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Assessing the Economic and Health Impacts of Greenhouse Gas Emissions: A Multivariate Analysis

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

This study investigates the impact of greenhouse gas (GHG) emissions on two critical outcomes: gross domestic product (GDP) and death rate (DR), using secondary data from Nigeria spanning 1960–2011. Unlike previous studies, this research incorporates DR as a measure of health impacts alongside GDP, providing a holistic view of GHG emissions' effects. Utilizing multiple linear regression and canonical correlation analyses, the study reveals significant associations between emissions and both dependent variables. Key findings indicate that while gaseous emissions positively influence GDP, liquid and solid emissions negatively affect it. Conversely, solid emissions show a strong positive relationship with DR, highlighting their health risks. These results underscore the dual challenge of balancing economic growth with public health in addressing GHG emissions. The study's insights offer valuable guidance for policymakers aiming to design effective climate mitigation strategies.

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Keywords: GHG; GDP; DR; canonical correlation; regression; F-test.

ABBREVIATIONS

DR : Death Rate
GDP : Gross Domestic Product
CC : Canonical Correlation
$H0i$: ITH Null Hypothesis
$H1j$: JTH Alternative Hypothesis
KTCO2E : Kilotonnes of Carbon Dioxide Equivalent. Which is a unit measurement for greenhouse gas emissions.

1. INTRODUCTION

The environment in which man lives needs to be adequately catered for in order to maintain balance in the ecosystem, so that the resources it offers can be optimized for the benefit of the occupants. Human activities have a direct impact on this outcome, determining whether it will be conducive or toxic to human life and living organisms in general (Achike & Anthony, 2014; Mikhaylov et al., 2020; Tagwi, 2022). Man needs energy (especially from fossil fuels) in various forms to ease transportation, manufacturing processes, agriculture, and so on. To meet these demands, particularly in agriculture, the use of chemical inputs is altering natural cycles and causing environmental damage (Ntiamoah et al., 2023; Okorie & Lin, 2022). Examples include water and air pollution, loss of biodiversity, and increased greenhouse gas (GHG) emissions. These problems are further intensified by activities like mining, industrial production, and other commercial ventures (Donou et al., 2024; Mikhaylov et al., 2020; Yue & Gao, 2018).

GHG emissions are simply the release of gases mainly composed of carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases into the Earth's atmosphere. The sources of these gases are mainly from human activities, including industrial, agricultural, and waste management (Chehabeddine & Tvaronavičienė, 2020; Moumen et al., 2019). These gases, when trapped, further accumulate to constitute the greenhouse effect, which leads to global warming (Lamb et al., 2021). As the global population is projected to reach 9 billion by2050 (Achike & Anthony, 2014; Mikhaylov et al., 2020), increasing pressure is being placed on sectors such as agriculture, forestry, and fisheries to ensure food security. This demand is driving the search for new lands, often leading to deforestation (Yue & Gao, 2018). Foreign investment in forest lands has been linked to environmental pollution and forest loss, which have dangerous consequences for ecosystems and global trade. Deforestation, particularly in Nigeria, is a major concern as it is a significant contributor to CO_2 emissions (Achike & Anthony, 2014; Adesiji & Obaniyi, 2012). When forests are cleared and trees are burned or decay, carbon is released into the atmosphere, increasing GHG concentrations and exacerbating global warming (Jeffry et al., 2021). The increasing concentration of GHGs is already having a negative effect on the environment, human health, and the economy (Atedhor, 2023). Without concerted efforts to reduce emissions, these impacts are expected to become more severe.

Several research studies have been carried out on the effect of energy consumption on GDP and other economic indicators (Apergis et al., 2010; Menyah & Wolde-Rufael, 2010; Shakeel et al., 2014; Tagwi, 2022; Zhang & Cheng, 2009), concerning geographical terrains (continents) and predominant activities in such territories. Cause-and-effect analysis has been conducted, and the relationship has been critically analyzed (Apergis et al., 2010; Asafu-Adjaye, 2000; Coondoo & Dinda, 2002; Nayan et al., 2013; Soytas et al., 2007; Ziramba,2009).

Tagwi (2022) conducted research investigating the effects of climate change (rainfall and temperature), carbon emissions, and renewable energy consumption on agricultural economic growth in South Africa over the period from 1972 to 2021. Using the ARDL (Auto Regressive Distributed Lag) model, the authors analyze both the short- and long-term relationships between these factors. The results depict that climate change has a short-term negative effect on agriculture, whereas, in the long term, agricultural growth can improve despite climate challenges. Carbon emissions are positively correlated with agricultural growth, whereas renewable energy usage appears to have no significant impact on economic growth in either the short or long term. For the Environmental

Kuznets Curve (EKC), CO_2 emissions increase with economic growth up to a point, after which they decrease as economies mature and implement cleaner technologies.

Mikhaylov et al., (2020) revealed how human activities significantly affect global climate change. This is evident in the proportion and concentration of greenhouse gases in the atmosphere. The effect of climate change on human health globally is examined, with a specific focus on African countries (Amuka et al., 2018). The energy balance method was employed to simulate trends in greenhouse gas emission predictions in various sectors until the year 2030. Data from their research revealed greenhouse gas emissions from different sectors, including industrial processes, transportation fuels, land use and biomass burning, waste disposal and treatment, electric power stations, fossil fuel retrieval, processing and distribution, and residential, commercial, and other sources, with the highest being from electric power stations, accounting for 25.6% of the data. The data source was from the European Environmental Agency. Recommendations were made that organizations should reduce carbon emissions into the air over the next 10 years. This can be achieved by switching to alternative sources of energy (water, solar, and wind) to meet the targets set by the Paris Agreement.

