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IMPACT OF RENEWABLE AND NON-RENEWABLE ENERGY CONSUMPTION ON CARBON DIOXIDE EMISSIONS IN GHANA

*[1]John Atsu Agbolosoo, [2]Dick Chune Midamba and [3]Michael Asante Biney

[1] *Faculty of Economics and Management, Department of Agricultural Economics, Institut Pertanian Bogor (IPB) University, Bogor, Indonesia*
[2] *Faculty of Agriculture and Environment, Department of Rural Development and Agribusiness, Gulu University, Gulu, Uganda*
[3] *Faculty of Geoengineering, Department of Environmental Engineering, University of Warmia and Mazury in Olsztyn, Sloneczna Str. 45G, 10-709 Olsztyn, Poland*

***Corresponding author:** agbolosoojohn@gmail.com

Abstract

Renewable energy is seen as a solution for reducing CO_2 emissions and promoting sustainability. Ghana could increase renewable energy integration, but faces grid integration challenges and lacks an enabling environment for development. The full extent of renewable energy's carbon reduction impact remains undocumented in Ghana, considering rapid globalization and population growth. This study examines renewable and non-renewable energy consumption's impact on Ghana's CO_2 emissions from 1990 to 2020, using econometric methods. The analysis uses data from World Development Indicators, Global Footprint Network, and FAOSTAT to assess ecological footprint, fossil fuel use, forest land reduction, nuclear power, and renewable energy consumption. Results show fossil fuel use increases long-term CO_2 emissions, while ecological footprints have short-term positive effects. Nuclear energy increases long-term emissions but reduces them short term, while renewable energy consistently reduces CO_2 emissions in both periods. The study concludes all variables impact CO_2 emissions in Ghana. Recommendations include implementing policies to promote renewable energy and limit emissions, introducing carbon tax on fossil fuels, and upgrading nuclear plants. As a Paris Agreement signatory, Ghana acknowledges nuclear power's role in providing low-carbon energy. The government should incentivize renewable energy sources, invest in clean technology research, and conduct public awareness campaigns. Environmental education in schools can help educate future generations about sustainability.

Keywords
Carbon emission, ecological footprint, renewable energy

Introduction

Coal, oil, and natural gas, which make up fossil fuel consumption, play a crucial role in the worldwide energy sector (World Bank, 2024b). Fossil fuels, as a primary energy source for general electricity generation, transportation, and industrial heating (Ali and Mujahid, 2024). In 2020, fossil fuels made up 80% of the world's total primary energy consumption, with energy consumption growing at an annual rate of 2.1% since the year 2000 (International Energy Agency, 2022). However, the burning of fossil fuels contributes 75% of the total global greenhouse gas emissions and 90% of the total global carbon dioxide (CO_2) emissions, which are key contributors to climate change (Scherr, 2023). The process of generating electricity by combusting fossil fuels, biomass, and industrial waste is highly polluting, releasing CO_2 and other harmful pollutants into the atmosphere. Moreover, the air pollutants released from burning fossil fuels significantly impact respiratory health and lead to premature deaths globally (International Energy Agency, 2022). The economic cost of air pollution from fossil fuels was estimated at approximately \$2.9 trillion in 2018 (Myllyvirta, 2020).

The energy sector, being the primary source of greenhouse gases, now places greater strain on the environment. Due to their clean and sustainable characteristics, renewable energy sources are increasingly adopted and utilized by developed and developing nations, particularly in the context of rapidly rising CO_2 emissions. Renewable energy has been recognized as a potential solution for reducing CO_2 emissions and promoting environmental sustainability (Ali and Mujahid, 2024). For example, renewable energy accounted for 30% of global electricity generation in 2022 and is projected to reach 42% by 2028 (International Energy Agency, 2023). The transition from fossil fuel consumption to renewable energy is one of the solutions to environmental problems in many developing countries, such as Ghana (Musah et al., 2024).

Not surprisingly, Ghana's energy generation is heavily reliant on thermal and hydroelectric sources, with 64.4% of power coming from thermal generation, primarily natural gas (International Trade Administration, 2023). The distribution of electricity supply by various energy sources in 2024 is depicted in Figure 1. Thermal and hydro power generation account for 64.4% and 34.4% of the total energy production, respectively. In contrast, renewable energy sources, including solar PV and biogas, contribute a mere 0.7% to the overall generation. This breakdown highlights the predominance of thermal generation in Ghana's energy mix, underscoring the crucial role that fuel availability for thermal plants plays in ensuring a reliable power supply and energy security within the Ghanaian power system.

Ghana has experienced consistent increases in CO_2 emissions over the last two decades, from 2,516.90 kilotons in 1990 to 19,401.16 kilotons in 2020 (World Bank, 2024b). According to the Justice et al. (2024) oil accounted for approximately

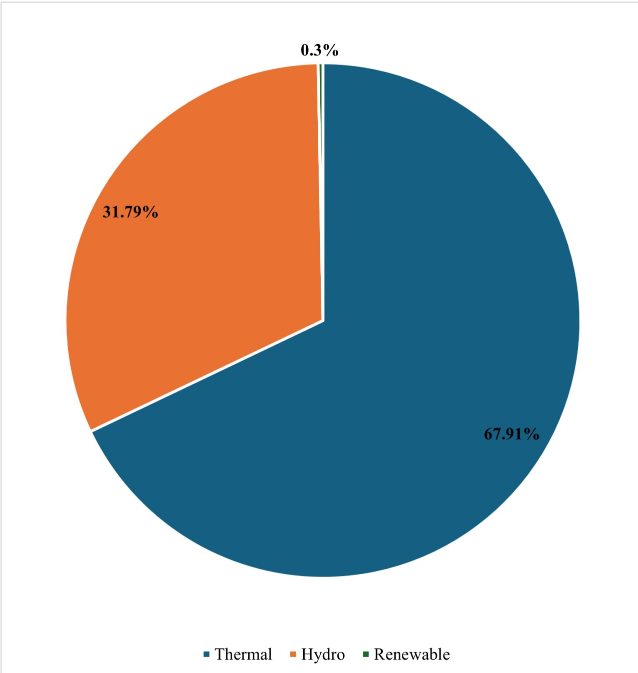

Figure 1. Electricity supply by generation sources in 2020 (Ghana Energy Commission, 2020)

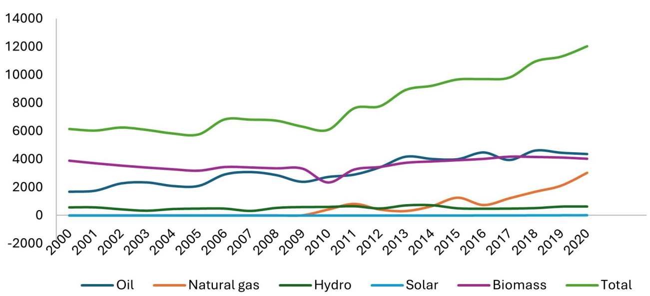

Figure 2. Total renewable and non-renewable energy supply in Ghana from 2000 to 2020 (Ghana Energy Commission, 2020)

38.3% of the total primary energy supply in 2019. Figure 2 depicts Ghana's total renewable and non-renewable energy supply from 2000 to 2020. According to the data, the oil supply increased from 1,688 ktoes in 2000 to 4,355 ktoes by 2020. In a similar trend, hydro supply rose from 568 ktoes to 627 ktoes over the same timeframe. Biomass supply climbed from 3,891 ktoes in 2000 to 4,177 ktoes in 2017, before declining to 4,029 ktoes by 2020. It is noteworthy that Ghana did not have a natural gas supply from 2000 to 2009, and solar energy was absent from 2000 to 2012. The highest solar energy supply was recorded in 2020, reaching 5 ktoes. Overall, Ghana's total energy supply doubled from 6,147 ktoes in 2000 to 12,030 ktoes in 2020.

According to the Ghana Energy Commission (2024) as depicted in Figure 3, between 2000 and 2020, final energy consumption increased from 5,468 ktoe to 8,644 ktoe, representing a 36.7% rise. During this period, electricity consumption in Ghana increased from 591 ktoe to 1,370 ktoe, representing a 6.9% rise. The use of petroleum also saw a significant rise, growing from 1,455 ktoe in 2000 to 4,248 ktoe in 2020, which means a 22.7% increase. Conversely, biomass consumption

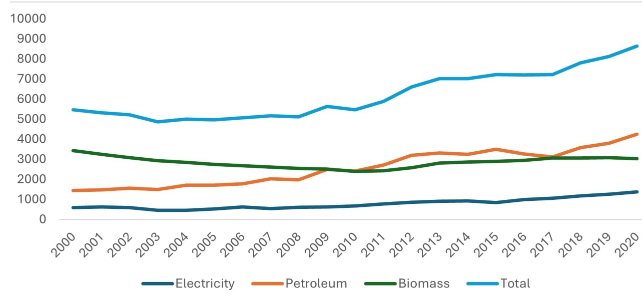

Figure 3. Trend in final energy consumption by fuel (Ghana Energy Commission, 2020)

decreased from 3,432 ktoe in 2000 to 3,026 ktoe in 2020, showing a 27.8% reduction over the same timeframe.

