in energy consumption by 1%. This finding is in line with Appiah et al. (2019) and Pata and Caglar (2021) and supports hypothesis H4.

The short-term estimation results are also shown in Table 6. It can be seen that two variables, namely the agricultural sector (negative sign) and economic growth (positive sign) were found to have no effect on carbon emissions. This is different from the productivity of the agricultural sector, which has the same sign as the long term, namely negative. The productivity coefficient of the agricultural sector has a statistically significant effect at the 5% level. If productivity increases by 1%, carbon emissions will decrease by. Meanwhile, energy consumption has a significant impact on carbon emissions by 0.366% if energy consumption increases by 1% in a short-term time series. ECT was found to be negative and significant. The ECT coefficient, namely −0.886, explains that the imbalance of 88.6% of short-term to long-term estimates will be corrected annually. The diagnostic results in Table 6 show that the estimates obtained are free from problems of normality, autocorrelation, heteroscedasticity and model misspecification. The stability of the models in Figures 3 and 4 explains the stable coefficient estimates in the long run. Thus, the estimates of this research are reliable and efficient.

After estimating short-term and long-term estimates, we enter the causality testing stage. The Toda-Yamomoto method is no different from the traditional Granger method. A two-way relationship will occur if X influences Y and vice versa Y affects X. A one-way relationship occurs if X only influences Y and vice versa. The decision has no relationship if X and Y are not found to have a significant effect. The results of the MWALD Toda-Yamamoto Granger causality test are presented in Table 7.

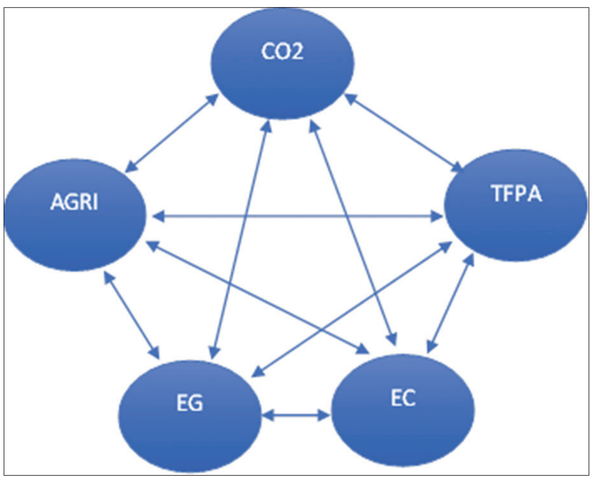
In detail, it was found that the causal relationship between the agricultural sector and carbon emissions has a reciprocal relationship at the 1% significance level. This finding is in line with Al-Mulali (2015) in 15 European countries, Ben Jebli and Ben Youssef (2019) in Brazil, and Hafeez et al. (2020) in the OBORI area but contrasts with the findings of Liu et al. (2017) in ASEAN, Otim et al. (2023) in East Africa. Testing the relationship between agricultural sector productivity and carbon emissions found a reciprocal relationship at the 1% level. A strong causal relationship also exists between fossil energy and carbon emissions. Furthermore, the causality between economic growth and carbon emissions was found to be a significant relationship even though there was a weak relationship from carbon emissions to economic growth (significance 10%). This is in line with the findings of Appiah et al. (2019), Qiao et al. (2019) in developed countries. Causal relationship at the 1% level between the contribution of the agricultural sector and agricultural productivity. Likewise, there is a two-way causal relationship between productivity and energy consumption and also economic growth. Lastly, there is a significant

Table 7: Causality results

Granger causality test	χ_2 *stat*	Prob. value
$lnAgri_t \neq lnCO_{2t}$	42.79***	0.000
$lnTFPA_t \neq lnCO_{2t}$	237.51***	0.000
$lnEC_t \neq lnCO_{2t}$	26.74***	0.000
$lnEG_t \neq lnCO_{2t}$	25.00***	0.000
$lnCO_{2t} \neq lnAgri_t$	17.59***	0.001
$lnTFPA_t \neq lnAgri_t$	17.27***	0.002
$lnEC_t \neq lnAgri_t$	18.60***	0.001
$lnEC_t \neq lnAgri_t$	51.91***	0.000
$lnCO_{2t} \neq lnTFPA_t$	31.70***	0.000
$lnAgri_t \neq lnTFPA_t$	36.12***	0.000
$lnEC_t \neq lnTFPA_t$	8.62*	0.071
$lnEG_t \neq lnTFPA_t$	26.77***	0.000
$lnCO_{2t} \neq lnEG_t$	8.90*	0.064
$lnAgri_t \neq lnEG_t$	8.17*	0.085
$lnTFPA_t \neq lnEG_t$	16.53***	0.002
$lnEC_t \neq lnEG_t$	29.8***	0.000
$lnCO_{2t} \neq lnEC_t$	17.56***	0.002
$lnAgri_t \neq lnEC_t$	18.51***	0.001
$lnTFPA_t \neq lnEC_t$	78.87***	0.000
$lnEG_t \neq lnEC_t$	11.09**	0.025