Hamrani et al. (2020) deployed three categories of machine learning models and compared their performance in predicting soil GHG emissions. GHG emissions data were collected from an agricultural research site in Quebec over the period from 2012 to 2017. The data include CO_2 and N_2O fluxes along with environmental variables such as air and soil temperature, precipitation, and humidity. From their study, the LSTM model proved to be the most effective in predicting both CO_2 and N_2O emissions from agricultural soils, especially for capturing short-term variations and peak emissions. Additionally, the Random Forest model offered a fast and effective alternative for CO_2 prediction but was less accurate for N_2O emissions.

Nayan et al. (2013) deployed the GMM (Generalized Method of Moments) estimator to ensure accurate results. In their study, the data used was from 23 selected countries over the period 2000–2011. Two models were considered, namely, the energy consumption model and the GDP model. Results from the former model revealed that GDP has a significant effect on energy consumption, while for the latter model, energy consumption has a less significant effect on real GDP per capita. Other significant determinants of energy consumption were energy price and investment.

Kumar et al., (2024) investigated the GHG emissions from rice crops under various treatment combinations (T1, T2, T7) of fertilizer management practices. The control treatment T1 had no nitrogen in its composition and recorded the lowest CO_2 emissions, though it had the least rice output. T2 had the highest CO_2 and N_2O emissions, with values of 1165 kg CO_2e ha^{-1} and 352 kg CO_2e ha^{-1}, respectively. The study highlighted the need to balance the drive for increased rice productivity with environmental sustainability.

In this work, the impact of greenhouse gas emissions on Gross Domestic Product (GDP) and the death rate (DR), representing economic and health impacts respectively, is explored. The death rate has not been considered in the literature, which is included in this research. Additionally, the relationships between the dependent variables (GDP & DR) and GHG emissions in Nigeria are examined on a multivariate level.

2. MATERIALS AND METHODS

2.1 Study Area

The study area, Nigeria, is situated in West Africa; it is located between the Sahel to the north and the Gulf of Guinea to the south in the Atlantic Ocean (“Nigeria,” 2024). It is regarded as an oil-producing state because it is endowed with crude oil and other mineral resources (Adesugba & Hoon, 2018). It is, therefore, characterized by many industrial activities involving fossil fuel processing, distribution, and consumption.

2.2 Data Source and Framework

The data sets used in this study were from secondary sources, the first collected from official government statistics on their website (https://www.nigerianstat.gov.ng/). The data spans a period of 51 years, from 1960 to 2011. The dataset is composed of greenhouse gas (GHG) emissions (liquid, solid, and gas), GDP, and DR, with the former constituting the independent variable and the latter the dependent variable, respectively. The second dataset used was from World Development Indicators, revealing greenhouse gas emissions of countries from 1990 to 2020 (Greenhouse Gas (GHG) Emissions Climate Watch, 2023).

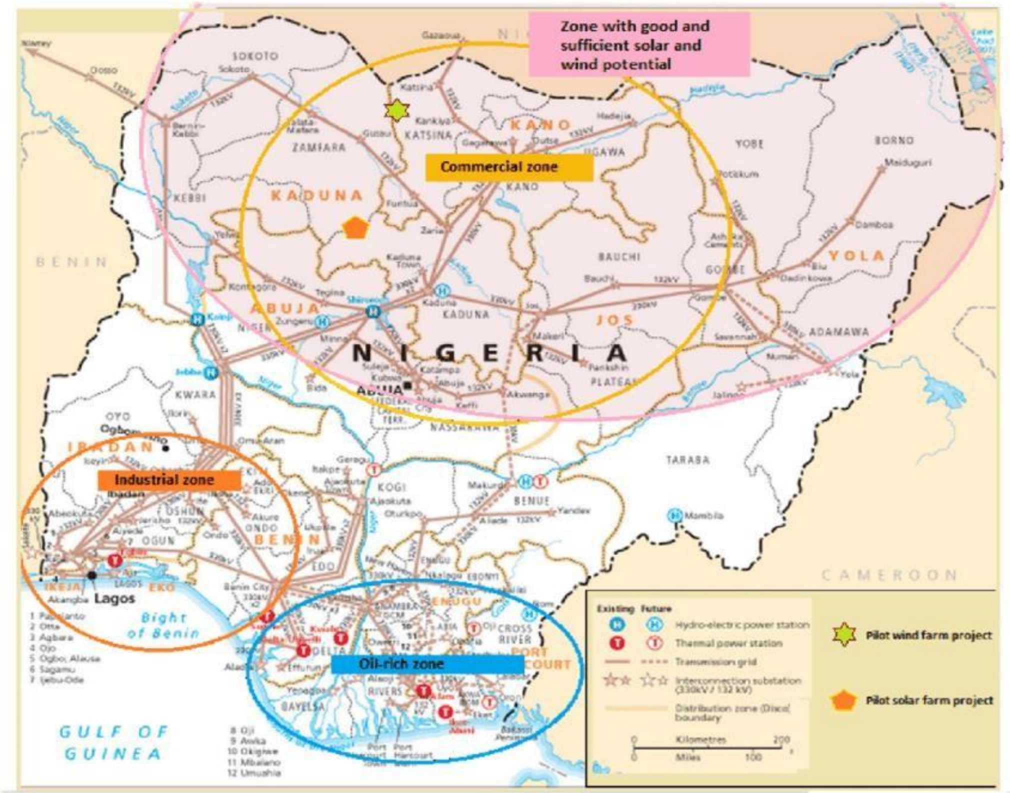

Fig. 1. Map of Nigeria showing energy resources, zones (Adewuyi et al., 2020)

3. METHODOLOGY

3.1 Multiple Regression

Multiple linear regression is a statistical technique that deploys two or more independent variables referred to as regressors, ($X_i s$) to predict the outcome of a dependent variable referred to as the regressand, (Y).