The combustion of these fuels is recognized as the highest emitter of greenhouse gases globally (Justice et al., 2024). CO_2 emissions from energy use constituted 34% of total greenhouse gas emissions in Ghana (OECD, 2023). Most CO_2 emissions in Ghana are attributed to the transport and agriculture sectors (International Energy Agency, 2024). In addition, CO_2 emissions from the power sector alone reached 7.6 million metric tons of CO_2 equivalent against 490,000 metric tons of CO_2 equivalent in the year 2000 (Sasu, 2024). Fossil fuel consumption also increased from 18.24% in 1990 to 52.54% in 2015 due to industrialization, which increased energy consumption, resulting in environmental pollution (World Bank, 2024b). Although nuclear energy is often promoted as a low-carbon alternative to fossil fuels, Ghana's National Energy Transition Framework highlights the importance of integrating nuclear power into its energy mix to achieve net-zero emissions by 2070 (Ministry of Energy, 2022). While nuclear power generates minimal direct CO_2 emissions during operation, significant concerns remain regarding safety, waste management, and public acceptance, which act as barriers to its implementation. Despite these challenges, the potential of nuclear energy to reduce Ghana's carbon footprint is considerable, as it could substantially displace fossil fuel consumption, resulting in lower overall emissions (Ministry of Energy, 2022). Renewable energy consumption has gained traction in Ghana as part of efforts to combat climate change and reduce CO_2 emissions. Despite possessing significant renewable resources, such as solar and wind, the share of renewables in Ghana's energy supply has been relatively low. For instance, solar energy constituted only 0.3% of the total energy supply as of a recent report (Justice et al., 2024). Nevertheless, studies indicate that financial factors significantly influence renewable energy consumption in Ghana, as this plays a crucial role in promoting renewable energy investments while simultaneously reducing CO_2 emissions (Kwakwa et al., 2024). Additionally, foreign direct investment (FDI) also affects renewable energy capacity. Fostering an environment conducive to FDI can accelerate the transition to renewable energies and contribute significantly to emission reduction.

However, the rate of production and consumption of renewable energy is still low. Ghana's total renewable energy production is projected to experience a decrease from 26% in 2010 to 23% in 2020 (Irena, 2015). According to Dehghan (2024) cost, technology, and dependence on fossil fuel sources, as well as regulatory barriers to renewable energy production and consumption. Despite the potential for increasing renewable energy sources in Ghana's energy mix, the country faces challenges in integrating these sources into its existing grids. The absence of an enabling environment for renewable energy impedes its penetration and development in Ghana. Research on energy consumption and CO_2 emissions in Ghana frequently emphasizes overall energy usage, fossil fuels, electricity production, or factors such as urbanization and economic growth, resulting in a lack of detailed analysis comparing renewable and non-renewable sources. For instance, Kwakwa et al. (2018) investigated how the extraction of natural resources impacts energy use and carbon emissions in Ghana. Their findings reveal that factors such as income, urbanization, and the extraction of natural resources are contributing to the country's environmental challenges, specifically the increase in carbon emissions and energy consumption. Ofori-Sasu et al. (2023) examined the impact of renewable energy consumption and carbon emissions in developing nations, focusing on the influence of capital markets. The findings indicated that while the use of renewable energy leads to an increase in carbon emissions, both stock and bond markets contribute to a reduction in these emissions. Gyimah et al. (2023) explored the influence of energy and economic growth on achieving a sustainable environment by reducing carbon emissions in Ghana. They employed a two-stage least squares estimation method and generalized method of moments, analyzing data from 1990 to 2018. The findings indicated that both renewable energy and fossil fuels contribute to carbon emissions, while economic growth does not affect Ghana's carbon emissions. None of these earlier studies took into account the use of nuclear energy, ecological footprints, and the loss of forest land, all of which play a significant role in contributing to carbon emissions in Ghana. This gap presents a chance for innovative studies specific to Ghana's situation. This study offers fresh insights by evaluating the differences in emission elasticities through the distinction between renewable and non-renewable energy usage. It enhances existing aggregate data by considering renewable energy utilization, fossil fuel consumption, nuclear energy use, forest land reduction, and ecological footprints. The study formulated the following hypothesis:

1. Fossil fuel consumption has a positive and significant impact on CO_2 emissions in Ghana
2. Renewable energy use negatively and significantly influences CO_2 emissions in Ghana
3. Nuclear energy consumption reduces CO_2 emissions in Ghana

The findings of this study could significantly contribute to the creation of governmental policies aimed at reducing environmental pollution in Ghana. The first section introduced renewable and non-renewable energy sources, followed by the methods used for the study, results and discussion, conclusion, and policy implications.

Literature Review

Over the past few decades, numerous studies have examined the effects of renewable and non-renewable energy sources on environmental pollution, using CO_2 emissions as a proxy for pollution. These studies have yielded diverse findings across different regions. The diverse findings can be attributed to the variations in government policies, socio-economic and institutional attributes. The methods are regions of studies have also contributed to the diverse findings. For example, Turedi and Turedi (2021) investigated the impact of renewable and non-renewable energy consumption and economic growth on CO_2 emissions in 53 developing countries, including Ghana, from 1990 to 2014. Employing the Generalized Methods of Moments (GMM) approach, their research revealed that renewable energy had a negative effect on CO_2 emissions, while non-renewable energy had a positive effect. On the contrast, another study by Destek and Sinha (2020) found that increased renewable energy consumption and trade openness reduced ecological footprints, whereas non-renewable energy consumption led to an increase. This research used ecological footprints as the dependent variable, along with independent variables such as GDP per capita, and renewable and non-renewable energy consumption, analyzing panel data from 1980-2014 using FMOLS and DOLS approaches.

Similarly, Aminu et al. (2023) examined the impact of renewable and non-renewable energy on carbon emissions in Pakistan. Their findings showed that income had a positive coefficient, while the square of income had a negative and statistically significant coefficient. This suggests that carbon emissions in the household sector increase at lower income levels but decrease as income levels rise. The study also found that population size has a positive effect on carbon emissions. The effects of biomass, non-renewable, and clean energy were particularly noteworthy, as increased household consumption of biomass and non-renewable energy led to higher carbon emissions. In rural areas, clean energy had a negative but statistically insignificant impact on carbon emissions, indicating a greater reliance on biomass and non-renewable energy consumption. Moreover, Ahmat et al. (2024) conducted research that demonstrated the positive effects of energy consumption, economic growth, and non-renewable energy on carbon dioxide (CO_2) emissions. Using dynamic ARDL analysis, their results showed that these factors had a positive influence on Malaysia's carbon dioxide (CO_2) emissions in both the short and long term. While these studies have presented results and policy recommendations, there is still need for additional studies, which are region based to inform the policymakers on the relevant policies for implementation. This work, therefore, contributes by assessing the impact of renewable and non-renewable energy consumption on carbon dioxide emissions in Ghana.

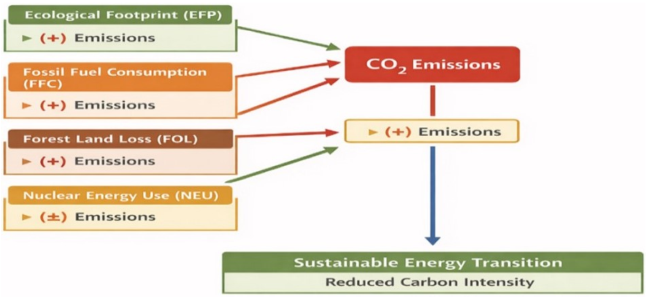

Figure 4. Conceptual framework showing the relationship between energy consumption, ecological factors, and CO_2 emissions in Ghana (1990-2020)

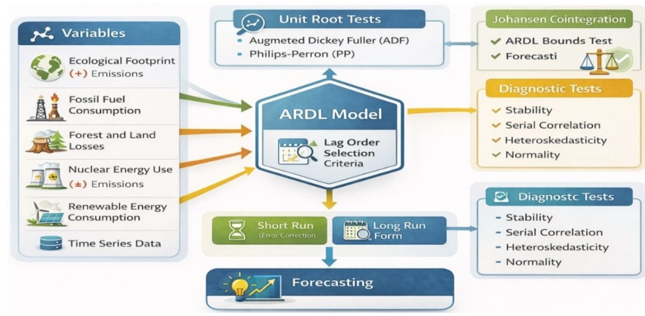

Figure 5. Analytical framework of influential factors of carbon emissions in Ghana

Materials and Methods

Conceptual framework

The conceptual framework of this study (Figure 4) integrates insights from the Environmental Kuznets Curve (EKC) and STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) models to explain how Ghana's CO_2 emissions are influenced by energy consumption patterns and ecological factors between 1990 and 2020. It postulates that carbon emissions result from the combined effects of renewable and non-renewable energy use, ecological footprint, forest land loss, and nuclear energy utilization. These relationships capture the interdependence between energy transition, environmental quality, and sustainable growth. In this framework, renewable energy consumption (REC) is expected to reduce CO_2 emissions by substituting carbon-intensive sources with cleaner energy and improving energy efficiency. In contrast, fossil fuel consumption (FFC) is anticipated to increase emissions due to combustion processes that release greenhouse gases. The ecological footprint (EFP) represents human demand on the environment and is expected to contribute positively to emissions as economic activity, consumption, and population expand. Forest land loss (FOL) indirectly increases emissions by reducing the natural capacity of carbon sequestration, while nuclear energy use (NEU) exhibits an ambivalent influence, it may reduce emissions by displacing fossil fuels in the short run but could raise them in the long term due to energy-intensive infrastructure and waste management processes.

