



GREENHOUSE GAS EMISSIONS AND NEONATAL MORTALITY IN NIGERIA

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Abstract: The rise in greenhouse gas emissions alongside persistent neonatal mortality in Nigeria has generated concern about the environmental-health nexus. This study examined the impact of greenhouse gas emissions on neonatal mortality rate in Nigeria from 1981 to 2023. The study employed the Johansen cointegration technique, Vector Error Correction Model (VECM), and Toda-Yamamoto causality test. Findings revealed that carbon dioxide emissions had a negative and significant effect on neonatal mortality in the long run, while methane and nitrous oxide emissions had positive and significant effects at the 5% level. Household consumption negatively and significantly affected neonatal mortality in the long run. In the short run, carbon dioxide, methane, and nitrous oxide emissions had positive but insignificant effects, whereas household consumption had a negative and significant effect. The study concludes that greenhouse gas emissions have heterogeneous effects on neonatal mortality. It recommends cleaner energy transition, stronger healthcare services, and inclusive development to improve neonatal survival.

Keywords: Greenhouse Gas Emission, Neonatal mortality, Carbon Dioxide Emission, Methane Emission, Nigeria

JEL Classification: Q54, I15, Q53

Introduction

Greenhouse gas (GHG) emissions have become one of the most important environmental and public health challenges confronting the global community. Since the Industrial Revolution, emissions generated largely through fossil-fuel combustion, land-use changes, deforestation, industrial production, agriculture,

and transportation have contributed substantially to the accumulation of heat-trapping gases in the atmosphere. The major greenhouse gases include carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), and fluorinated gases, which differ in their atmospheric concentration, persistence, and global warming potential (Wilkinson et al., 2024). The continued increase in these emissions has accelerated global warming and contributed to changes in temperature patterns, rainfall variability, droughts, flooding, declining air quality, and other climate-related risks. Consequently, the consequences of GHG emissions extend beyond environmental degradation to encompass substantial socioeconomic and public health implications (Zhang et al., 2024).

The health consequences of rising GHG emissions are particularly important because their effects operate through both direct and indirect pathways. Increased concentrations of greenhouse gases alter climatic conditions, while the associated changes in temperature, precipitation, atmospheric chemistry, and ecological systems influence human exposure to environmental hazards. Extreme heat, deteriorating air quality, floods, droughts, changing patterns of infectious diseases, food insecurity, and disruptions to health systems are among the pathways through which climate change can affect population health. These effects are not uniformly distributed across populations. Infants, pregnant women, older persons, and individuals living in environmentally vulnerable communities are particularly susceptible because of their biological and socioeconomic vulnerabilities. Thus, the consequences of GHG emissions constitute not only an environmental challenge but also an emerging dimension of public health policy.

The problem is particularly significant in developing countries, where rapid population growth, urbanisation, economic expansion, energy poverty, and limited environmental regulatory capacity can intensify exposure to emission-related risks. Although developing countries have historically contributed less to cumulative global emissions than many industrialised economies, their populations are often more vulnerable to the health consequences of environmental and climatic changes (Pierre et al., 2025). In sub-Saharan Africa, agriculture, land-use change, deforestation, household energy consumption, transportation, and fossil-fuel-dependent economic activities constitute important sources of emissions. Smallholder agriculture and livestock production account for a substantial proportion of agricultural emissions in the region, while deforestation and land conversion release carbon stored in vegetation and soils (Food and Agriculture

Organization [FAO], 2021). At the household level, widespread dependence on biomass fuels for cooking also contributes to indoor and ambient air pollution. The World Health Organization (WHO, 2023) reports that a large proportion of households in sub-Saharan Africa continue to rely on polluting cooking fuels, thereby increasing exposure to harmful combustion products.

Nigeria presents a particularly important case in examining the relationship between environmental emissions and health outcomes. As one of Africa's largest economies and a major oil- and gas-producing country, Nigeria's emission profile is influenced by petroleum production, gas flaring, transportation, electricity generation, industrial activities, agriculture, deforestation, and household energy consumption. Rapid population growth and urbanisation have further increased energy demand and the associated environmental pressures. A substantial proportion of Nigerian households continue to rely on biomass fuels such as firewood, charcoal, and crop residues for cooking, while inadequate and unreliable electricity supply has encouraged widespread dependence on petrol- and diesel-powered generators. These energy-use patterns increase exposure to combustion-related pollutants and contribute to the country's overall environmental burden (Ogungbenle & Rufus, 2022; Akeem, 2024). In addition, petroleum exploration and production, particularly gas flaring, remains an important source of emissions and environmental degradation in oil-producing areas of the country. Deforestation resulting from agricultural expansion, logging, and fuelwood collection further contributes to the release of stored carbon and the deterioration of environmental quality.