Two multiple linear regression models are considered here:

$$GDP_t = (L_t;\ S_t;\ G_t) \implies GDP_t = \beta_0 + \beta_1 L_t + \beta_2 S_t + \beta_3 G_t + \varepsilon_i \quad (1)$$

$$DR_t = (L_t;\ S_t;\ G_t) \implies DR_t = \beta_0 + \beta_1 L_t + \beta_2 S_t + \beta_3 G_t + \varepsilon_i \quad (2)$$

3.2 Log Transformation of Variable

Here, regression is considered on the natural logarithms of the dependent variable, Y, $i.e$ log(Y). The reason for this is to handle heteroscedasticity, influence of outliers, skewness of data, and linearize non-linear relationships.

$$log\ GDP_t = (L_t;\ S_t;\ G_t) \implies log\ GDP_t = \beta_0 + \beta_1 L_t + \beta_2 S_t + \beta_3 G_t + \varepsilon_i \quad (3)$$

$$log\ DR_t = (L_t;\ S_t;\ G_t) \implies log\ DR_t = \beta_0 + \beta_1 L_t + \beta_2 S_t + \beta_3 G_t + \varepsilon_i \quad (4)$$

where.

$GDP_t = gross\ domestic\ product\ during\ period\ t$
$DR_t = death\ rate\ during\ period\ t$
$L_t = liquid\ form\ of\ GHG\ emissions\ at\ period\ t$

S_t = *solid form of GHG emissions at period t*
G_t = *gaseous form of GHG emissions at period t*
β_i *are regression coefficients*, *where* i = 0, 1, 2, ε_i = *is the error term*

3.3 Canonical Correlation

This is a multivariate statistical technique that studies the relationships between multiple dependent and independent variables. It determines the linear combinations of variables from each set that are most highly correlated with each other. It is simply an extension of simple correlation (bivariate), focusing on groups of variables. It determines the maximum correlation between 2 groups of variables, making it suitable for this study as we have multiple dependent and independent variables.

$$\text{Let } U = a_1X_1 + a_2X_2 + a_3X_3 = a'X \quad (5)$$

$$V = b_1Y_1 + b_2Y_2 = b'Y \quad (6)$$

such that $X_1 = L$, $X_2 = S$, $X_3 = G$, $Y_1 = GDP$, and $Y_2 = DR$

$a = [a_1, a_2, a_3,]$ and $b = [b_1, b_2, b_3,]$ are vectors of coefficients (canonical weights) to be determined. U and V are linear combinations of X and Y. The canonical correlations, cc are the square roots of the eigenvalues of the following matrix.

$$R_{YY}^{-1} R_{YX} R_{XX}^{-1} R_{XY} \quad (7)$$

Where R_{XY} and R_{YX} are the Covariance matrices between X and Y, and Y and X $respectively$, R_{XX} is the covariance matrix of X with itself, and R_{YY} is the covariance matrix of Y and itself.

3.4 Hypothesis

H_{01}: *GDP has no relationship with GHG emissions*

H_{11}: *GDP has a significant relationship with GHG emissions*

H_{02}: *DR has no relationship with GHG emissions*

H_{12}: *DR has a significant relationship with GHG emissions*

H_{03}: *GDP & DR has no relationship with GHG emissions*

H_{13}: *GDP & DR has a significant relationship with GHG emissions*

The data is explored from the descriptive statistics, then the regression to obtain model coefficients. Analysis of Variance (ANOVA) was carried out to test the significance of the model. Analyses were conducted on RStudio version 2024.09.0 (© 2009 – 2024 Posit Software, PBC).

4. RESULTS AND DISCUSSION

The scatter plots from Fig. 2 – Fig. 7 depict the pairwise trend of independent and dependent variables.

The bar plot in Fig. 8. Depicts the ghg emissions from Nigeria within the period 1990- 2020, it can be observed that there is on average an upward trend, implying higher emissions as the year's progresses.