Formally, these relationships can be expressed as:

$$CO_2 \text{ emissions} = f(\text{EFP}, \text{FFC}, \text{FOL}, \text{NEU}, \text{REC}) \quad (1)$$

This conceptualization aligns with the EKC hypothesis, which suggests that environmental degradation initially increases with income and industrialization but eventually declines as economies advance, adopt renewable technologies, and strengthen environmental governance. The framework thus implies that Ghana's pathway to lower carbon intensity depends on a structural shift toward renewable and nuclear energy, combined with ecological conservation and reduced dependence on fossil fuels.

Analytical Framework

The analytical framework derived from the study's research objectives is depicted in Figure 5. This framework outlines the necessary steps to tackle Ghana's energy consumption and environmental pollution issues. The study's variables, including environmental pollution, renewable and non-renewable energy, ecological footprint, and forest land loss, are expected to demonstrate significant and positive correlations during both the pre- and post-estimation phases. Some variables may contribute to environmental pollution, such as CO_2 emissions, either directly or indirectly. Moreover, environmental pollution could potentially influence other independent variables within the ARDL model. The figure also highlights the three stages of econometric model estimation using ARDL model selection approaches: pre-ARDL model selection involving unit root tests, lag length criteria, and co-integration; the ARDL model selection itself, which includes long-run form and bounds tests, and error correction; and post-ARDL model estimation, which conducts serial correlation, heteroscedasticity, normality, CUSUM stability, Theil inequality coefficient, and Symmetric MAPE tests. The results of these graphs are demonstrated in Figure 8, Figure 9 and Figure 10.

Study Area

The study was conducted in Ghana, a country located in West Africa, popularly known as the Republic of Ghana. It lies adjacent to the Gulf of Guinea and the Atlantic Ocean to the south, sharing a border with Côte d'Ivoire to the west, Burkina Faso to the north, and Togo to the east. Ghana covers an area of 239,567 km^2 (92,497 sq mi), spanning diverse ecologies from coastal savannas to tropical rainforests. With a population of nearly 35 million, Ghana is the second-most populous country in West Africa, and its capital and largest city is Accra. Ghana is divided into 16 administrative regions. Figure 6 represents the proportion of the regional population with access to electricity in Ghana. The national population electricity access rate was 88.85% in 2023, with the Greater Accra Region having the highest rate at 99.4% and the Savannah Region having the lowest rate at 61.4%.

3.4 Data source

The empirical data used was panel data generated from 1990 to 2020. Carbon dioxide (CO_2) emissions were used as the

Figure 6. Ghana's regional population with access to electricity (Ghana Energy Commission, 2023)

dependent variable due to their global influence on economic growth and development of emerging economies. In contrast, explanatory variables were ecological footprint, fossil fuel consumption, forest land losses due to emissions, nuclear energy use, and renewable energy consumption. These variables play crucial roles in increasing and decreasing carbon dioxide emissions. Most of the selected variables were obtained from the World Development Indicators website (World Bank, 2024a), Global Footprint Network (Global Footprint Networks, 2024), and FAOSTAT websites (Food and Agriculture Organization of the United Nations, 2024) respectively. Table 1 illustrates the variables utilized in the present study. These variables play a significant role in environmental pollution in Ghana.

Theoretical and econometric model specification

Augmented Dickey-Fuller and Philips-Perron unit root tests

The study utilized Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to check the stationarity of the economic variables, ensuring their suitability for policy decision-making and preventing unit root issues (Dickey and Fuller, 1979; Philips and Perron, 1988). The ADF and PP unit root test equations are specified as:

$$\Delta z_t = \delta_0 + \delta_1 Z_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta Z_{t-i} + \mu_t \tag{2}$$

$$\Delta z_t = \delta_0 + \delta_1 t + \delta_2 Z_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta Z_{t-i} + \mu_t \tag{3}$$

The ADF and PP tests were performed with interception and trend in the study. The ADF regression tests the presence of the unit root of Z_t where t and k mean the time and number of lags included in the unit root testing regression. The ΔZ_{t-1} denotes the first difference of the variable with k lags. The term μ_t adjusts the errors of autocorrelation, while $\alpha_i, \delta_0, \delta_1$ and δ_2 estimated parameters. The null hypothesis of $H_0 : \delta_1 = 0$ has a unit root against the alternative hypothesis $H_A : \delta_1 \neq 0$ are stationary in the equations eq. (2) and eq. (3) as postulated by Dritsakis (2004). The results showed that most of the variables were not stationary at their level, but they became stationary after differencing once, indicating integration by order one I(1) (Ceesay et al., 2021).

It is advisable to determine the optimal lag order of your variables to obtain efficient and unbiased ARDL estimates. The number of lags is determined by information criteria based on the sample size (Atchadé and Nougbodé, 2024; Ceesay et al., 2021). This is a lag whose estimated model provides the smallest criterion value. The optimal lag is the one that presents the weakest and least information criterion (Atchadé and Nougbodé, 2024).

ARDL Model

The Autoregressive Distributed Lag model is widely recognized as the most efficient econometric approach for analysing economic variables that exhibit either I(0) or I(1) stationarity (Frimpong and Oteng, 2006). The model was introduced by Pesaran et al. (2001) and Pesaran and Shin (1998) and this approach has a variety of flexibilities over the traditional cointegration proposed by Engle & Granger (Granger and Engle, 1987). This model was utilized to assess the explanatory variables' short- and long-run relationships on CO_2 emissions. One of the key benefits of the ARDL approach is its ability to generate both short and long-run elasticities for small sample sizes while employing the ordinary least squares method for cointegration between variables. Furthermore, the ARDL model offers flexibility in the order of integration of variables and is suitable for explanatory variables that exhibit I(0), I(1), or mutually integrated variables and may be applied to obtain consistent estimates (Haug, 2002). However, it may not be as effective in cases in which the variables exhibit I(2) stationarity. This study employs ARDL to analyse the long-run relationships and short-run relationships between ecological footprint, fossil fuel consumption, forest land losses, nuclear energy consumption, renewable energy usage, and CO_2 emissions. The basic linear function of the Ghana carbon emission function is given by:

$$\mathrm{CO_2} = f(\mathrm{EFP}, \mathrm{FFC}, \mathrm{FOL}, \mathrm{NEU}, \mathrm{REC}) \tag{4}$$

The model is expressed as follows:

$$\begin{aligned} \mathrm{CO2}_t = &\beta_0 + \beta_1 \mathrm{EFP}_t + \beta_2 \mathrm{FFC}_t + \beta_3 \mathrm{FOL}_t \\ &+ \beta_4 \mathrm{NEU}_t + \beta_5 \mathrm{REC}_t + \varepsilon_t \end{aligned} \tag{5}$$

where: β_0 is the Intercept or constant, β_1-β_5: Coefficient of the explanatory variables, $\mathrm{CO}_{2,t}$; Carbon dioxide emissions in a kiloton, EFP_t: Ecological footprint in Global hectares per person, FFC_t: Fossil fuel consumption measured in % of total