The health implications of these environmental pressures are considerable. In addition to their contribution to climate change, emission-generating activities can increase human exposure to air pollutants and create environmental conditions that adversely affect health. This is particularly important for maternal and neonatal health because pregnancy and the neonatal period constitute highly sensitive stages of the life course. Exposure to elevated temperatures and air pollution during pregnancy has been associated with adverse birth outcomes, while maternal exposure to environmental hazards may affect foetal development, birth weight, gestational age, and neonatal survival. Furthermore, climate-related changes can alter the geographical and seasonal distribution of infectious diseases, increase food and water insecurity, and disrupt access to essential maternal and newborn health services. In settings characterised by weak health infrastructure and limited

adaptive capacity, these pathways may reinforce existing risks of maternal and neonatal mortality.

Neonatal mortality remains a major public health challenge in Nigeria. The neonatal period, defined as the first 28 days after birth, represents one of the most vulnerable stages of human development, with a substantial proportion of under-five deaths occurring during this period. Nigeria continues to experience a relatively high neonatal mortality burden compared with many other countries, reflecting persistent challenges associated with prematurity, birth complications, infections, low birth weight, inadequate maternal healthcare, poor sanitation, malnutrition, and limited access to quality newborn care. Although socioeconomic conditions and health-system deficiencies are well-established determinants of neonatal mortality, increasing attention is being given to the role of environmental conditions in shaping newborn survival.

The potential relationship between GHG emissions and neonatal mortality can be explained through several interconnected mechanisms. First, emission-generating activities may increase exposure to air pollution, particularly where households depend on firewood, charcoal, kerosene, or other polluting fuels for cooking. Pregnant women and newborns living in such environments may be exposed to harmful combustion products that can adversely affect respiratory health and pregnancy outcomes. Second, increasing temperatures associated with climate change can expose pregnant women to heat stress, potentially increasing the risk of adverse birth outcomes, including preterm delivery and low birth weight. Third, changes in rainfall and temperature patterns can affect the transmission of climate-sensitive diseases, including malaria, which may adversely affect maternal health and pregnancy outcomes. Fourth, climate-related floods and droughts can disrupt food production, increase food insecurity, damage healthcare infrastructure, and reduce access to essential maternal and neonatal services. These pathways suggest that the relationship between GHG emissions and neonatal mortality may extend beyond a simple pollution-mortality relationship to encompass a broader interaction between environmental conditions, maternal health, household vulnerability, and healthcare access.

The Nigerian government's response to environmental and climate-related risks has included several policy and institutional initiatives aimed at reducing emissions and strengthening climate resilience. These include the country's Nationally Determined Contribution (NDC) under the Paris Agreement, the Climate Change Act of 2021, initiatives aimed at reducing methane emissions and gas flaring,

and the Energy Transition Plan launched in 2022. Climate-smart agriculture and forestry initiatives have also been promoted as mechanisms for reducing emissions while improving resilience in the agricultural sector (FAO, 2016; United Nations Framework Convention on Climate Change [UNFCCC], 2021). These interventions demonstrate increasing recognition of the relationship between environmental sustainability, energy policy, economic development, and public welfare. However, the extent to which efforts to reduce GHG emissions can generate measurable improvements in neonatal health remains insufficiently established.

The emerging empirical literature provides evidence that environmental pollution and climate-related factors can influence health outcomes, but the specific relationship between GHG emissions and neonatal mortality in Nigeria remains inadequately investigated. Existing studies have examined the effects of environmental pollution, greenhouse gas emissions, climate change, and related environmental factors on broader health outcomes (Benjamin et al., 2023; Olawale, 2023; Oyedele, 2022). Other studies have reported associations between exposure to air pollution and adverse infant health outcomes. For instance, Akinyemi et al. (2022) found that infants born in areas characterised by higher levels of air pollution faced greater risks of mortality during the neonatal period. However, evidence focusing specifically on the aggregate relationship between GHG emissions and neonatal mortality in Nigeria remains limited.