Table 1 gives insight into the characteristics of the data used in this study; it describes the shape and some features of the data. The mean, median, variance, maximum, and minimum values of the variables that have been studied are displayed. All variables are skewed positively, with Solid being highly skewed and having the highest value (2.588989). Additionally, Solid alone appears to be leptokurtic, having a kurtosis (5.535710) greater than 3, while all others are platykurtic (with kurtosis less than 3). The result of the Jarque-Bera test revealed that only Solid is not normally distributed since its p-value is less than 5%; all other variables are normally distributed, having p-values greater than 5%. The simple correlation matrix in Table 2 reveals the association between variables. There exists a strong negative association between the dependent variables (logGDP & logDR), implying that as one of the variables increases, the other decreases at a high rate. That is, an increase in the death rate leads to a decrease in the gross domestic product, whereas the independent variables have a moderately positive association between them except for Solid & Gas, which have a noticeable weak negative correlation, suggesting that an increase in a certain variable suggests an increase in another, while in other instances, the reverse is the case (decrease). This nature of association leads to the formulation of regression models to provide depth and insight into their interactions. Table 3 reveals the variance-covariance matrix of the variables. Table 1. gives an insight into the characteristics of the data used in this study, it describes the shape and some features of the data. The mean, median, variance, maximum and minimum values of the variables that have been studied are displayed. All variables are skewed positively with the Solid been highly skewed having the highest value (2.588989). Also, Solid alone appears to be leptokurtic having kurtosis (5.535710) > 3 while all others are platykurtic (having kurtosis < 3). The result of the Jarque-Bera test revealed that only Solid is not normally distributed since it's p-value is less than 5%, all other variables are normally distributed having p-value greater than 5%. The simple correlation matrix in Table 2. reveals the association between variables. There exists a strong negative association between the dependent variables (logGDP & logDR) implying that, as one of the variables increases the other decreases at a high rate. That is, an increase in the death rate leads to a decrease in the gross domestic product, whereas the independent variables have a moderately positive association between them except solid & gas having a noticeable weak negative correlation, suggesting an increase in a certain variable suggests an increase in another and other instances reverse is the case (decrease). This nature of association leads to the formulation of regression models to give depth and insight into their interactions. Table 3. reveals the variance- covariance matrix of the variables.

