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

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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*

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## 1. INTRODUCTION

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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

\*Corresponding author: E-mail: da2054@hw.ac.uk, david.aji@fuwukari.edu.ng;

25 on. To meet these demands, particularly in agriculture, the use of chemical inputs is altering  
26 natural cycles and causing environmental damage (Ntiamoah et al., 2023; Okorie & Lin, 2022).  
27 Examples include water and air pollution, loss of biodiversity, and increased greenhouse gas  
28 (GHG) emissions. These problems are further intensified by activities like mining, industrial  
29 production, and other commercial ventures (Donou et al., 2024; Mikhaylov et al., 2020; Yue &  
30 Gao, 2018).

31 GHG emissions are simply the release of gases mainly composed of carbon dioxide (CO<sub>2</sub>),  
32 methane (CH<sub>4</sub>), nitrous oxide (N<sub>2</sub>O), and fluorinated gases into the Earth's atmosphere. The  
33 sources of these gases are mainly from human activities, including industrial, agricultural, and  
34 waste management (Chehabeddine & Tvaronavičienė, 2020; Moumen et al., 2019). These  
35 gases, when trapped, further accumulate to constitute the greenhouse effect, which leads to  
36 global warming (Lamb et al., 2021). As the global population is projected to reach 9 billion by  
37 2050 (Achike & Anthony, 2014; Mikhaylov et al., 2020), increasing pressure is being placed  
38 on sectors such as agriculture, forestry, and fisheries to ensure food security. This demand is  
39 driving the search for new lands, often leading to deforestation (Yue & Gao, 2018). Foreign  
40 investment in forest lands has been linked to environmental pollution and forest loss, which  
41 have dangerous consequences for ecosystems and global trade. Deforestation, particularly in  
42 Nigeria, is a major concern as it is a significant contributor to CO<sub>2</sub> emissions (Achike &  
43 Anthony, 2014; Adesiji & Obaniyi, 2012). When forests are cleared and trees are burned or  
44 decay, carbon is released into the atmosphere, increasing GHG concentrations and  
45 exacerbating global warming (Jeffrey et al., 2021). The increasing concentration of GHGs is  
46 already having a negative effect on the environment, human health, and the economy  
47 (Atedhor, 2023). Without concerted efforts to reduce emissions, these impacts are expected  
48 to become more severe.

49 Several research studies have been carried out on the effect of energy consumption on GDP  
50 and other economic indicators (Apergis et al., 2010; Menyah & Wolde-Rufael, 2010; Shakeel  
51 et al., 2014; Tagwi, 2022; Zhang & Cheng, 2009), concerning geographical terrains  
52 (continents) and predominant activities in such territories. Cause-and-effect analysis has been  
53 conducted, and the relationship has been critically analyzed (Apergis et al., 2010; Asafu-  
54 Adjaye, 2000; Coondoo & Dinda, 2002; Nayan et al., 2013; Soytaş et al., 2007; Ziramba,  
55 2009).

56 (Tagwi, 2022) conducted research investigating the effects of climate change (rainfall and  
57 temperature), carbon emissions, and renewable energy consumption on agricultural economic

58 growth in South Africa over the period from 1972 to 2021. Using the ARDL (Auto Regressive  
59 Distributed Lag) model, the authors analyze both the short- and long-term relationships  
60 between these factors. The results depict that climate change has a short-term negative effect  
61 on agriculture, whereas, in the long term, agricultural growth can improve despite climate  
62 challenges. Carbon emissions are positively correlated with agricultural growth, whereas  
63 renewable energy usage appears to have no significant impact on economic growth in either  
64 the short or long term. For the Environmental Kuznets Curve (EKC), CO<sub>2</sub> emissions increase  
65 with economic growth up to a point, after which they decrease as economies mature and  
66 implement cleaner technologies.

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

81 (Hamrani et al., 2020) deployed three categories of machine learning models and compared  
82 their performance in predicting soil GHG emissions. GHG emissions data were collected from  
83 an agricultural research site in Quebec over the period from 2012 to 2017. The data include  
84 CO<sub>2</sub> and N<sub>2</sub>O fluxes along with environmental variables such as air and soil temperature,  
85 precipitation, and humidity. From their study, the LSTM model proved to be the most effective  
86 in predicting both CO<sub>2</sub> and N<sub>2</sub>O emissions from agricultural soils, especially for capturing  
87 short-term variations and peak emissions. Additionally, the Random Forest model offered a  
88 fast and effective alternative for CO<sub>2</sub> prediction but was less accurate for N<sub>2</sub>O emissions.