Author calculation. ≠ explains the null hypothesis, namely that X does not granger cause Y. *, **, and *** represent significance levels of 10%, 5%, and 1%

Figure 5: Summary causality



causal relationship between economic growth and the contribution of the agricultural sector. Overall, the relationship between variables has a two-way reciprocal relationship (feedback). A summary of the relationship between the variables above is presented in Figure 5. It can be concluded that indications of carbon emissions in Indonesia occur not from just one cause but from various directions. The direct influence comes from the agricultural sector, agricultural productivity, economic growth and fossil energy consumption. Indirectly, it can also be seen that energy consumption drives economic growth, resulting in carbon emissions. Productivity will increase if there is a boost in demand due to increased economic growth and the availability of sufficient energy.

5. CONCLUSION AND POLICY RECOMMENDATION

This research provides an empirical study of the relationship between the agricultural sector, agricultural sector productivity, economic growth and energy consumption on carbon emissions in Indonesia from 1990 to 2021. Relationship testing was carried out using the ARDL approach. The analysis stage starts from testing stationarity with Augmented Dickey-Fuller (ADF) where the research variables have different levels of integration. Similar findings were carried out when testing the stationarity of the lag structure by Zivot and Andews (ZA). This confirms that the ARDL method can be applied to research. The existence of cointegration has been confirmed with the Bound test and Bayer and Hanck at a significance level of 1%.

We found that the contribution of the agricultural sector had a positive impact so that carbon emissions increased by 0.998% in the long term. But in the short term, something different was found, namely that it had no impact. Next, the productivity of the agricultural sector in the short term and long term found consistent signs. The productivity of the agricultural sector can reduce carbon emissions by 0.568% in the short term and 1.657% in the long term. For economic growth, significant carbon emissions occur only in the long term at 0.837%. Fossil energy consumption has a positive and significant effect on carbon emissions in the short and long term. Short-term carbon emissions have increased from fossil energy consumption by 0.366% and 0.413%.

Furthermore, the results of research causality testing show a reciprocal relationship, both direct and indirect. A two-way relationship was directly found between the agricultural sector and carbon emissions. Bidirectional relationship of agricultural productivity and carbon emissions. The two-way relationship of economic growth and carbon emissions. The relationship between fossil energy consumption and carbon emissions. Indirectly, the four variables are interconnected and have a significant impact on carbon emissions and vice versa.

Based on these findings, there are several policies that need to be taken. First, the agricultural sector in Indonesia has so far made a major contribution to supporting the economy. By increasing agricultural output, community welfare will improve. But the use of increased output is still based on raw results. In terms of input, the agricultural sector still uses massive amounts of fertilizer and pesticides. Therefore, the agricultural sector needs to make changes to the expected output from this sector based on environmentally friendly materials. Second, productivity in the agricultural sector must be accompanied by advances in environmentally friendly technology. The goal is to increase productivity without increasing carbon emissions. Third, efforts are needed to direct conventional economic growth into green economic growth. Fourth, the use of fossil energy needs to be reduced gradually and renewable energy needs to be increased.

This research is not without limitations, researchers only focus on the agricultural sector, agricultural sector productivity, economic growth, and fossil energy consumption on carbon emissions in Indonesia. However, the sample for this study is still very limited. Future research can add samples or retest with panel data on countries with the same status. Then future research can use asymmetric methods to see different influences in order to get a more specific analysis. Finally, future researchers can add renewable energy variables to the research.

REFERENCES

Abdullah, L. (2015), Linear relationship between CO_2 emissions and economic variables: Evidence from a developed country and a developing country. Journal of Sustainable Development, 8(2), 66-72.

Adekoya, O.B., Ajayi, G.E., Suhrab, M., Oliyide, J.A. (2022), How critical are resource rents, agriculture, growth, and renewable energy to environmental degradation in the resource-rich African countries? The role of institutional quality. Energy Policy, 164, 112888.

Adem, M., Solomon, N., Movahhed Moghaddam, S., Ozunu, A., Azadi, H. (2020), The nexus of economic growth and environmental degradation in Ethiopia: Time series analysis. Climate and Development, 12(10), 943-954.