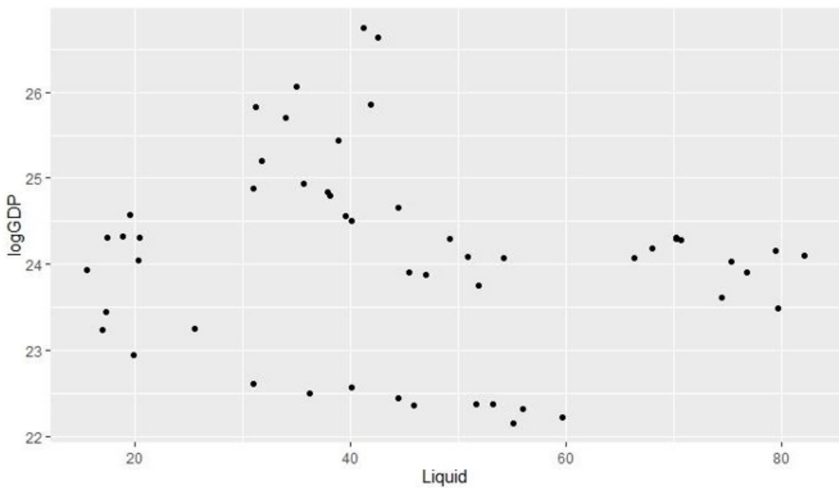

Fig. 2. Scatter plot of logGDP versus liquid form

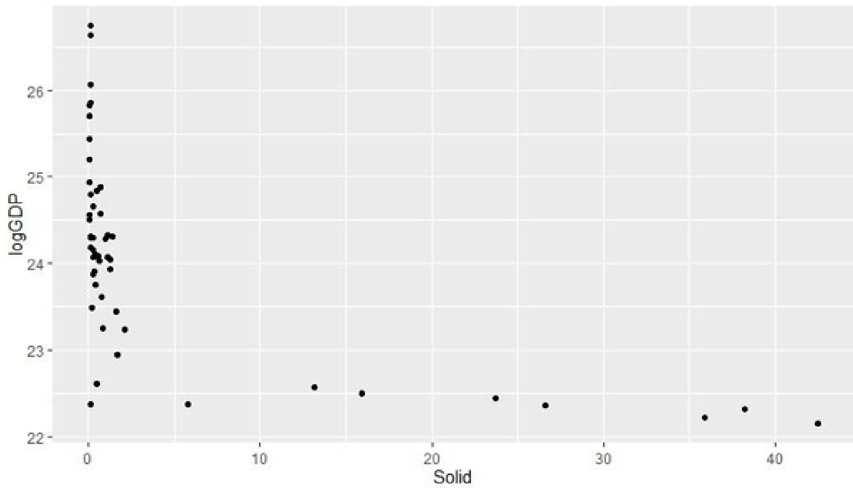

Fig. 3. Scatter plot of logGDP versus solid form

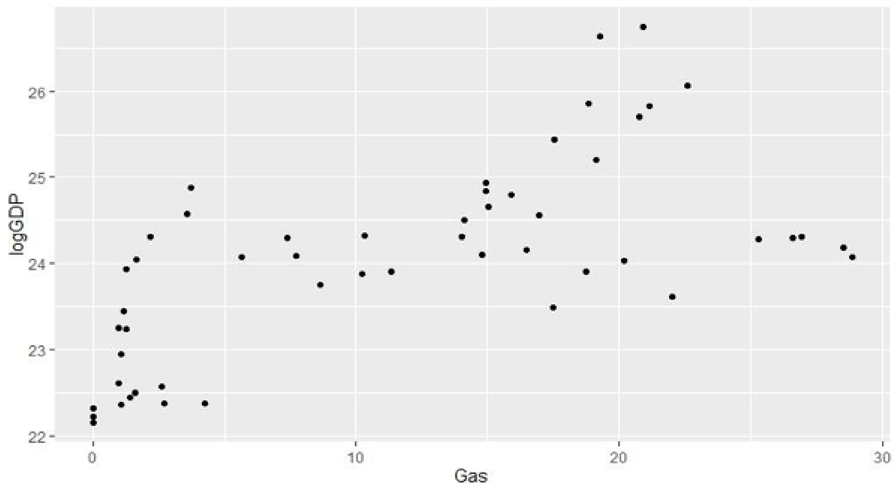

Fig. 4. Scatter plot of logGDP versus gaseous form

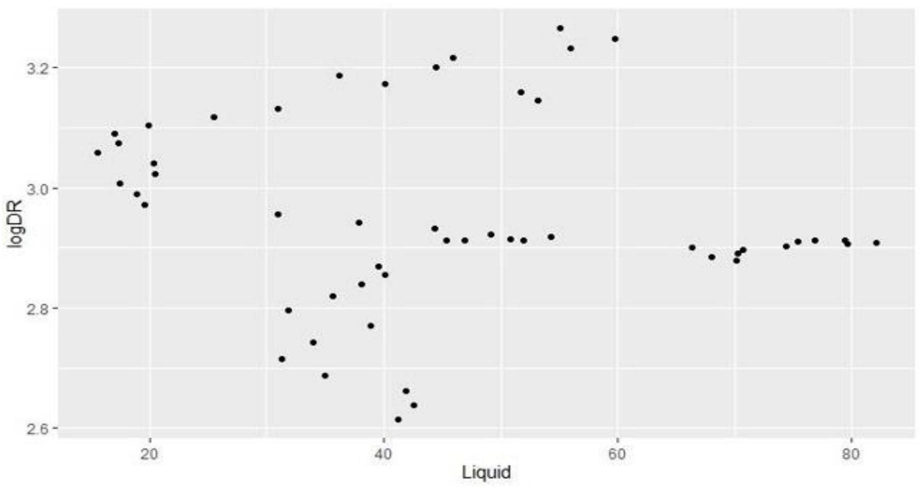

Fig. 5. Scatter plot of logDR versus liquid form

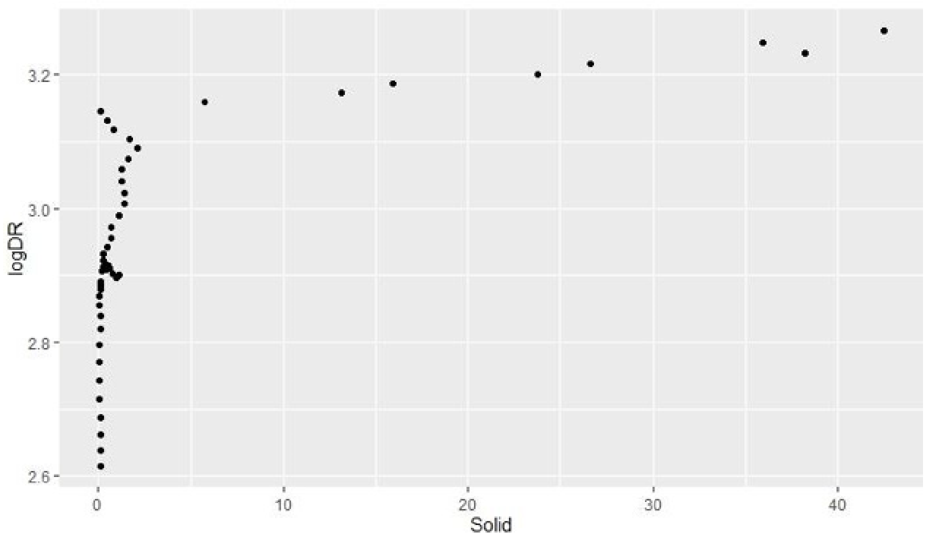

Fig. 6. Scatter plot of logDR versus solid form

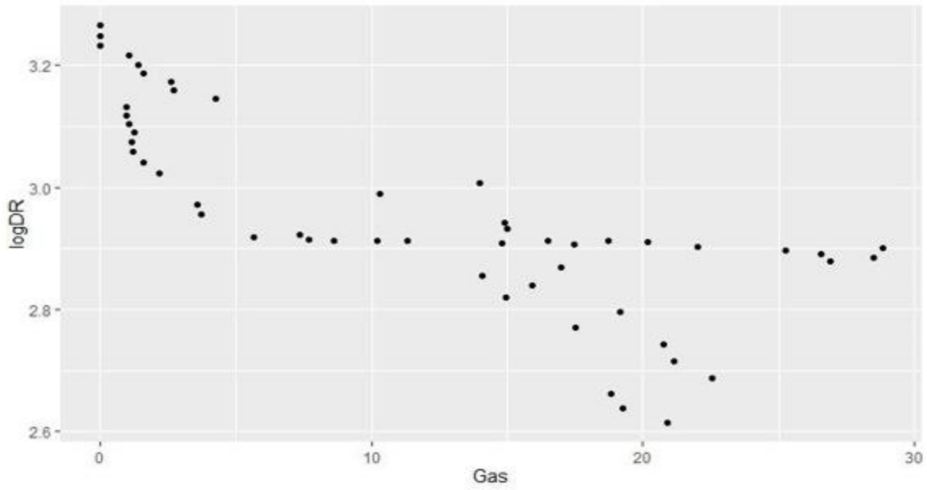

Fig. 7. Scatter plot of logGDP versus gaseous form

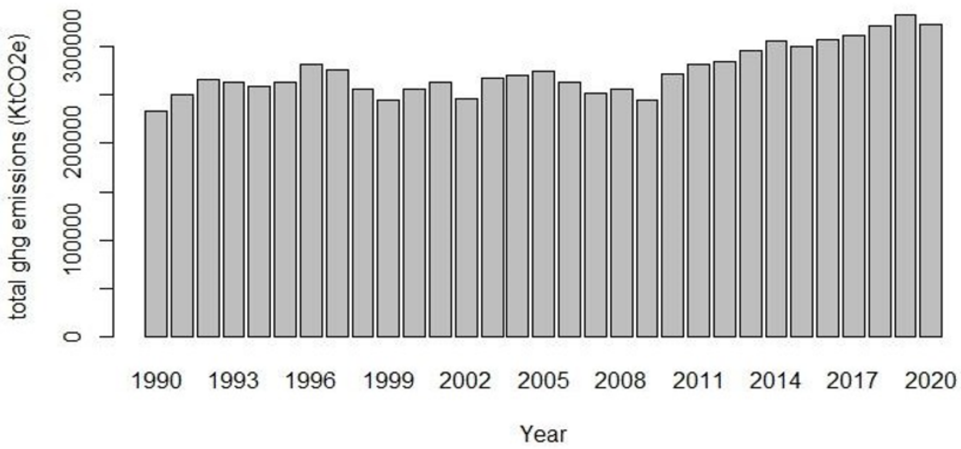

Fig. 8. Total GHG emissions from Nigeria (1990-2020) (*greenhouse gas (ghg) emissions climate watch, 2023)*

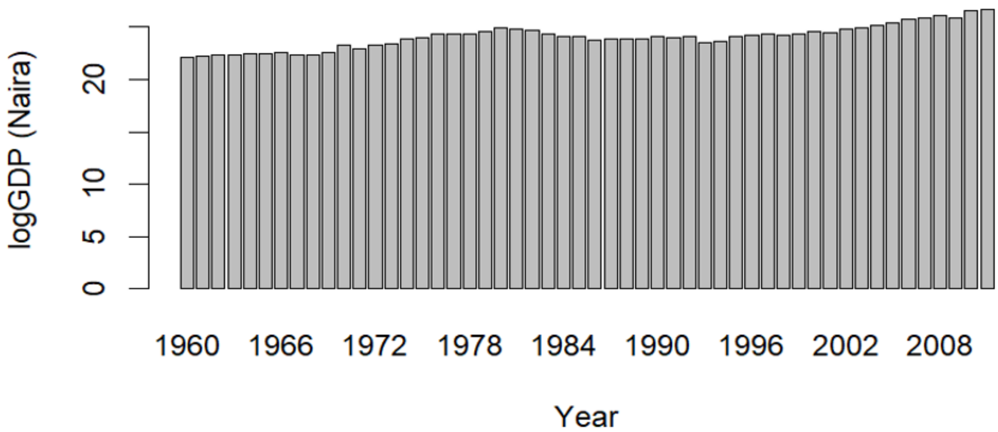

Fig. 9. Log Gross Domestic Product (GDP) of Nigeria from (1960-2011) (https://www.nigerianstat.gov.ng/)

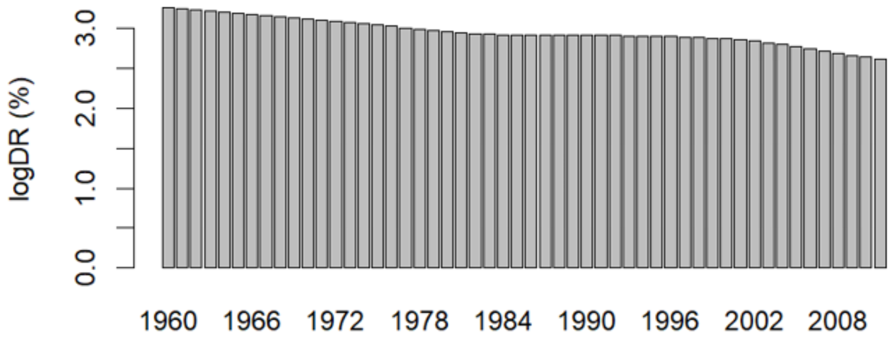

Fig. 10. Log Death Rate (DR) of Nigeria from (1960-2011) (https://www.nigerianstat.gov.ng/)