89 (Nayan et al., 2013) deployed the GMM (Generalized Method of Moments) estimator to ensure  
90 accurate results. In their study, the data used was from 23 selected countries over the period

91 2000–2011. Two models were considered, namely, the energy consumption model and the  
92 GDP model. Results from the former model revealed that GDP has a significant effect on  
93 energy consumption, while for the latter model, energy consumption has a less significant  
94 effect on real GDP per capita. Other significant determinants of energy consumption were  
95 energy price and investment.

96 (Kumar et al., 2024) investigated the GHG emissions from rice crops under various treatment  
97 combinations ( $T_1, T_2, \dots, T_7$ ) of fertilizer management practices. The control treatment  $T_1$  had  
98 no nitrogen in its composition and recorded the lowest  $\text{CO}_2$  emissions, though it had the least  
99 rice output.  $T_2$  had the highest  $\text{CO}_2$  and  $\text{N}_2\text{O}$  emissions, with values of  $1165 \text{ kg CO}_2\text{e ha}^{-1}$   
100 and  $352 \text{ kg CO}_2\text{e ha}^{-1}$ , respectively. The study highlighted the need to balance the drive for  
101 increased rice productivity with environmental sustainability.

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

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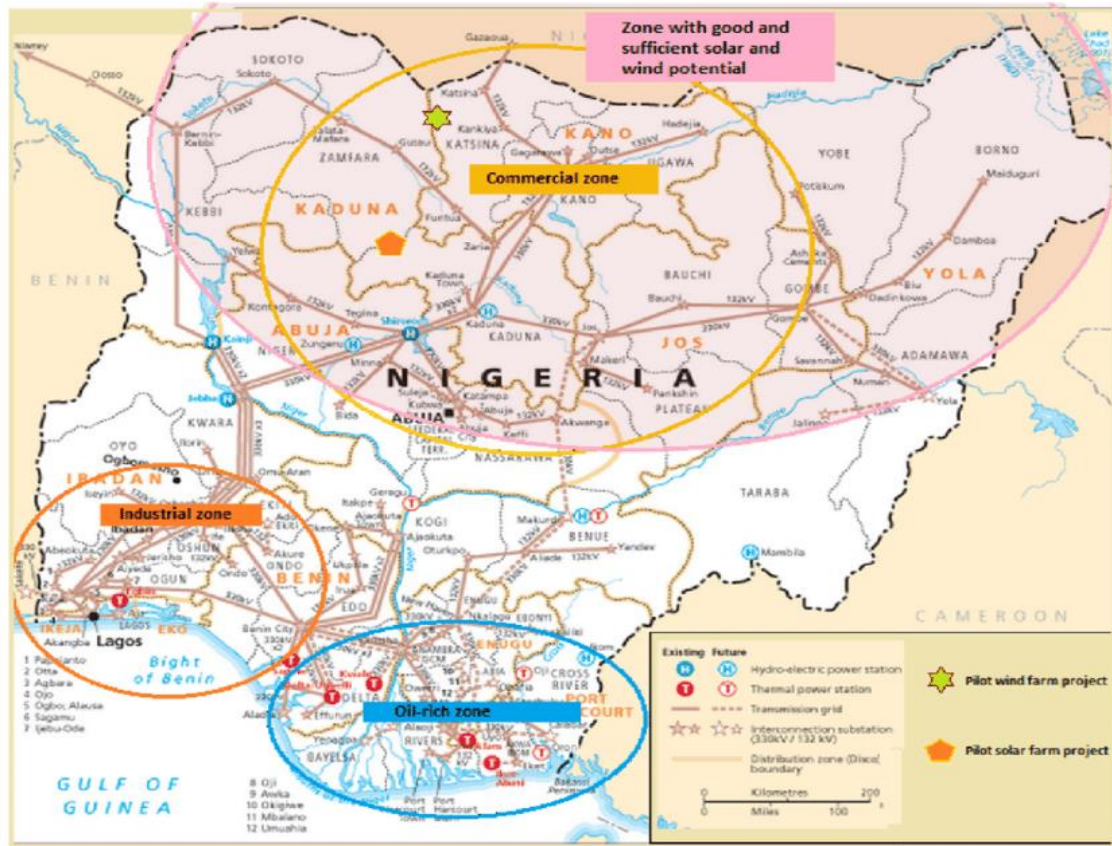
## 108 **2. MATERIAL AND METHODS**

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### 110 **2.1 Study area**

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

115 activities involving fossil fuel processing, distribution, and consumption.