Ahmed, Z., Wang, Z., Mahmood, F., Hafeez, M., Ali, N. (2019), Does globalization increase the ecological footprint? Empirical evidence from Malaysia. Environmental Science and Pollution Research, 26(18), 18565-18582.

Alhassan, H. (2021), The effect of agricultural total factor productivity on environmental degradation in sub-Saharan Africa. Scientific African, 12, e00740.

Al-Mulali, U. (2015), The impact of biofuel energy consumption on GDP growth, Co_2 emission, agricultural crop prices, and agricultural production. International Journal of Green Energy, 12(11), 1100-1106.

Al-Mulali, U., Fereidouni, H. G., Bin Mohammed, M. A. H., & Lee, J. Y. M. (2016), Agriculture investment, output growth, and CO_2 emissions relationship. Energy Sources, Part B: Economics, Planning and Policy, 11(7), 665-671.

Appiah, K., Du, J., Poku, J. (2018), Causal relationship between agricultural production and carbon dioxide emissions in selected emerging economies. Environmental Science and Pollution Research, 25(25), 24764-24777.

Appiah, K., Du, J., Yeboah, M., Appiah, R. (2019), Causal correlation between energy use and carbon emissions in selected emerging economies-panel model approach. Environmental Science and Pollution Research, 26(8), 7896-7912.

Aydoğan, B., Vardar, G. (2020), Evaluating the role of renewable energy, economic growth and agriculture on CO_2 emission in E7 countries. International Journal of Sustainable Energy, 39(4), 335-348.

Balogh, J.M. (2022), The impacts of agricultural development and trade on CO_2 emissions? Evidence from the Non-European Union countries. Environmental Science and Policy, 137, 99-108.

Banerjee, A., Dolado, J.J., Mestre, R. (1998), Error-correction mechanism tests for cointegration in a single-equation framework. Journal of Time Series Analysis, 19(3), 267-283.

Bayer, C., Hanck, C. (2013), Combining non-cointegration tests. Journal of Time Series Analysis, 34(1), 83-95.

Ben Jebli, M., Ben Youssef, S. (2019), Combustible renewables and waste consumption, agriculture, CO_2 emissions and economic growth in Brazil. Carbon Management, 10(3), 309-321.

Boswijk, H.P. (1994), Testing for an unstable root in conditional and structural error correction models. Journal of Econometrics, 63(1), 37-60.

Chowdhury, S., Khan, S., Sarker, M.F.H., Islam, M.K., Tamal, M.A., Khan, N.A. (2022), Does agricultural ecology cause environmental degradation? Empirical evidence from Bangladesh. Heliyon, 8(6), e09750.

Dickey, D.A., Fuller, W.A. (1981), Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49(4), 1057-1072.

Edoja, P.E., Aye, G.C., Abu, O. (2016), Dynamic relationship among CO_2 emission, agricultural productivity and food security in Nigeria. Cogent Economics and Finance, 4(1), 1204809.

Energy Internasional Agency (EIA), (2022), CO2 Emission 2022. Available from: https://www.iea.org/reports/co2-emissions-in-2022. [Last accessed on 2024 May 05.]

Engle, R.F., Granger, C.W.J. (1987), Co-integration and error correction: Representation, estimation, and testing. Econometrica, 55(2), 251-276.

Fachrurrozi, K., Masbar, R., Aliasuddin, Seftarita, C. (2022), Energy-growth-globalization (EGG) nexus in N-11 countries. Heliyon, 8(9), e10522.

Global Carbon Budget, (2023), Fossil CO_2 emissions at record high in 2023. Available from: https://globalcarbonbudget.org/fossil-co2-emissions-at-record-high-in-2023. [Last accessed on 2024 Jan 20].

Hafeez, M., Yuan, C., Shah, W.U.H., Mahmood, M.T., Li, X., Iqbal, K. (2020), Evaluating the relationship among agriculture, energy demand, finance and environmental degradation in one belt and one road economies. Carbon Management, 11(2), 139-154.

Ikhsan, I., Fachrurrozi, K., Nasir, M., Elfiana, E., Nurjannah, N. (2022), Energy-growth nexus in Indonesia: Fresh evidence from asymmetric causality test. International Journal of Energy Economics and Policy, 12(1), 396-400.

Johansen, S. (1991), Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. Econometrica, 59(6), 1551-1580.

Khurshid, N., Khurshid, J., Shakoor, U., Ali, K. (2022), Asymmetric effect of agriculture value added on CO_2 emission: Does globalization and energy consumption matter for Pakistan. Frontiers in Energy Research, 10, 1053234.

Liu, X., Zhang, S., Bae, J. (2017), The impact of renewable energy and agriculture on carbon dioxide emissions: Investigating the environmental Kuznets curve in four selected ASEAN countries. Journal of Cleaner Production, 164, 1239-1247.