Table 1. Descriptive statistics

	log GDP	log DR	Liquid	Solid	Gas
Observations (n)	52	52	52	52	52
Minimum	22.158350	2.615496	15.517750	0.015114	0.000000
Maximum	26.744289	3.264805	82.123880	42.518840	28.848980
1st Quartile	23.395670	2.883608	31.672103	0.124291	2.055874
3rd Quartile	24.600558	3.077716	55.325992	1.286846	18.890455
Mean	24.065091	2.954924	45.003468	4.327135	11.624690
Median	24.093980	2.913790	42.204780	0.418869	12.651905
Sum	1251.384745	153.656029	2340.180310	225.011045	604.483864
SE Mean	0.157660	0.022426	2.628732	1.419224	1.257094
LCL Mean	23.748576	2.909902	39.726068	1.477924	9.100968
UCL Mean	24.381606	2.999945	50.280867	7.176347	14.148411
Variance	1.292540	0.026151	359.332100	104.738261	82.174841
Std Deviation	1.136899	0.161713	18.956057	10.234171	9.065034
Skewness	0.205570	0.036157	0.295778	2.588989	0.190702
Kurtosis	-0.356546	-0.590282	-0.906248	5.535710	-1.339701
Jarque-Bera	0.54259	0.54259	2.2724	136.33	3.8505
Probability	0.7689	0.7624	0.321	2.2E-16	0.1458