Table 1. Description of variables used in the study

Variable	Description	Measurement	Sources
CO2	Carbon dioxide emissions	Kiloton (kt)	WDI
EFP	Ecological footprint	Global hectares (gha per person)	Global footprint network
FFC	Fossil fuel consumption	% of total energy consumption	WDI
FOL	Forest land losses	1000 Hectare (ha)	FAOSTAT
NEU	Nuclear energy use	% of total energy use	WDI
REC	Renewable energy consumption	% of total final energy consumption	WDI

consumption, FOL_t: Forest land losses in million tons, NEU_t: Nuclear energy use measured % of total energy use, REC_t: Renewable energy consumption measured in % of total final energy consumption, ε_t : Error term Converting equation 5 into the natural logarithm gives equation 6, which is specified as:

$$\begin{aligned} \ln \text{CO}_{2,t} =& \alpha_0 + \beta_1 \ln \text{EFP}_t + \beta_2 \ln \text{FFC}_t + \beta_3 \ln \text{FOL}_t \\ &+ \beta_4 \ln \text{NEU}_t + \beta_5 \ln \text{REC}_t + \varepsilon_t \end{aligned} \tag{6}$$

$$\begin{aligned} \Delta \ln \text{CO}_{2,t} =& \beta_0 + \sum_{k=1}^{m} \beta_1 \Delta \ln \text{CO2}_{t-k} + \sum_{k=1}^{m} \beta_2 \Delta \ln \text{EFP}_{t-k} \\ &+ \sum_{k=1}^{m} \beta_3 \Delta \ln \text{FFC}_{t-k} + \sum_{k=1}^{m} \beta_4 \Delta \ln \text{FOL}_{t-k} \\ &+ \sum_{k=1}^{m} \beta_5 \Delta \ln \text{NEU}_{t-k} + \sum_{k=1}^{m} \beta_6 \Delta \ln \text{REC}_{t-k} \\ &+ \lambda_1 \ln \text{CO2}_{t-1} + \lambda_2 \ln \text{EFP}_{t-1} + \lambda_3 \ln \text{FFC}_{t-1} \\ &+ \lambda_4 \ln \text{FOL}_{t-1} + \lambda_5 \ln \text{NEU}_{t-1} + \lambda_6 \ln \text{REC}_{t-1} + \varepsilon_t \end{aligned} \tag{7}$$

In this study, α_0 represents the drift component while Δ indicates the first difference, u_t means the white noise. To determine the optimal lag length, the study employs the Akaike information criterion (AIC). After establishing the long-run relationship between variables, the error correction model (ECM) is used to analyze the short-run dynamics. The ECM's general form is given by:

$$\begin{aligned} \Delta \ln \text{CO}_{2,t} =& \beta_0 + \sum_{k=1}^{m} \beta_1 \Delta \ln \text{CO2}_{t-k} + \sum_{k=1}^{m} \beta_2 \Delta \ln \text{EFP}_{t-k} \\ &+ \sum_{k=1}^{m} \beta_3 \Delta \ln \text{FFC}_{t-k} + \sum_{k=1}^{m} \beta_4 \Delta \ln \text{FOL}_{t-k} \\ &+ \sum_{k=1}^{m} \beta_5 \Delta \ln \text{NEU}_{t-k} + \sum_{k=1}^{m} \beta_6 \Delta \ln \text{REC}_{t-k} \\ &+ \phi \text{ECM}_{t-1} + \varepsilon_t \end{aligned} \tag{8}$$

where Δ represents the first difference while ϕ is the coefficients of ECM for short-run dynamics. The ECM shows the speed of adjustment in long-run equilibrium after a shock in the short run.

Bound cointegration test

The bound cointegration test is applicable in cases where several integrated variables of varying orders I(0), I(1) are accessible. The bound cointegration model is specified as:

$$\begin{aligned} \Delta y_t =& \delta_1 Y_{t-1} + \delta_2 X_{t-1} + \sum_{k=1}^{m} \alpha_i \Delta y_{t-k} \\ &+ \sum_{l=0}^{n-1} \beta_l \Delta x_{t-l} + \pi_0 + \pi_t + e_t \end{aligned} \tag{9}$$

The study hypotheses are formulated as: $H_0 : \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ $H_1 : \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq 0$ The test process involves computing the Fisher statistic (F_c) for various scenarios and thresholds, in addition to simulating critical values (Pesaran et al., 2001). Specifically, the upper bound applies to variables with an order of integration of 1, while the lower bounds pertain to the variables I(0) (Frimpong and Oteng, 2006). It is essential to emphasize that the simulated critical values are crucial in this context. If the F-value is greater than the bounded upper value, then there is cointegration, but if the F-value is less than the bounded upper value, then there is no cointegration (Atchadé and Nougbodé, 2024).

CUSUM, CUSUMQ, Theil Inequality Coefficient, and SMAPE

After the F-bounds test, the research assessed the ARDL model's stability using Cumulative Sum of Recursive Residuals (CUSUM) and Cumulative Sum of Squares of Recursive Residuals (CUSUMQ) graphs to ensure that the estimated coefficients remain consistent over time (Nasrullah et al., 2021; Yuliati et al., 2020). The model is stable if these plots stay within critical bounds at a 5% significance level (Jumhur, 2020; Naeem et al., 2021). These tests are crucial for validating long-term relationships, as instability may indicate that predictions are inconsistent across different periods. To evaluate forecast accuracy, the investigation utilized the Theil Inequality Coefficient and Symmetric Mean Absolute Percentage Error (SMAPE). SMAPE measures forecast accuracy by calculating the percentage error relative to actual values, balancing over- and under-forecasting. It is handy for ARDL models due to its effectiveness with zero values and bounded nature, preventing distortion from extreme values (Eren and Baets, 2024; Naeem et al., 2021). The Theil Inequality Coefficient compares predicted and actual values to assess forecast performance, with values closer to zero indicating better predictive accuracy (Getachew and Assefa, 2020). The results

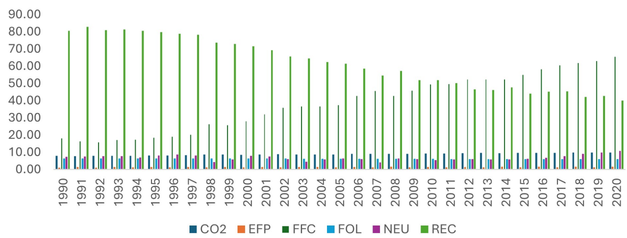

Figure 7. Dynamics of Carbon dioxide emissions on renewable and non-renewable energy consumption in Ghana

of these graphs are demonstrated in Figure 8, Figure 9, and Figure 10, respectively, under the discussion section.

Results and Discussion

Descriptive Statistics

The annual time series in the present investigation uses the influence of ecological footprint, fossil fuel consumption, nuclear energy consumption, and renewable energy use on CO_2 emission in Ghana. This section presents all results in their log-transformed format. Table 2 presents the descriptive statistics of all variables used in the ARDL estimation model. The mean CO_2 emissions were 8.85 kt during the study year, and the ecological footprint had a mean value of 1.33 GHP. Fossil fuel consumption accounted for 38.88%, forest land losses due to carbon emissions were 6.21 ha, nuclear energy use was 6.83%, and renewable energy consumption was 61.56%.

Figure 7 illustrates the dynamics of Carbon dioxide emissions in relation to ecological footprint, fossil fuel consumption, forestland losses, non-renewable energy usage, and renewable energy consumption in Ghana from 1990 to 2020. Increasing trends in CO_2 and renewable and non-renewable energy variables were observed throughout the period. In 2013, all variables decreased, and then increased again in 2016. Ghana experienced a decline in renewable energy consumption, alongside an increase in non-renewable energy usage, from 2013 to 2016, resulting in heightened carbon emissions due to a greater reliance on fossil fuels for energy production.

Lag order selection

Before employing the ARDL bound test, the current investigation uses criteria for determining the lag length to explain the autoregressive length of time series data. Results are presented in Table 3. The study adopted the famous lag selection information criteria including, LogL, likelihood ratio (LR) statistic, final predictor error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quin information criterion (HQ) to select the optimal lag order for the Vector Autoregression model, which is thoroughly explained in the materials and methods. The estimated results recommend lag 1 as appropriate because of LR, FPE, SC, and HQ, but AIC has a good value of 0.78.

Stationarity test results

The study adopted has two lag orders while estimating the ARDL bound test. The current empirical study checks the stationarity of the dataset through the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. The results are presented in Table 4, which indicates that CO_2 emissions, ecological footprint, fossil fuel consumption, and forest land losses are stationary at level I(0). In contrast, nuclear energy use and renewable energy consumption are stationary at first differences I(1).

ARDL bound test results

Table 5 illustrates that F-statistics exceed the upper bounds I(0) and I(1) values with 1%, 5%, and 10% significance levels, suggesting long-run dynamics proved by the ARDL model (Pesaran et al., 2001). The estimation output indicates that the explanatory variables have a significant effect on CO_2 emissions. This study utilized the ARDL bound to check the long run cointegration among the variables, and the results are reported in Table 5. Results indicated that the computed F-statistic value is 3.7, which is above the lower bound and upper bound at 5% and 10% levels of significance, so the study rejects the null hypothesis of no co-integration (Pesaran et al., 2001).