This gap is important for at least three reasons. First, much of the existing literature treats environmental pollution, climate change, and greenhouse gas emissions as interchangeable concepts, despite their distinct measurement characteristics and transmission mechanisms. Second, studies of neonatal mortality in Nigeria have predominantly concentrated on proximate socioeconomic, demographic, maternal, and healthcare determinants, with comparatively limited attention to environmental emissions as a macro-level determinant of neonatal survival. Third, the Nigerian context is characterised by a combination of high environmental vulnerability, widespread household dependence on polluting energy sources, rapid urbanisation, petroleum-related activities, and persistent neonatal mortality. Understanding whether changes in GHG emissions are associated with changes in neonatal mortality is therefore important for determining whether environmental policy can also serve as an instrument for improving population health.

Moreover, the relationship between GHG emissions and neonatal mortality may not necessarily be linear. At relatively low levels of environmental degradation,

incremental increases in emissions may have limited observable effects on neonatal mortality, whereas beyond certain environmental or socioeconomic thresholds, additional emissions may generate disproportionately larger health consequences. Conversely, improvements in environmental quality may not immediately translate into reductions in neonatal mortality where other constraints, such as inadequate healthcare infrastructure, poverty, maternal health risks, or poor sanitation, remain binding. This possibility underscores the importance of empirically examining the magnitude and direction of the relationship rather than assuming that changes in emissions automatically translate into proportional changes in neonatal mortality.

Against this background, this study examines the impact of greenhouse gas emissions on neonatal mortality in Nigeria. The study is motivated by the need to expand the analysis of neonatal mortality beyond conventional demographic, socioeconomic, and healthcare determinants by explicitly incorporating environmental conditions into the analysis. By investigating the relationship between GHG emissions and neonatal mortality, the study seeks to provide empirical evidence on whether environmental degradation constitutes a significant determinant of newborn survival in Nigeria. The findings are expected to contribute to the literature on the climate-health nexus and provide evidence that can inform environmental, energy, public health, and maternal and neonatal health policies. In particular, the study may provide a basis for assessing whether emission-reduction strategies can generate health co-benefits and whether environmental policies should be more explicitly integrated into Nigeria's strategies for reducing neonatal mortality.

Literature Review

This study is grounded on Grossman health model, which was first presented by Michael Grossman in his groundbreaking 1972 work on the idea of Health Capital and the Demand for Health, which is considered a landmark contribution to the field of health economics (Grossman, 1972). This theoretical framework offers a strong economic lens through which to view people's choices about health investments and reinterprets health as a type of capital stock, similar to human or physical capital. According to the Grossman model, people invest in their health as a long-term capital stock to improve their productivity and general well-being (Kenkel, 1991). The model posits that individuals inherit an initial stock of health at birth, which depreciates over time due to aging, illness, or lifestyle factors but can be augmented

through investments such as medical care, healthy behaviors, and time allocation. The model's dynamic nature, which takes lifetime health decisions into account, is one of its main characteristics. By balancing the costs (such as medical expenses and exercise time) against the benefits (such as increased longevity, reduced sick days, and increased productivity), people maximise their investments in their health. According to the model, people will spend more on their health when the benefits like more time spent working or relaxing are high and less when the costs are greater or when their health deteriorates quickly (as they age). The Grossman model provides a helpful lens through which to view how health investments affect neonatal outcomes in the context of neonatal mortality and greenhouse gas emissions. In order to improve their newborns' health capital, parents especially mothers invest in their own health during pregnancy through prenatal care and nutrition. Greenhouse gas emissions, as an environmental factor, can indirectly affect neonatal health by increasing risks like heat stress or air pollution, which may reduce the effectiveness of health investments. The Grossman model highlights the need for policies that enhance access to healthcare and mitigate environmental risks to improve neonatal health outcomes.

A growing number of empirical studies examine the relationship between environmental factors and health outcomes in developing and developed countries. A study by Waltona et al. (2025) examined the connection between UK mortality rates and emissions. Using life-table analysis and an incidence or prevalence model, mortality and multi-morbidity impacts were estimated for the years 2019-2154 (a lifetime after 2050). The findings indicated that because emissions raised the incidence of disease, they had a negative impact on mortality. Javanshirova (2024) used data from 1982–2022 to investigate how emissions affected Azerbaijan's infant mortality rates (IMR). Using the ARDL technique, the study's findings demonstrated that rising CO₂ emissions raised the infant mortality rate.

Benjamin et al. (2023) examined the effects of emissions and fossil fuel consumption on the infant and under-5 mortality rates in Nigeria between 1981 and 2019 using the Autoregressive Distributed Lag model. According to the analysis, both in the short run and long run, carbon dioxide emissions increased infant and under-5 mortality rates. Anugwom (2023) looked at how Nigerian health outcomes were affected by greenhouse gas emissions between 1990 and 2021. The results of the data analysis, which employed the Vector Error Correction Model (VECM), showed that greenhouse gas emissions have a detrimental effect on Nigerian health outcomes.