Table 2. Correlation matrix (Pearson's)

$$\rho = \begin{bmatrix} variable & logGDP & logDR & liquid & solid & gas \\ logGDP & 1.0000000 & -0.9397350 & -0.1387798 & -0.5989205 & 0.6478934 \\ logDR & -0.9397350 & 1.0000000 & -0.1025083 & 0.6582682 & -0.7826115 \\ liquid & -0.1387798 & -0.1025083 & 1.0000000 & 0.1012665 & 0.4802593 \\ solid & -0.5989205 & 0.6582682 & 0.1012665 & 1.0000000 & -0.4791950 \\ gas & 0.6478934 & -0.7826115 & 0.4802593 & -0.4791950 & 1.0000000 \end{bmatrix}$$

Table 3. Variance-covariance matrix

$$\sum = \begin{bmatrix} variable & logGDP & logDR & liquid & solid & gas \\ logGDP & 1.292540 & -0.17277202 & -2.990861 & 6.968574 & 6.677210 \\ logDR & -0.17277202 & 0.02615122 & -0.31423379 & 1.08943546 & -1.14725947 \\ liquid & -2.990861 & -0.31423379 & 359.3320996 & 19.645661 & 82.5264542 \\ solid & 6.968574 & 1.08943546 & 19.645661 & 104.738261 & -44.456413 \\ gas & 6.677210 & -1.14725947 & 82.5264542 & -44.456413 & 82.174841 \end{bmatrix}$$

Table 4a. Regression results in the logGDP model

	Estimate	Std. error	t statistic	Prob	Model Significance	
Intercept	24.337531	0.234930	103.597	2E-16‘***’	R-square	0.6973
Liquid	-0.031180	0.006017	-5.182	4.3E-06‘***’	Adj. R-square	0.6782
Solid	-0.016751	0.011138	-1.504	0.139	F-statistic	36.84
Gas	0.103507	0.014262	7.257	2.97E-09‘***’	Prob.*	1.67E-12‘***’

*Significance levels: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’, 0.1 ‘ ’, 1*

Table 4b. Regression results of logDR model

	Estimate	Std. error	t statistic	Prob	Model Significance	
Intercept	3.0042595	0.0301647	99.595	2E-16‘***’	R-square	0.7532
Liquid	0.0020620	0.0007726	2.669	0.01035‘*’	Adj. R-square	0.7378
Solid	0.0041667	0.0014301	2.914	0.00541‘**’	F-statistic	48.84
Gas	-0.013779	0.0018312	-7.524	1.2E-09‘***’	Prob*.	1.3E-14‘***’

*Significance levels: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’, 0.1 ‘ ’, 1*

Table 5. Canonical correlations

		Stat	Approx.	df1	df2	Prob.*
Cc1	0.8733005	0.1136586	30.80363	6	94	0.00‘***’
Cc2	0.7218916	0.4788726	26.11772	2	48	2.11E-08‘***’
		X Coeff			**Y Coeff**	
Gas	-0.0123759	-0.0093683	-0.0157534	logGDP	0.0711156	-0.3531482
Liquid	0.0005746	0.0090769	0.0020830	logDR	1.3186979	-2.1621870
Solid	0.0049277	-0.0042853	-0.0159887			

*Significance levels: 0 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘.’, 0.1 ‘ ’, 1*

The regression model is significant (p-value =1.67E-12), implying there exists a significant relationship between the independent variables and GDP, further supporting the decision to reject H_{01}. The higher the value of the adjusted R-squared, the better it fits the data; the adjusted R-squared implies the independent variables can account for 67.8% of the variation in GDP. All regression coefficients are significant except for "solid." The first estimated regression model is as follows:

$$logGDP = 24.337531 - 0.031180L - 0.016751S + 0.103507G$$

The model suggests that for every unit increase in independent variables, GDP decreases by 0.031180 and 0.016751, and increases by 0.103507 units, respectively.

The Breusch Pagan test for heteroscedasticity yielded (p -value = 0.09) larger than the level of significance (0.01) which implies Constant variance.

The second model, the log DR model, is also statistically significant (p-value = 1.3E- 14), suggesting that there exists a significant relationship between the independent variables and the death rate. This informs us of our decision not to reject H_{12}. The predictors can account for 73.4% of the variation in the death rate (Adjusted R-squared = 0.7378). The regression coefficients are all significant; thus, the model is effective.

$$logDR = 3.0042595 + 0.0020620L + 0.0041667S - 0.013779G$$

The above model implies that for every unit increase in the independent variables (liquid, solid, and gas), DR increases by 0.0020620 and 0.0041667, respectively, while it decreases by 0.013779 units.

The Breusch Pagan test for heteroscedasticity yielded (p -value = 0.005) larger than the level of significance (0.001) implying Constant variance.