Long and Short-run Estimation Results

This made the ARDL the best-suited technique for investigating the estimators when variables are stationary at both levels and in first differences. As indicated in Table 6, the coefficient of ECT (-1) is -0.433, which is statistically significant at a 1% significance level. This coefficient is applied to calculate the rate of adjustment from short-run fluctuations to long-run equilibrium, and it shows that the yearly rate of adjustment is 43.3% (Ahmat et al., 2024; Getachew and Assefa, 2020). To verify the cointegration relationship between CO_2 emissions and explanatory variables, we computed the ARDL bounds test based on the outcome of the ADF and PP unit root tests for stationarity.

Fossil fuel consumption and CO_2 emissions

The long-run magnitude of the elasticity coefficient of fossil fuel consumption has a significant impact on carbon emissions at a 10% significance level. CO_2 emissions are positively correlated with fossil fuel consumption, and a 1% increase in fossil fuel consumption is expected to result in a 0.093% increase in CO_2 emissions in the long run. The findings reveal that Ghana's drive for economic advancement and industrialization has resulted in a heightened need for energy, primarily met by fossil fuels. This results in increased CO_2 emissions as more fuel is consumed to support development and urban expansion. With fossil fuel usage surpassing that of renewable energy sources in Ghana's energy mix, the proportion of energy generated with substantial emissions has grown, worsening the country's carbon footprint. It's fascinating to learn that in Ghana, the production of cement and the manufacturing of petrochemicals emit significant quantities of air pollutants

Table 2. Descriptive results

Variables	Observations	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
CO_2	31	8.85	0.66	7.72	9.87	-0.17	1.83
EFP	31	1.33	0.14	1.07	1.59	0.28	2.27
FFC	31	38.88	16.22	16.09	65.81	0.01	1.67
FOL	31	6.21	0.14	5.99	6.39	-0.11	1.38
NEU	31	6.83	1.54	4.09	10.83	0.47	3.16
REC	31	61.56	14.62	40	82.90	0.08	1.51

Source: Author's computation (2024)

Table 3. Lag order criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	155.15	NA	0.000171	8.36	8.64	8.44
1	49.34	249.57*	2.57e-08*	-0.51	1.47*	0.11*
2	89.37	44.17	2.77e-08	-0.78*	2.89	0.37

Source: Author's computation (2024). Note * indicates optimal lag order selected based on the minimal criterion of LR, FPE, AIC, and HQ.

Table 4. ADF and PP Unit root results

Variables	ADF level	PP level	Integration order
lnCO2	-4.563***	-3.527**	I(0)
lnEFP	-3.408*	-22.956***	I(0)
lnFFC	-4.130**	-4.159**	I(0)
lnFOL	-3.619**	-1.370	I(0)
lnNEU	1.594	-1.211	I(1)
lnREC	-1.200	-3.301*	I(1)

at 10%, 5%, and 1% significance level..

into the atmosphere, contributing to global warming and climate change. Increasing emissions are contributing to air pollution, exacerbating climate change, and posing significant health risks to the population. Ghana is facing environmental challenges, including rising temperatures and changes in rainfall patterns, which are exacerbated by greenhouse gas emissions resulting from the consumption of fossil fuels. The findings support other previous research, such as Dehghan (2024), Agyeman et al. (2021), Gyimah et al. (2023), Obayagbona (2023) and Otim et al. (2023) which found that fossil fuel consumption increases carbon emissions.

Ecological footprint and CO_2 emissions

The empirical findings of the ARDL model, presented in Table 6, reveal the interaction between ecological footprint and carbon dioxide emissions. The results reveal that the ecological footprint has a positive and significant effect on carbon emissions at a 5% significance level. This suggests that a 1% increase in ecological footprint corresponds to a 0.158% increase in carbon emissions. The research revealed that a larger ecological footprint is associated with greater resource consumption and waste generation, which in turn is closely linked to increased carbon emissions. Ghana's economic growth has led to increased energy use, manufacturing, and transportation, which depend heavily on fossil fuels, resulting in higher CO_2 emissions. As the country shifts from biomass to petroleum-based energy, the carbon intensity rises, elevating emissions. Population growth and urbanization drive up demand for housing, transportation, goods, and services, requiring energy and contributing to emissions. Greater trade openness leads to more goods being produced and transported, expanding the ecological footprint and emissions. This macroeconomic growth increases reliance on fossil fuels and natural resources, boosting carbon emissions. The ecological footprint serves as both an indicator and driver of the country's rising greenhouse gas emissions (Agyeman et al., 2021; Gyimah et al., 2023; Obayagbona, 2023). The finding is consistent with the findings of Abbas et al. (2021) and Szigeti et al. (2017) that ecological footprint has a positive and significant effect on CO_2 emissions in Pakistan.

Nuclear energy usage and CO_2 emissions

Nuclear energy use has a positive and significant relationship with CO_2 emissions in the long run. The findings reveal that as the use of nuclear energy in Ghana increases, CO_2 emissions increase by 0.105%. The result showed that the long-term increase in carbon emissions is associated with the rising overall energy demand. As Ghana's economy grows and more individuals gain access to energy, the total electricity demand is anticipated to rise. Suppose this demand expands more

Table 5. ARDL bound test results

Equation	Lag	F-statistic	Probability
CO_2 = f(EFP,FFL,FOL,NEU,REC)	(1,1,1,2,2,1)	3.7	0.0000
Threshold	**10%**	**5%**	**1%**
Lower bound I(0)	2.9	2.39	3.06
Upper bound I(1)	3	3.38	4.15

Source: Author's computation (2024).

Table 6. ARDL estimation of CO_2 emissions

Long-run estimates			Short-run estimates		
Variable	**Coefficient**	**Prob.**	**Variable**	**Coefficient**	**Prob.**
LnFFU	0.093*	0.0871	D(FFU)	0.004	0.5763
LnEFP	1.055	0.3579	D(EFP)	0.158**	0.0102
LnNEU	0.105**	0.0506	D(NEU)	-0.057***	0.0001
LnREC	-0.169**	0.0317	D(REC)	-0.048***	0.0001
LnFOL	2.719	0.1822	D(FOL)	0.857	0.3784
Constant	3.958	0.5938	Coint. Eq (-1) *	-0.433***	0.0000

Source: Author's computation (2024). Note: *, **, and *** are significant at 10%, 5%, and 1% significance level.

rapidly than the implementation of nuclear and renewable energy sources. In that case, fossil fuel power plants may increase their output to cover the gap, resulting in higher overall emissions even with nuclear energy included. Moreover, the increased reliance on nuclear power in Ghana is frequently associated with a rise in fossil fuel usage in areas like transportation and manufacturing, resulting in an overall increase in carbon emissions (Abokyi et al., 2019). The complete life cycle of nuclear energy involves initial CO_2 emissions during phases like construction, mining, and fuel processing, which are spread out over many years of nearly zero emissions during operation. In the short term, replacing fossil fuels, such as the prevalent thermal plants in Ghana, with emerging nuclear capacity offers immediate benefits by reducing emissions, despite the minor initial emissions, resulting in net reductions at a 1% significance level. Short-term negative impacts occur due to the swift replacement of high-emission sources amid Ghana's energy shortages, where nuclear planning is linked to immediate efficiency improvements or a reduction in fossil fuel use. The result confirms the findings of Saidi and Omri (2020) and Nathaniel et al. (2021) found that nuclear energy usage increases carbon emissions.

Meanwhile, in the short run, nuclear energy usage had a negative and statistically significant influence on carbon dioxide emissions at a 1% significance level. The negative coefficient indicates that a one-unit increase in nuclear energy usage results in a 0.057% decrease in carbon dioxide emissions in the short run. The study indicates that by integrating nuclear energy into its electricity network, Ghana replaces power produced from fossil fuels, particularly oil and gas plants, which are the main sources of CO_2 emissions. Nuclear energy provides a low-carbon alternative, with emissions over its entire lifecycle similar to those of renewable energy sources and significantly lower than those from fossil fuels. Once nuclear power is added to the grid, it reduces dependence on electricity generated from fossil fuels, leading to a short-term decrease in CO_2 emissions in Ghana. In the long term, when cumulative emissions from construction across various projects or expansions become predominant without a corresponding increase in operational offsets, particularly during the data collection planning stages, the overall impact becomes positive, indicating unadjusted full-cycle costs. This long-term positivity arises due to adjustment delays: high capital expenses postpone reaching full capacity, while the demand generated by dependable baseload power stimulates economic activity and necessitates fossil fuel backups during ramp-ups, thereby increasing emissions through rebound effects. This is consistent with ARDL error-correction mechanisms, where short-term dynamics capture transitional substitution, but long-term equilibrium reveals emissions driven by the scale of infrastructure development. Similar evidence was reported by Alghamdi et al. (2024) that nuclear energy reduces carbon dioxide emissions in the G20 countries.