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117 **Fig. 1. Map of Nigeria showing energy resources, distribution, and socio-economic**  
118 **zones** (Adewuyi et al., 2020)

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## 120 **2.2 Data source and framework**

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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).

134 **2.3 Methodology**

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136 **2.3.1 Multiple Regression**

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

140 Two multiple linear regression models are considered here:

141  $GDP_t = f(L_t; S_t; G_t) \Rightarrow GDP_t = \beta_0 + \beta_1 L_t + \beta_2 S_t + \beta_3 G_t + \varepsilon_i$  (1)

142  $DR_t = f(L_t; S_t; G_t) \Rightarrow DR_t = \beta_0 + \beta_1 L_t + \beta_2 S_t + \beta_3 G_t + \varepsilon_i$  (2)

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144 **2.3.2 Log Transformation of Variable**

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

148

149  $\log GDP_t = f(L_t; S_t; G_t) \Rightarrow \log GDP_t = \beta_0 + \beta_1 L_t + \beta_2 S_t + \beta_3 G_t + \varepsilon_i$  (3)

150  $\log DR_t = f(L_t; S_t; G_t) \Rightarrow \log DR_t = \beta_0 + \beta_1 L_t + \beta_2 S_t + \beta_3 G_t + \varepsilon_i$  (4)

151 where.

152  $GDP_t =$  gross domestic product during period  $t$

153  $DR_t =$  death rate during period  $t$

154  $L_t =$  liquid form of GHG emissions at period  $t$

155  $\beta_i$  are regression coefficients, where  $i = 0, 1, 2, 3$

156  $G_t =$  gaseous form of GHG emissions at period  $t$

157  $G_t =$  gaseous form of GHG emissions at period  $t$

158  $\varepsilon_i =$  is the error term

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160 **2.3.3 Canonical Correlation**

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

167 Let  $U = a_1 X_1 + a_2 X_2 + a_3 X_3 = a'X$  (5)

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169  $V = b_1 Y_1 + b_2 Y_2 = b'Y$  (6)

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

172  $a = [a_1, a_2, a_3,]$  and  $b = [b_1, b_2, b_3,]$  are vectors of coefficients (canonical weights) to be

173 determined.  $U$  and  $V$  are linear combinations of  $X$  and  $Y$ . The canonical correlations,  $cc$  are the

174 square roots of the eigenvalues of the following matrix.

175

$$176 \quad R_{YY}^{-1} R_{YX} R_{XX}^{-1} R_{XY} \quad (7)$$

177

178 Where  $R_{XY}$  and  $R_{YX}$  are the Covariance matrices between  $X$  and  $Y$ ,

179 and  $Y$  and  $X$  respectively,  $R_{XX}$  is the covariance matrix of  $X$  with itself, and  $R_{YY}$  is the

180 covariance matrix of  $Y$  and itself.

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### 182 **2.3.4 Hypothesis**

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

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

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

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

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

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

190

191 The data is explored from the descriptive statistics, then the regression to obtain

192 model coefficients. Analysis of Variance (ANOVA) was carried out to test the significance of

193 the model. Analyses were conducted on RStudio version 2024.09.0 (© 2009 – 2024 Posit

194 Software, PBC).

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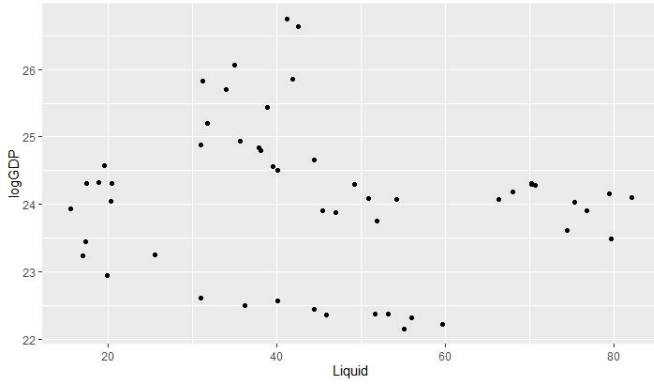
## 196 **3. RESULTS AND DISCUSSION**