The canonical correlations are significant, both having very small p-values (0.00 and 2.11E- 08), implying that the two groups of variables have meaningful associations between them, leading to the non-rejection of the hypothesis H_{13}. The first canonical correlation (0.8733005) suggests a strong correlation between the sets of variables. Therefore, the GHG emissions can explain the variability in GDP and DR. The second canonical correlation (0.7218916) also supports this claim. The canonical coefficients (X coeff, Y coeff) depict how each variable contributes to the canonical variates.

From the models obtained, we observed that the liquid and solid forms of emissions reduce GDP, while the gaseous form increases GDP. This is illustrated by Fig. 11. Regarding the death rate, the situation is reversed. The liquid and solid forms of emissions increase the death rate, while the gaseous form decreases it. This is illustrated by Fig. 12. This observation might be explained by the following facts: Firstly, the gas form of emission in the area under study corresponds to the lowest maximum source of emission at 28.848980 $KtCO_2e$, while the maximum for the liquid and solid forms was 82.123880 $KtCO_2e$ and 42.518840 $KtCO_2e$, respectively. It may be argued that gaseous emissions are mainly from heavy industries usually located on the outskirts of cities where they are situated. The more a country produces, the higher its GDP over time. The location of these industries minimizes their effect on the health of the inhabitants. Meanwhile, the increase in the death rate from the liquid and solid forms can be linked to everyday activities within the populace, such as transportation, cooking, road construction, and so on, which involve the combustion of fuels. The proximity of these activities to human settlements implies a high risk of air pollution, which can be toxic to humans. It is therefore recommended that energy efficient technologies should be implemented, migration to alternative sources of energy, such as gas, solar and hydraulic sources should be emphasized and adequately utilized. Agricultural programs such as afforestation should be encouraged and implemented all over the country to maintain balance in the ecosystem.

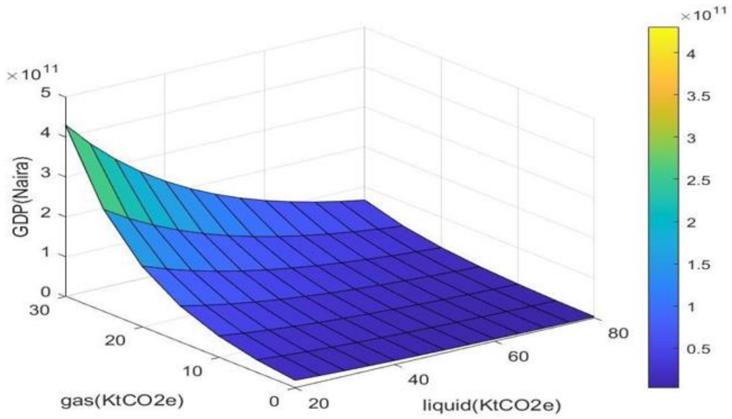

Fig. 11. 3D plot of GDP model with solid as constant

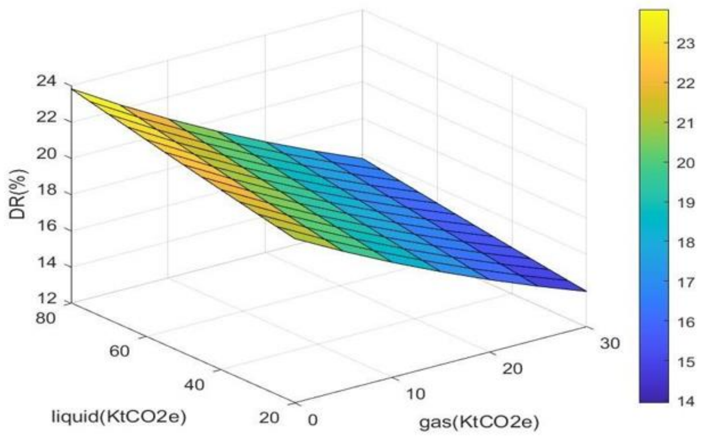

Fig. 12. 3D plot of DR model with solid as constant

5. CONCLUSION

The study results reveal that GHG emissions have a significant effect on gross domestic product and death rates. From the death rate model, it was revealed that an increase in GHG emissions can have adverse effects on human health, thereby leading to an increase in the death rate, which, by extension, can affect life expectancy. Since these emissions release substances into the atmosphere, they have adverse effects on the balance of the ecosystem. Humans inhale the polluted air into their systems, which can have toxic effects in the body. It is necessary to note that most of the research reviewed in the literature studies has not specifically considered the impact of these emissions on the death rate. For the second model, GHG emissions also have a significant effect on GDP, further aligning with previous studies (Achike & Anthony, 2014; Apergis et al., 2010; Menyah & Wolde-Rufael, 2010). In our GDP model, it was revealed that the liquid and solid forms of greenhouse gas emissions led to a decrease in GDP, whereas the gaseous form led to an increase in GDP. This suggests that attention should be given to the two forms to increase gross domestic product. Meanwhile, on the multivariate level, the groups of variables were seen to be strongly correlated, indicating that the quantum of emissions will affect the dependent variables. This approach was necessary because restricting the association to a univariate scope may not fully capture the dynamics of the relationship.

GHG emissions are a major concern in many countries characterized by activities that support these emissions. The populace needs to be healthy before they can build the economy. The first form of wealth must be the individual's health because this is the foundation of every other activity that can be embarked upon. This study has revealed the significance of these emissions to the environment, making it unsafe for the inhabitants. The present investigation may be expanded to other countries' available data.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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