Renewable energy consumption and CO_2 emissions

In addition, renewable energy consumption had a negative and significant effect on carbon dioxide emissions at 5% and 1% significance levels. The negative sign indicates that an increase in renewable energy consumption reduces carbon emissions by 0.169% in the long run and 0.048% in the short run. The primary reason for the reduction in carbon emissions is the adoption of renewable energy, which leads to improvements in energy efficiency, resulting in lower energy consumption and, consequently, lower carbon dioxide emissions. Additionally, renewable energy has the potential to serve as a viable alternative to conventional energy sources, promoting better environmental quality. Ghana is successfully reducing its dependence on power generation from fossil fuels by increasing the share of renewable energy sources in its energy mix, resulting in a decrease in emissions from the energy sector. The country can achieve a substantial reduction in emissions from the manufacturing and transport sectors by incorporating renewable energy into the power grid and encouraging the use of electric vehicles. This is crucial as emissions are expected to rise due to the growing population and economic activities. Ghana's National Energy Transition Framework and updated Nationally Determined Contributions aim to reduce carbon emissions by promoting the adoption of renewable energy. The target is to have renewables reach 10% of the energy mix by 2030 and achieve net zero by 2060. These targets should avert a major emissions increase that could grow fivefold by 2050 without intervention (Ghana Energy Commission, 2023, 2024). The outcome is coherent with Hasanov et al. (2024) and Adebayo et al. (2022) found that renewable energy reduces carbon emissions in the long run and the short run.

Hypothesis Results

The study formulated three hypotheses on the impact of fossil fuel consumption, renewable energy use, and nuclear energy consumption on CO_2 emissions in Ghana. The results of the first hypothesis formulation indicated that fossil fuel consumption has a positive and significant impact on CO_2 emissions in Ghana, as predicted, due to Ghana's petroleum consumption rising steadily from 1,445 Ktoe in 2000 to 4,318 Ktoe by 2022. This trend shows a significant annual growth rate, contributing to increased carbon emissions. In 2022, electricity generation from fossil fuels in Ghana reached 14.85 billion kilowatt-hours, an increase from 2020, highlighting the connection between fuel use, energy production, and carbon emissions. Therefore, we reject the null hypothesis and conclude that fossil fuel consumption positively and significantly impacts carbon emissions in Ghana (Ghana Energy Commission, 2023).

The second hypothesis posited that renewable energy has a negative and significant impact on carbon emissions in Ghana. The confirms that the use of renewable energy in Ghana reduces carbon emissions. Renewable energy adoption in Ghana reduces emissions by replacing fossil fuels with low-emission sources, thereby aligning with the country's climate goals. Ghana's energy sector has relied heavily on fossil fuels for electricity and transportation, contributing to increased emissions. By increasing solar, wind, hydro, and biomass sources, the country can reduce dependence on carbon sources. Ghana's National Energy Transition Framework emphasizes renewables for decarbonization, targeting net-zero by 2060. Government projections show renewables will provide over 75% of the needed emission reductions (Ghana Energy Commission, 2023, 2024).

The third hypothesis posits that Nuclear energy consumption has a negative and significant impact on carbon emissions in Ghana. The study's findings confirm that nuclear energy use has a negative influence on carbon emissions, as increased nuclear consumption leads to decreased emissions in Ghana. Nuclear energy is expected to reduce carbon emissions by replacing fossil fuel-based electricity generation with a low-carbon alternative, directly lowering power sector emissions in the short term (Soto and Martinez-Cobas, 2024). This effect occurs upon nuclear plant operation and is driven by the need to decarbonize Ghana's thermal-based grid. This demonstrates an inverse relationship where nuclear energy correlates with reduced emissions over a shorter period (Milne et al., 2024).

Diagnostic results

The diagnostic tests were conducted to verify normality, homoskedasticity, and serial correlation, and the error term and study outcomes are presented in Table 7. The results indicate that the dataset is normally distributed, and no issues with homoscedasticity or serial autocorrelation were detected. Table 7 outlines the expected results from the diagnostic evaluation of the ARDL model, utilizing measures such as R-squared, Adjusted R-squared, Durbin Watson, normality (Jarque-Bera), homoskedasticity (ARCH), serial correlation LM (Breusch Godfrey), and the Ramsey reset effect. The analysis indicated that the ARDL model's R-squared value of 0.824 implies that around 82.4% of the fluctuations in the dependent variable are accounted for by the independent variables and their lags included in the model. This demonstrates a strong fit, indicating that the model effectively captures the majority of the data's dynamics. The Adjusted R-squared value of 0.765 indicates that, even after adjusting for the number of predictors, approximately 76.5% of the variance in the dependent variable is still explained by the model. The 0.059 difference (0.824-0.765) here suggests that multiple predictors are inflating the standard R2 without adequately justifying their inclusion when adjusted.

The ARDL model's Durbin-Watson statistic of 2.339 indicates that there is no substantial evidence of first-order autocorrelation in the regression residuals, and it also signifies a well-fitting model. The results suggested that the normality value (1.414) with a probability value (0.4931) exceeded the 0.05 threshold. Consequently, the null hypothesis was rejected, confirming that the data follows a normal distribution. The ARCH test for homoskedasticity yielded a statistical value of 0.121, with a probability value of 0.7309, which was above the 0.05 threshold, leading to the rejection of the null hypothesis and acceptance of the alternative, indicating no ARCH effect in the data. The Breusch-Godfrey serial correlation LM test produced a statistical value of 0.825 and a probability value of 0.6328, surpassing the 0.05 threshold, suggesting an absence of serial correlation among the explanatory variables. The results of the Ramsey reset test, with an F-statistic of 5.882 and a p-value of 0.0294, indicate a rejection of the null hypothesis regarding correct model specification at the 5% significance level, thereby confirming a functional form misspecification

Table 7. Diagnostic test results

Diagnostic test	F-statistics	Probability
R-Squared	0.824	-
Adjusted R Squared	0.765	-
Durbin-Watson	2.339	-
Normality (Jarque-Bera)	1.414	0.4931
Homoskedasticity (ARCH)	0.121	0.7309
Serial Correlation LM (Breusch Godfrey)	0.825	0.6328
Ramsey Reset	5.882	0.0294

Source: Author's computation (2024)

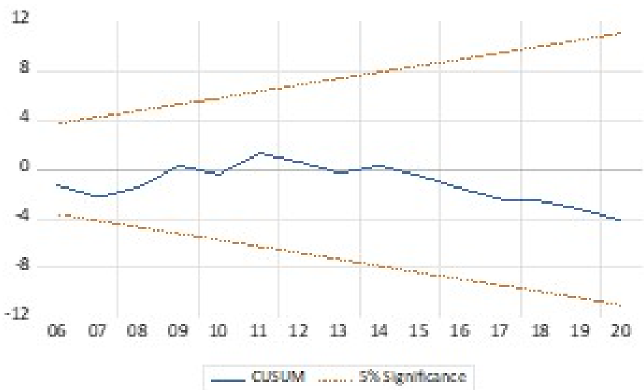

Figure 8. CUSUM

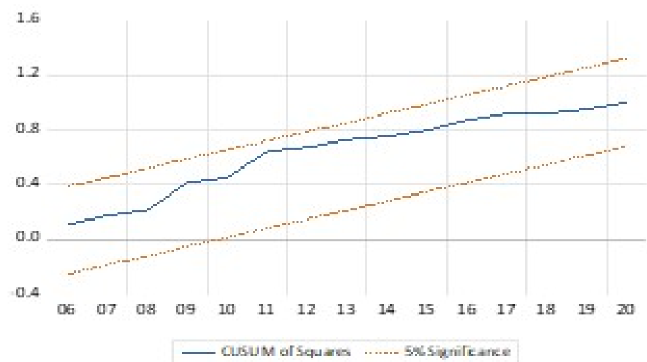

Figure 9. CUSUM of Squares

in the ARDL model due to the transformations of variables that are typical in econometric time series analysis.

Stability Results of ARDL

The cumulative sum and the cumulative sum of squares result for ARDL are presented in Figure 8 and Figure 9, depict. The cumulative sum (CUSUM) and SUM of Squares (CUSUMQ) tests were carried out to check the goodness of fit for the ARDL model as proposed by Brown et al. (1975). After verifying the cointegration relationship between CO_2 emissions, ecological footprint, fossil fuel consumption, forest land losses, nuclear energy use, and renewable energy consumption, the plots are within the critical bounds at the 5% significance level. This indicates that the coefficients of the ARDL model were stable, and the overall fit of the model was good. The findings of the study are confirmed by Chandio et al. (2020), Nasrullah et al. (2021) and Zhai et al. (2017).

4.8 Forecasting Results (Theil Inequality Coefficient and Symmetric Mean Absolute Percentage Error)

We evaluated the precision of the ARDL model by employing a static forecasting chart for carbon dioxide emissions from 1990 to 2020. The research utilizes forecasting evaluation through the Theil Inequality Coefficient (TIC) and Symmetric Mean Absolute Percentage Error (SMAPE) within the ARDL model to thoroughly evaluate out-of-sample predictive accuracy, addressing the shortcomings of in-sample diagnostics such as the previous failure of the Ramsey RESET test.