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

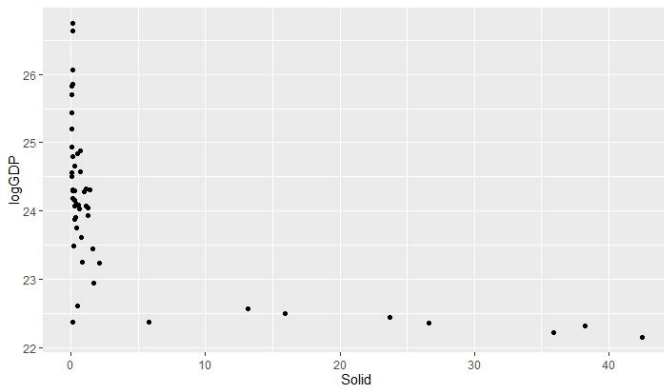
199 variables.

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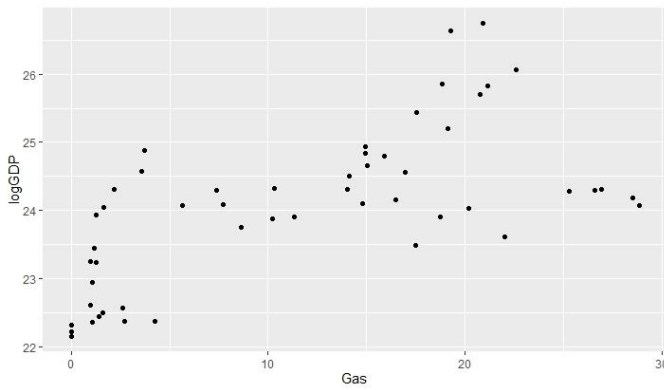
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202 **Fig. 2. Scatter plot of logGDP versus liquid form**



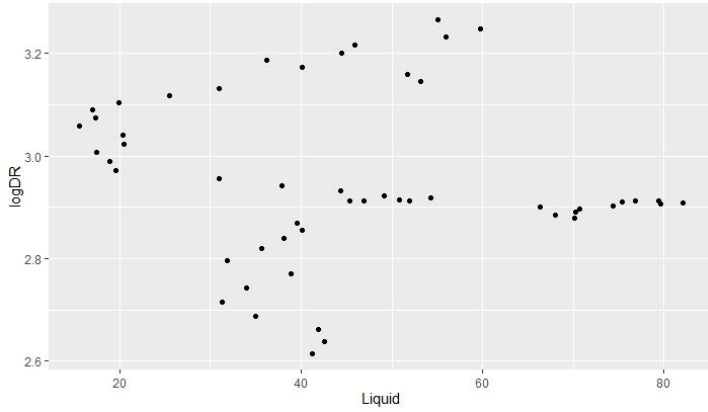
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204 **Fig. 3. Scatter plot of logGDP versus solid form**



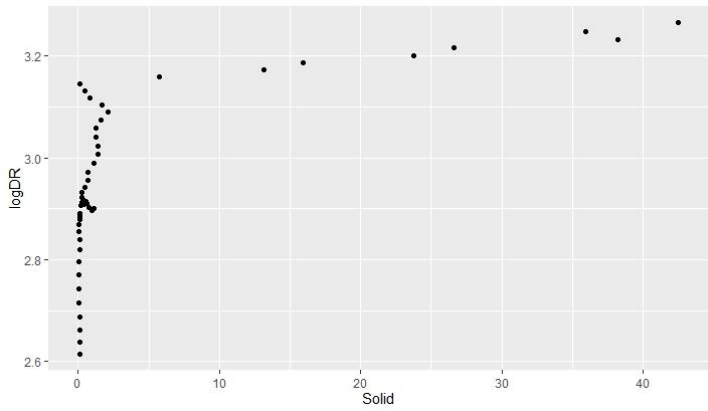
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206 **Fig. 4. Scatter plot of logGDP versus gaseous form**