Mavrotas, G., Kelly, R. (2001), Old wine in new bottles: Testing causality between savings and growth. Manchester School, 69, 97-105.

Narayan, P.K. (2005), The saving and investment nexus for China: Evidence from cointegration tests. Applied Economics, 37(17), 1979-1990.

Nathaniel, S., Nwodo, O., Adediran, A., Sharma, G., Shah, M., Adeleye, N. (2019), Ecological footprint, urbanization, and energy consumption in South Africa: Including the excluded. Environmental Science and Pollution Research, 26(26), 27168-27179.

Nwaka, I.D., Nwogu, M.U., Uma, K.E., Ike, G.N. (2020), Agricultural production and CO_2 emissions from two sources in the ECOWAS region: New insights from quantile regression and decomposition analysis. Science of the Total Environment, 748, 141329.

Otim, J., Watundu, S., Mutenyo, J., Bagire, V., Adaramola, M.S. (2023), Effects of carbon dioxide emissions on agricultural production indexes in East African community countries: Pooled mean group and fixed effect approaches. Energy Nexus, 12, 100247.

Pata, U.K., Caglar, A.E. (2021), Investigating the EKC hypothesis with renewable energy consumption, human capital, globalization and trade openness for China: Evidence from augmented ARDL approach with a structural break. Energy, 216, 119220.

Pesaran, M.H., Shin, Y., Smith, R.J. (2001), Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289-326.

Qiao, H., Zheng, F., Jiang, H., Dong, K. (2019), The greenhouse effect of the agriculture-economic growth-renewable energy nexus: Evidence from G20 countries. Science of the Total Environment, 671, 722-731.

Raihan, A., Ibrahim, S., Ahmed, D. (2023), World development sustainability dynamic impacts of economic growth, energy use, tourism, and agricultural productivity on carbon dioxide emissions in Egypt. World Development Sustainability, 2, 100059.

Raihan, A., Muhtasim, D.A., Farhana, S., Hasan, M.A.U., Pavel, M.I., Faruk, O., Rahman, M., Mahmood, A. (2022), Nexus between economic growth, energy use, urbanization, agricultural productivity, and carbon dioxide emissions: New insights from Bangladesh. Energy Nexus, 8, 100144.

Rehman, A., Ozturk, I., Zhang, D. (2019), The causal connection between CO_2 emissions and agricultural productivity in Pakistan: Empirical evidence from an autoregressive distributed lag bounds testing approach. Applied Sciences, 9(8), 9081692.

Selvanathan, S., Jayasinghe, M. S., Selvanathan, E. A., Abbas, S. A., & Iftekhar, M. S. (2022), Energy consumption, agriculture, forestation and CO2 emission nexus: an application to OECD countries. Applied Economics, 55(37), 4359-4376.

Shahbaz, M., Khan, S., Ali, A., Bhattacharya, M. (2017), The impact of globalization on Co2 emissions in China. Singapore Economic Review, 62(4), 929-957.

Toda, H.Y., Yamamoto, T. (1995), Statistical inference in vector autoregressions with possibly integrated processes. Journal of Econometrics, 66(1-2), 225-250.

Uddin, M.M.M. (2020), What are the dynamic links between agriculture and manufacturing growth and environmental degradation? Evidence from different panel income countries. Environmental and Sustainability Indicators, 7, 100041.

Waheed, R., Chang, D., Sarwar, S., Chen, W. (2018), Forest, agriculture, renewable energy, and CO_2 emission. Journal of Cleaner Production, 172, 4231-4238.

Wang, D.H., Hussain, R.Y., Ahmad, I. (2023), Nexus between agriculture productivity and carbon emissions a moderating role of transportation; Evidence from China. Frontiers in Environmental Science, 10, 1065000.

WDI. (2024), World Development Indicator. Available from: https://databank.worldbank.org/country/IDN/556d8fa6/Popular_countries. [Last accessed on 2024 Jan 20].

Zhang, L., Pang, J., Chen, X., Lu, Z. (2019), Carbon emissions, energy consumption and economic growth: Evidence from the agricultural sector of China's main grain-producing areas. Science of the Total Environment, 665(222), 1017-1025.

Zhou, G., Li, H., Ozturk, I., Ullah, S. (2022), Shocks in agricultural productivity and CO_2 emissions: New environmental challenges for China in the green economy. Economic Research-Ekonomska Istrazivanja, 35(1), 5790-5806.

Zivot, E., Andrews, D.W.K. (1992), Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. Journal of Business and Economic Statistics, 10(3), 251-270.