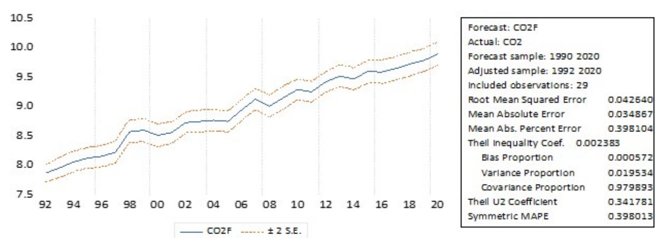

Figure 10. Actual and forecasted CO_2 emissions during the period of 1990 to 2020 via the ARDL model

These methods adhere to econometric standards for predictive validity, ensuring that the findings can guide policy despite issues with in-sample analysis. The forecasting outcomes are depicted in Figure 10. Among all models, the ARDL model exhibited the lowest values for Root Mean Square Errors and Theil Inequality coefficient. The ARDL Root Mean Squared Error for CO_2 emissions (0.042640) is deemed most suitable for forecasting, as it most closely approximates the actual value. The Theil Inequality coefficient, typically ranging between 0 and 1, approaches zero (0.002383), signifying superior ARDL model performance by reflecting minimal disparity between predicted and actual values (Getachew and Assefa, 2020). The Symmetric MAPE value of 0.398013 indicates that the average absolute percentage difference between predictions and actual values is 39.8%, which falls within an acceptable forecasting range (Getachew and Assefa, 2020).

Conclusion

This study examines the impact of ecological footprint, fossil fuel consumption, forest land loss, nuclear energy use, and renewable energy consumption on CO_2 emissions in Ghana from 1990 to 2020. Findings reveal that fossil fuel consumption increases long-term CO_2 emissions, while the ecological footprint has a short-term positive impact. Nuclear energy raises long-term CO_2 emissions but reduces them short-term. Renewable energy consistently decreases CO_2 emissions in both periods.

Policy Implications

To reduce CO_2 emissions in Ghana, policymakers should focus on increasing the adoption of renewable energy by offering subsidies, incentives, and investing in infrastructure, as this approach consistently reduces emissions in both the short and long term. To decrease reliance on fossil fuels, they should consider implementing carbon taxes or gradually eliminating subsidies, as these measures counteract the significant long-term positive impact on emissions. The expansion of nuclear energy should be limited, as its long-term benefits are overshadowed by increased emissions despite short-term advantages; instead, the emphasis should be on safer renewable options. Reforestation initiatives and ecological footprint regulations, such as sustainable land-use policies, should be implemented to alleviate short-term environmental pressures caused by human activities.

Study Limitation and Future Research

The study focused on examining the impact of fossil fuel consumption, renewable energy consumption, ecological footprint, forest land reduction due to emissions, and nuclear energy use on carbon emissions in Ghana. This analysis was conducted using limited data over a restricted timeframe and employed the ARDL Model. In future studies, it is important to incorporate economic variables such as Ghana's economic and population growth, industrialization, urbanization, trade, foreign direct investment, carbon taxation, fossil fuel usage, renewable energy consumption, and nuclear energy. These variables also impact carbon emissions, and utilizing more recent data along with advanced econometric models for analysis is recommended. By addressing these limitations and exploring potential research directions, studies can offer enhanced recommendations for Ghana's policies to effectively reduce carbon emissions through optimized strategies for utilizing both renewable and non-renewable energy sources.

Author contributions

Conceptualization, JAA; methodology, JAA; software JAA; validation MB; formal analysis, and investigation JAA; resources JAA, and DCM, data curation, JAA, and DCM, writing; JAA and DCM, writing-reviewing and editing, JAA & DCM, visualization; JAA and DCM, supervision, MB. All authors have read and agreed to publish the manuscript.

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Data availability statement

The dataset generated during the research is available.

Conflict of interest statement

The authors declare that they have no conflict of interest.

References

Abbas, S., Kousar, S., and Pervaiz, A. (2021). Effects of energy consumption and ecological footprint on CO_2 emissions: An empirical evidence from Pakistan. *Environment, Development and Sustainability*, 23(9):13364–13381. https://doi.org/10.1007/s10668-020-01216-9.

Abokyi, E., Appiah-Konadu, P., Abokyi, F., and Oteng-Abayie, E. F. (2019). Industrial growth and emissions of CO_2 in Ghana: The role of financial development and fossil fuel consumption. *Energy Reports*, 5:1339–1353. https://doi.org/10.1016/j.egyr.2019.09.002.

Adebayo, T. S., Awosusi, A. A., Rjoub, H., Agyekum, E. B., and Kirikkaleli, D. (2022). The influence of renewable energy usage on consumption-based carbon emissions in MINT economies. *Heliyon*, 8(2). https://doi.org/10.1016/j.heliyon.2022.e08941.

Agyeman, R., Dong, L., and Mamoud, H. (2021). Drivers of Carbon Dioxide (CO_2) Emissions in Ghana: A Comparative Analysis on Consumption of Energy by the Industry, Agriculture, Residential and the Transport Sector (2000-2018). *Journal of Energy Technologies and Policy*, 10(5):1–12. https://doi.org/10.7176/jetp/11-5-01.

Ahmat, N., Christopher, S., Saputra, J., Sukemi, M. N., and Nawawi, M. N. (2024). The Impact of Energy Consumption, Economic Growth, and Non-Renewable Energy on Carbon Dioxide Emission in Malaysia. *International Journal of Energy Economics and Policy*, 15(1):143–152. https://doi.org/10.32479/ijeep.17350.

Alghamdi, F. M., Kamel, A. R., SidAhmed Mustafa, M., Bahloul, M. M., Alsolmi, M. M., and Abonazel, M. R. (2024). A statistical study for the impact of REMS and nuclear energy on carbon dioxide emissions reductions in G20 countries. *Journal of Radiation Research and Applied Sciences*, 17(3):100993. https://doi.org/10.1016/j.jrras.2024.100993.

Ali, S. R. and Mujahid, N. (2024). Sectoral carbon dioxide emissions and environmental sustainability in Pakistan. *Environmental and Sustainability Indicators*, 23. https://doi.org/10.1016/j.indic.2024.100448.

Aminu, N., Clifton, N., and Mahe, S. (2023). From pollution to prosperity: Investigating the Environmental Kuznets curve and pollution-haven hypothesis in sub-Saharan Africa's industrial sector. *Journal of Environmental Management*, 342. https://doi.org/10.1016/j.jenvman.2023.118147.

Atchadé, M. N. and Nougbodé, H. (2024). Statistical investigation on the relationship between climate change, food availability, agricultural productivity, and economic expansion. *Heliyon*, 10(12):1–13. https://doi.org/10.1016/j.heliyon.2024.e32520.

Brown, R. L., Durbins, J., and Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society. Series B (Methodological)*, 37(2):149–192.

Ceesay, E. K., Francis, P. C., Jawneh, S., Njie, M., Belford, C., and Fanneh, M. M. (2021). Climate change, growth in agriculture value-added, food availability and economic growth nexus in the Gambia: A Granger causality and ARDL modeling approach. *SN Business & Economics*, 1(7). https://doi.org/10.1007/s43546-021-00100-6.

Chandio, A. A., Magsi, H., and Ozturk, I. (2020). Examining the effects of climate change on rice production: case study of Pakistan. *Environmental Science and Pollution Research*, 27(8):7812–7822. https://doi.org/10.1007/s11356-019-07486-9.

Dehghan, S. Z. (2024). Renewable energy and CO_2 emissions: Does human capital matter? *Energy Reports*, 11:3474–3491. https://doi.org/10.1016/j.egyr.2024.03.021.

Destek, M. A. and Sinha, A. (2020). Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic Co-operation and development countries. *Journal of Cleaner Production*, 242. https://doi.org/10.1016/j.jclepro.2019.118537.

Dickey, D. A. and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with unit root. *Journal of the American Statistical Association*, pages 427–431.

Dritsakis, N. (2004). Tourism as a long-run economic growth factor: An empirical investigation for Greece using causality analysis. *Tourism Economics*, 10(3):305–316. https://doi.org/10.5367/0000000041895094.

Eren, M. and Baets, B. D. (2024). Forecasting Turkey's Primary Energy Demand Based on Fuzzy Auto-regressive Distributed Lag Models with Symmetric and Non-symmetric Triangular Coefficients. *International Journal of Fuzzy Systems*. https://doi.org/10.1007/s40815-024-01773-5.

Food and Agriculture Organization of the United Nations (2024). Ghana: Emissions from Forests. https://www.fao.org/.