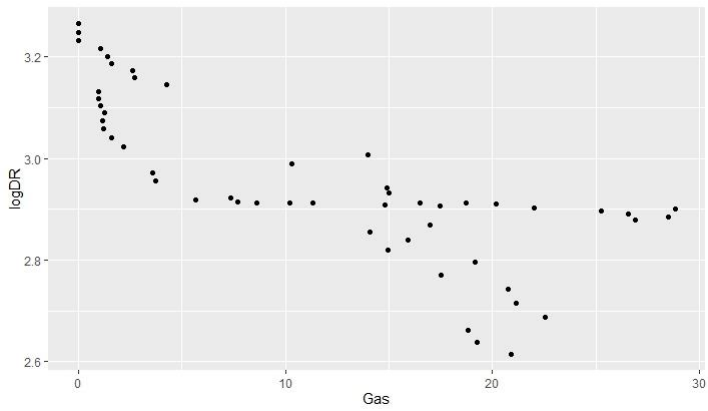
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208 **Fig. 5. Scatter plot of logDR versus liquid form**

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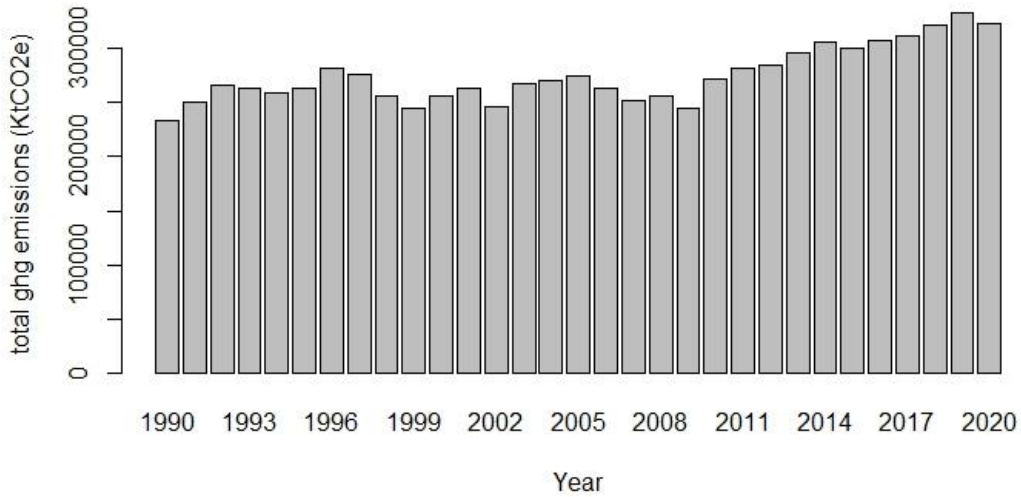
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211 **Fig. 6. Scatter plot of logDR versus solid form**

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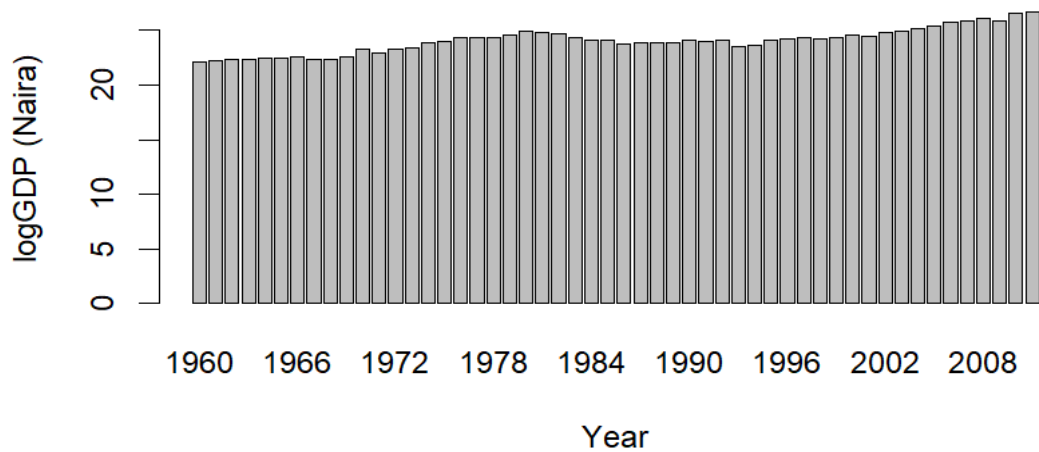