Olawale (2023) carried out a study about carbon dioxide emissions and adult mortality rate in Nigeria, utilizing the Autoregressive Distributed Lag technique from 1980 to 2019. The results showed that CO₂ emissions increase adult mortality rates both in the short and long run.

Oyedele (2022) investigated the effects of emissions on health in Nigeria between 1980 and 2016. A bound cointegration approach and an autoregressive distributed lag model were also used in the study, which broke down carbon dioxide emissions by sector and fuel type using two health outcome measures (mortality and life expectancy). The findings showed that both infant and under-five mortality rates were significantly explained by total carbon dioxide emissions. But when broken down, carbon dioxide emissions from solid fuels were the main cause of adverse health effects.

Adeleye et al. (2022) examined these inherent relationships using mortality rates, renewable energy, carbon emissions (a stand-in for environmental degradation), and real per capita income. Using an unbalanced sample of 47 Sub-Saharan African nations between 2005 and 2019, this study found that higher mortality rates were linked to both carbon emissions and renewable energy. Rasoulinezhad et al. (2020) examined the relationship between CO₂ emissions, mortality rate, and economic factors in the Commonwealth of Independent States (CIS) region from 1993 to 2018. They also examined the effects of CO₂ emissions and the use of fossil fuels. According to the generalised method of moments (GMM) estimation result, CO₂ emissions had the biggest detrimental impact on the death rate in the CIS.

Ogunbenle and Rufus (2022) used data from 1981 to 2019 and the Autoregressive Distributed Lags (ARDL) Model to investigate the relationship between carbon emissions and Nigeria's mortality rate. The study discovered a positive correlation between the mortality rate and carbon emissions. From the review of literature, it shows that there are existing studies on the impact of greenhouse gas emissions on mortality rate. However, how neonatal mortality rate is affected by different greenhouse gas emissions such as Carbone emission, methane and nitrous oxide has been rarely studied hence, the need for further research. Furthermore, previous research has not revealed how neonatal mortality rate respond to shocks in greenhouse gas emission in Nigeria thus, this study seeks to fill this gap.

Methodology

This study relied on secondary data obtained from a single source. Data of neonatal mortality, carbon emission, methane, and nitrous oxide, and data on consumption

obtained from World Bank database for the period between 1981 and 2023. Neonatal Mortality which is the number of deaths of newborns within the first 28 days of life (0–27 days) per 1,000 live births is measured in Percent. Carbon emission as a Greenhouse gas emission release through human (anthropogenic) activities such as the burning of fossil fuels, industrial processes, and land-use changes is measured in percent. Methane (CH_4) is release during decomposition of organic matter in wetlands or digestive system of animals and is measured in percent. Nitrous oxide (N_2O) as emission is caused by human actions on the soil or agricultural activities and is caused percent. Household consumption is the goods and services used by households for final consumption and is measured in percent.

This study adopted the model of Javanshirova. (2024) who explored the impact of carbon emissions on infant mortality rate. The model was specified as:

$$IMR = f(CO_2) \quad (1)$$

Where; IMR is infant mortality rate, and CO_2 is carbon emission.

However, this study modified the model by including other greenhouse gas emission such as methane (CH_4), and nitrous oxide (N_2O). The study also replaced infant mortality rate with neonatal mortality rate as dependent variable in the model in line with the objective of the study. In addition, given that the nature and quality of food consume can promote health or reduce susceptibility to disease, this study used consumption as a control variable.

$$NMR = f(CO_2, CH_4, N_2O, CSP) \quad (2)$$

Where; NMR is Neonatal mortality rate, CO_2 is Carbon emission, CH_4 is methane, N_2O is nitrous oxide and CSP is household consumption.

The stochastic form of the model is specified as:

$$NMR_t = \beta_0 + \beta_1 CO_{2t} + \beta_2 CH_{4t} + \beta_3 N_{2O_t} + \beta_4 CSP_t + \mu_t \quad (3)$$

Where; β_0 is the intercept of the model, $\beta_1 - \beta_4$ are the model parameters to be estimated.