Frimpong, M. and Oteng, E. F. (2006). Bound Testing Approach: An examination of foreign direct investment, trade and growth relationships. *MPRA Paper No 32*, pages 1–19.

Getachew, D. and Assefa, E. (2020). Energy Use, Economic Growth, and Carbon Dioxide Nexus in Ethiopia: An Auto Regressive Distributed Lag-Bound Test of Co-Integration Analysis. *Ethiopian Journal of Economics*, 19(1):1–42.

Ghana Energy Commission (2020). 2020 Energy (Supply and Demand) Outlook for Ghana. Technical report, Ghana Energy Commission.

Ghana Energy Commission (2023). National Energy Statistical Bulletin: Energy Statistics and Balances. Technical report, Ghana Energy Commission. www.energycom.gov.gh.

Ghana Energy Commission (2024). National Energy Statistical Bulletin 2024. Technical report, Ghana Energy Commission. www.energycom.gov.gh.

Global Footprint Networks (2024). Ghana-Ecological Footprints vs Biocapacity (gha per person). Available at https://www.footprintnetwork.org/.

Granger, C. W. J. and Engle, R. F. (1987). Econometric forecasting: A brief survey of current and future techniques. *Climatic Change*, 11(1–2):117–139. https://doi.org/10.1007/BF00138798.

Gyimah, J., Hayford, I. S., Nwigwe, U. A., and Opoku, E. O. (2023). The role of energy and economic growth towards sustainable environment through carbon emissions mitigation. *PLOS Climate*, 2(3):e0000116. https://doi.org/10.1371/journal.pclm.0000116.

Hasanov, F. J., Mukhtarov, S., Suleymanov, E., and Shannak, S. (2024). The role of renewable energy and total factor productivity in reducing carbon emissions: A case of top-ranked nations in the renewable energy country attractiveness index. *Journal of Environmental Management*, 361. https://doi.org/10.1016/j.jenvman.2024.121220.

Haug, A. A. (2002). Temporal aggregation and the power of cointegration test: a Monte Carlo study. *Oxford Bullet of Economics and Statistics*, 64(4):399–412.

International Energy Agency (2022). World Energy Outlook 2022. Technical report, International Energy Agency. www.iea.org/t&c/.

International Energy Agency (2023). Renewables 2023: Analysis and forecast to 2028. Technical report, International Energy Agency. www.iea.org.

International Energy Agency (2024). How much CO_2 does Ghana emit? https://www.iea.org/.

International Trade Administration (2023). Ghana-Country Commercial Guide. Department of Commerce, United States of America.

Irena (2015). Ghana Renewables Readiness Assessment. https://www.africanpowerplatform.org/resources/reports/west-africa/ghana/2246-ghana-renewables-readiness-assessment.html.

Jumhur (2020). Penerapan Autoregressive Distributed Lag Dalam Memodelkan Pengaruh Inflasi, Pertumbuhan Ekonomi, Dan Fdi Terhadap Pengangguran Di Indonesia. *Jurnal Ekonomi Bisnis Dan Kewirausahaan*, 9(3):250–265. https://doi.org/10.26418/jebik.v9vi3.41332.

Justice, G., Nyantakyi, G., and Isaac, S. H. (2024). The effect of renewable energy on carbon emissions through globalization. *Heliyon*, 10(5):e26894. https://doi.org/10.1016/J.HELIYON.2024.E26894.

Kwakwa, P. A., Aboagye, S., Acheampong, V., and Achaamah, A. (2024). Renewable energy consumption and carbon dioxide emissions in Ghana: the effect of financial strength of listed financial institutions. *IJESM*, 18(1):162–182. https://doi.org/10.1108/IJESM-02-2022-0001.

Kwakwa, P. A., Alhassan, H., and Adu, G. (2018). Effect of natural resources extraction on energy consumption and carbon dioxide emission in Ghana.

Milne, L., Ragosa, G., Tomei, J., and Watson, J. (2024). Realising Ghana's nuclear power plans: opportunities and challenges. CCG Policy Brief 1, Climate Compatible Growth Programme Policy Brief Series.

Ministry of Energy (2022). Ghana's National Energy Transition Framework (2022-2070).

Musah, M., Onifade, S. T., Ankrah, I., Gyamfi, B. A., and Amoako, G. K. (2024). Achieving net-zero emission target in Africa: Are sustainable energy innovations and financialization crucial for environmental sustainability of sub-Saharan African state? *Applied Energy*, 364. https://doi.org/10.1016/j.apenergy.2024.123120.

Myllyvirta, L. (2020). Quantifying the Economic Costs of Air Pollution from Fossil Fuels Key messages.

Naeem, M., Yu, J., Aamir, M., Khan, S. A., Adeleye, O., and Khan, Z. (2021). Comparative analysis of machine learning approaches to analyze and predict the COVID-19 outbreak. *PeerJ Computer Science*, 7. https://doi.org/10.7717/PEERJ-CS.746.

Nasrullah, M., Rizwanullah, M., Yu, X., Jo, H., Sohail, M. T., and Liang, L. (2021). Autoregressive distributed lag (Ardl) approach to study the impact of climate change and other factors on rice production in South Korea. *Journal of Water and Climate Change*, 12(6):2256–2270. https://doi.org/10.2166/wcc.2021.030.

Nathaniel, S. P., Alam, M. S., Murshed, M., Mahmood, H., and Ahmad, P. (2021). The roles of nuclear energy, renewable energy, and economic growth in the abatement of carbon dioxide emissions in the G7 countries. *Environmental Science and Pollution Research*, 28(35):47957–47972. https://doi.org/10.1007/s11356-021-13728-6.

Obayagbona, J. (2023). Carbon footprint and economic growth in Nigeria and Ghana. *Research Papers in Economics and Finance*, 7(2):18–43. https://doi.org/10.18559/ref.2023.2.771.

OECD (2023). Supplement to effective carbon rates. Technical report, OECD. https://oe.cd/ECR2023-brochure.

Ofori-Sasu, D., Abor, J. Y., Agyekum Donkor, G. N., and Otchere, I. (2023). Renewable energy consumption and carbon emissions in developing countries: the role of capital markets. *International Journal of Sustainable Energy*, 42(1):1407–1429. https://doi.org/10.1080/14786451.2023.2268857.

Otim, J., Watundu, S., Mutenyo, J., and Bagire, V. (2023). Fossil Fuel Energy Consumption, Economic Growth, Urbanization, and Carbon Dioxide Emissions in Kenya. *International Journal of Energy Economics and Policy*, 13(3):457–468. https://doi.org/10.32479/ijeep.14292.

Pesaran, M. H. and Shin, Y. (1998). An autoregressive distributed-lag modelling approach to cointegration analysis. *Econometrics Society Monographs*, 31:371–413.

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

Philips, P. C. B. and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2):335–346.

Saidi, K. and Omri, A. (2020). Reducing CO_2 emissions in OECD countries: Do renewable and nuclear energy matter? *Progress in Nuclear Energy*, 126. https://doi.org/10.1016/j.pnucene.2020.103425.

Sasu, D. D. (2024). Power sector emissions in Ghana from 2000 to 2021. Stastista.

Scherr, R. (2023). Climate Action: 4 Contributors to climate change. Earth Day.

Soto, G. H. and Martinez-Cobas, X. (2024). Nuclear energy generation's impact on the CO_2 emissions and ecological footprint among European Union countries. *Science of the Total Environment*, 945:173844. https://doi.org/10.1016/j.scitotenv.2024.173844.

Szigeti, C., Toth, G., and Szabo, D. R. (2017). Decoupling-Shifts in Ecological Footprint Intensity of Nations in the Last Decade. *Ecological Indicators*, 72:111–117.

Turedi, N. and Turedi, S. (2021). The Effects of Renewable and Non-renewable Energy Consumption and Economic Growth on CO_2 Emissions: Empirical Evidence from Developing Countries. *Business and Economics Research Journal*, 12(4):751–765. https://doi.org/10.20409/berj.2021.350.

World Bank (2024a). Databank -Ghana: World Development Indicators. Available at https://databank.worldbank.org/source/world-development-indicators.

World Bank (2024b). Ghana carbon (CO_2) emissions 1990-2024. World Bank. Available at https://data.worldbank.org/.

Yuliati, L., Mukti, A. F., and Riniati (2020). Autoregressive Distributed Lag (ARDL) approach for re-testing the Fisher effect in Indonesia. *Jurnal Perspektif Pembiayaan Dan Pembangunan Daerah*, 8(3):209–218. https://doi.org/10.22437/ppd.v8i3.9200.

Zhai, S., Song, G., Qin, Y., Ye, X., and Lee, J. (2017). Modeling the impacts of climate change and technical progress on the wheat yield in inland China: An autoregressive distributed lag approach. *PLoS ONE*, 12(9). https://doi.org/10.1371/journal.pone.0184474.