213  
214 **Fig. 7. Scatter plot of logGDP versus gaseous form**

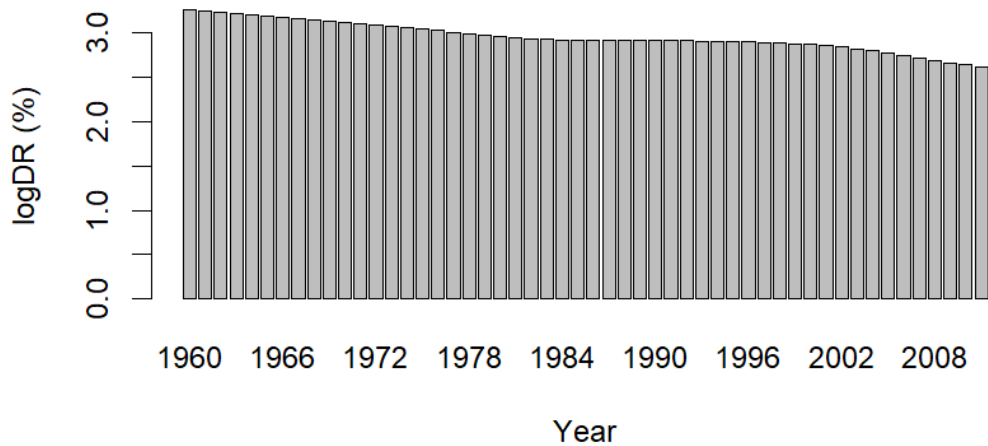
215 The bar plot in Fig. 8. Depicts the ghg emissions from Nigeria within the period 1990-  
 216 2020, it can be observed that there is on average an upward trend, implying higher emissions  
 217 as the year's progresses.  
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 220 **Fig. 8. Total GHG emissions from Nigeria (1990-2020) (greenhouse gas (ghg) emissions**  
 221 **climate watch, 2023)**  
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 228 **Fig. 9. log Gross Domestic Product (GDP) of Nigeria from (1960-2011)**  
 229 **(<https://www.nigerianstat.gov.ng/>)**



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

236 Table 1 gives insight into the characteristics of the data used in this study; it describes  
237 the shape and some features of the data. The mean, median, variance, maximum, and  
238 minimum values of the variables that have been studied are displayed. All variables are  
239 skewed positively, with Solid being highly skewed and having the highest value (2.588989).  
240 Additionally, Solid alone appears to be leptokurtic, having a kurtosis (5.535710) greater than  
241 3, while all others are platykurtic (with kurtosis less than 3). The result of the Jarque-Bera test  
242 revealed that only Solid is not normally distributed since its p-value is less than 5%; all other  
243 variables are normally distributed, having p-values greater than 5%. The simple correlation  
244 matrix in Table 2 reveals the association between variables. There exists a strong negative  
245 association between the dependent variables (logGDP & logDR), implying that as one of the  
246 variables increases, the other decreases at a high rate. That is, an increase in the death rate  
247 leads to a decrease in the gross domestic product, whereas the independent variables have  
248 a moderately positive association between them except for Solid & Gas, which have a  
249 noticeable weak negative correlation, suggesting that an increase in a certain variable  
250 suggests an increase in another, while in other instances, the reverse is the case (decrease).  
251 This nature of association leads to the formulation of regression models to provide depth and  
252 insight into their interactions. Table 3 reveals the variance-covariance matrix of the variables.  
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268 covariance matrix of the variables.

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291 **Table 1. Descriptive statistics**

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

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297 **Table 2. Correlation matrix (Pearson's)**

$$\rho = \begin{bmatrix} \text{variable} & \text{logGDP} & \text{logDR} & \text{liquid} & \text{solid} & \text{gas} \\ \text{logGDP} & 1.000000 & -0.9397350 & -0.1387798 & -0.5989205 & 0.6478934 \\ \text{logDR} & -0.9397350 & 1.000000 & -0.1025083 & 0.6582682 & -0.7826115 \\ \text{liquid} & -0.1387798 & -0.1025083 & 1.000000 & 0.1012665 & 0.4802593 \\ \text{solid} & -0.5989205 & 0.6582682 & 0.1012665 & 1.000000 & -0.4791950 \\ \text{gas} & 0.6478934 & -0.7826115 & 0.4802593 & -0.4791950 & 1.000000 \end{bmatrix}$$

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305 **Table 3. Variance-covariance matrix**

306  $\Sigma =$ 

<i>variable</i>	<i>logGDP</i>	<i>logDR</i>	<i>liquid</i>	<i>solid</i>	<i>gas</i>
<i>logGDP</i>	1.292540	-0.17277202	-2.990861	6.968574	6.677210
<i>logDR</i>	-0.17277202	0.02615122	-0.31423379	1.08943546	-1.14725947
<i>liquid</i>	-2.990861	-0.31423379	359.3320996	19.645661	82.5264542
<i>solid</i>	6.968574	1.08943546	19.645661	104.738261	-44.456413
<i>gas</i>	6.677210	-1.14725947	82.5264542	-44.456413	82.174841

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309 **Table 4a. Regression results in the logGDP model**

	Estimate	Std. error	t statistic	Prob	Model Significance	
<b>Intercept</b>	24.337531	0.234930	103.597	2E-16 <sup>****</sup>	<b>R-square</b>	0.6973
<b>Liquid</b>	-0.031180	0.006017	-5.182	4.3E-06 <sup>****</sup>	<b>Adj. R-square</b>	0.6782
<b>Solid</b>	-0.016751	0.011138	-1.504	0.139	<b>F-statistic</b>	36.84
<b>Gas</b>	0.103507	0.014262	7.257	2.97E-09 <sup>****</sup>	<b>Prob.*</b>	1.67E-12 <sup>****</sup>

310 \*Significance levels: 0 <sup>\*\*\*\*</sup>, 0.001 <sup>\*\*\*</sup>, 0.01 <sup>\*\*</sup>, 0.05 <sup>\*</sup>, 0.1 <sup>'</sup>, 1

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

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

318 The model suggests that for every unit increase in independent variables, GDP decreases by  
 319 0.031180 and 0.016751, and increases by 0.103507 units, respectively.

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

322

323 **Table 4b. Regression results of logDR model**

	Estimate	Std. error	t statistic	Prob	Model Significance	
<b>Intercept</b>	3.0042595	0.0301647	99.595	2E-16 <sup>****</sup>	<b>R-square</b>	0.7532
<b>Liquid</b>	0.0020620	0.0007726	2.669	0.01035 <sup>**</sup>	<b>Adj. R-square</b>	0.7378
<b>Solid</b>	0.0041667	0.0014301	2.914	0.00541 <sup>***</sup>	<b>F-statistic</b>	48.84
<b>Gas</b>	-0.013779	0.0018312	-7.524	1.2E-09 <sup>****</sup>	<b>Prob*.</b>	1.3E-14 <sup>****</sup>

324 \*Significance levels: 0 <sup>\*\*\*\*</sup>, 0.001 <sup>\*\*\*</sup>, 0.01 <sup>\*\*</sup>, 0.05 <sup>\*</sup>, 0.1 <sup>'</sup>, 1

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

330 
$$\log DR = 3.0042595 + 0.0020620L + 0.0041667S - 0.013779G$$

331 The above model implies that for every unit increase in the independent variables (liquid, solid,  
 332 and gas), DR increases by 0.0020620 and 0.0041667, respectively, while it decreases by  
 333 0.013779 units.

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

336

337

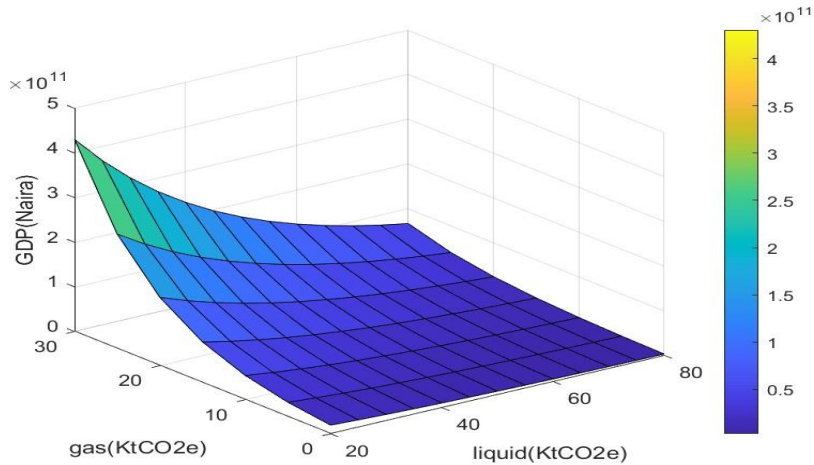
338 **Table 5. Canonical correlations**

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

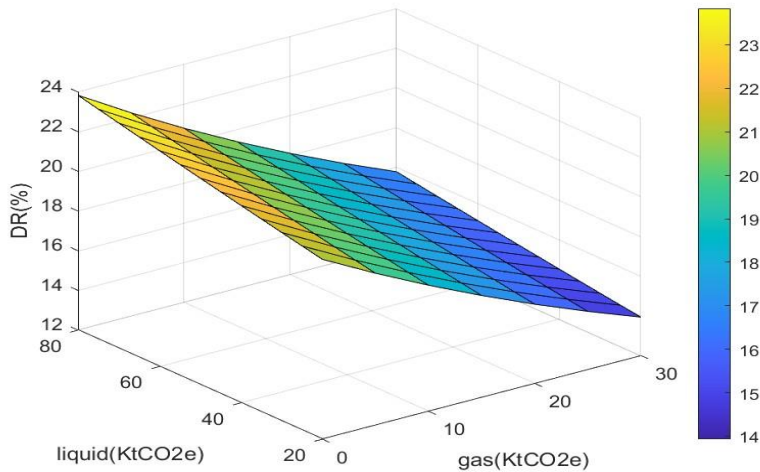
339 \*Significance levels: 0 \*\*\*\*, 0.001 \*\*\*, 0.01 \*\*, 0.05 ', 0.1 ' , 1

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

347



348  
 349 **Fig. 11. 3D plot of GDP model with solid as constant**  
 350  
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352  
 353 **Fig. 12. 3D plot of DR model with solid as constant**  
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355 From the models obtained, we observed that the liquid and solid forms of emissions reduce  
 356 GDP, while the gaseous form increases GDP. This is illustrated by Fig. 11. Regarding the  
 357 death rate, the situation is reversed. The liquid and solid forms of emissions increase the death  
 358 rate, while the gaseous form decreases it. This is illustrated by Fig. 12. This observation might  
 359 be explained by the following facts: Firstly, the gas form of emission in the area under study  
 360 corresponds to the lowest maximum source of emission at 28.848980 KtCO<sub>2</sub>e, while the  
 361 maximum for the liquid and solid forms was 82.123880 KtCO<sub>2</sub>e and 42.518840 KtCO<sub>2</sub>e,  
 362 respectively. It may be argued that gaseous emissions are mainly from heavy industries  
 363 usually located on the outskirts of cities where they are situated. The more a country produces,  
 364 the higher its GDP over time. The location of these industries minimizes their effect on the

365 health of the inhabitants. Meanwhile, the increase in the death rate from the liquid and solid  
366 forms can be linked to everyday activities within the populace, such as transportation, cooking,  
367 road construction, and so on, which involve the combustion of fuels. The proximity of these  
368 activities to human settlements implies a high risk of air pollution, which can be toxic to  
369 humans. It is therefore recommended that energy efficient technologies should be  
370 implemented, migration to alternative sources of energy, such as gas, solar and hydraulic  
371 sources should be emphasized and adequately utilized. Agricultural programs such as  
372 afforestation, should be encouraged and implemented all over the country to maintain balance  
373 in the ecosystem.

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#### **4. CONCLUSION**

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

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

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402 **COMPETING INTERESTS**

403 Authors have declared that no competing interests exist.

404

405 **AUTHORS' CONTRIBUTIONS**

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

408

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## 507 **DEFINITIONS, ACRONYMS, ABBREVIATIONS**

508 **DR** – Death rate

509 **GDP** – Gross Domestic Product

510 **Cc** – Canonical correlation

511  $H_{0i}$  –  $i^{\text{th}}$  null hypothesis

512  $H_{1j}$  –  $j^{\text{th}}$  alternative hypothesis

513 **KtCO<sub>2</sub>e** – Kilotonnes of Carbon dioxide equivalent. Which is a unit measurement for  
514 greenhouse gas emissions.

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