The transformed model is written as:

$$NMR_t = \beta_0 + \beta_1 CO_{2t} + \beta_2 CH_{4t} + \beta_3 N_{2O_t} + \beta_4 LNCSP_t + \mu_t \quad (4)$$

The study used a semi-log model and only consumption (measured in billion naira) is transformed to stabilize the variance and linearize the series, while other variables which are in rate and percentages are not log. The reason for not transforming

the variables in percentages or rate into log form is because log transformations are **undefined for zero or negative values** and rate or percentages can assume such properties (zero or negative). Thus, if variable such as neonatal mortality rate is zero in a year, log application will fail. The specified model in equation 3 addresses objectives 1 and 2 respectively.

This study used Augmented Dicker-Fuller (ADF) unit root test developed by Dickey and Fuller, (1979), and further confirmed the stationarity of the series using Phillips and Perron (1988) unit root test. The study utilized Johansen Cointegration Technique and Vector Error Correction Method (VECM) for estimation. The Johansen Cointegration Technique developed by Johansen (1988), and Johansen and Juselius (1990) stands out as a powerful and rigorous multivariate method for identifying and estimating long-run relationships among multiple time series variables. Using the model variables, the Johansen cointegration model is specified in the VAR framework as:

$$\Delta NMR_t = \beta_0 + \beta_1 \Delta NMR_{t-i} + \beta_2 \Delta CO_{2t-i} + \beta_3 \Delta CH_{4t-i} + \beta_4 \Delta N_2O_{t-i} + \beta_5 \Delta LNCSP_{t-i} + \varepsilon_{1t} \quad (7)$$

$$\Delta CO_{2t} = \beta_0 + \beta_1 \Delta NMR_{t-i} + \beta_2 \Delta CO_{2t-i} + \beta_3 \Delta CH_{4t-i} + \beta_4 \Delta N_2O_{t-i} + \beta_5 \Delta LNCSP_{t-i} + \varepsilon_{1t} \quad (8)$$

$$\Delta CH_{4t} = \beta_0 + \beta_1 \Delta NMR_{t-i} + \beta_2 \Delta CO_{2t-i} + \beta_3 \Delta CH_{4t-i} + \beta_4 \Delta N_2O_{t-i} + \beta_5 \Delta LNCSP_{t-i} + \varepsilon_{1t} \quad (9)$$

$$\Delta N_2O_t = \beta_0 + \beta_1 \Delta NMR_{t-i} + \beta_2 \Delta CO_{2t-i} + \beta_3 \Delta CH_{4t-i} + \beta_4 \Delta N_2O_{t-i} + \beta_5 \Delta LNCSP_{t-i} + \varepsilon_{1t} \quad (10)$$

$$\Delta LNCSP_t = \beta_0 + \beta_1 \Delta NMR_{t-i} + \beta_2 \Delta CO_{2t-i} + \beta_3 \Delta CH_{4t-i} + \beta_4 \Delta N_2O_{t-i} + \beta_5 \Delta LNCSP_{t-i} + \varepsilon_{1t} \quad (11)$$

The specification of the Johansen cointegration model in a VAR framework considered all variables endogenously determine. An essential econometric framework for examining the dynamic relationships between several cointegrated non-stationary time series variables is the Vector Error Correction Model (VECM). In order to correct the disequilibrium error, the study also employed the error correction mechanism to model the dynamic relationship that the short-run and long-run dynamics captured. The short and long-run dynamics preposition serves

as detection of disequilibrium error whenever they exist and provide information on how long it would take to correct them.

$$\Delta NMR_t = \beta_0 + \sum_{i=1}^{p-1} \beta_{1i} \Delta NMR_{t-i} + \sum_{i=1}^{p-1} \beta_{2i} \Delta CO_{2t-i} + \sum_{i=1}^{p-1} \beta_{3i} \Delta CH_{4t-i} + \sum_{i=1}^{p-1} \beta_{4i} \Delta N_2 O_{t-i} + \sum_{i=1}^{p-1} \beta_{5i} \Delta LNCSP_{t-i} + \Omega_1 ECM_{t-1} + \varepsilon_{1t} \quad (12)$$

$$\Delta CO_{2t} = \beta_0 + \sum_{i=1}^{p-1} \beta_{1i} \Delta NMR_{t-i} + \sum_{i=1}^{p-1} \beta_{2i} \Delta CO_{2t-i} + \sum_{i=1}^{p-1} \beta_{3i} \Delta CH_{4t-i} + \sum_{i=1}^{p-1} \beta_{4i} \Delta N_2 O_{t-i} + \sum_{i=1}^{p-1} \beta_{5i} \Delta LNCSP_{t-i} + \Omega_1 ECM_{t-1} + \varepsilon_{1t} \quad (13)$$

$$\Delta CH_{4t} = \beta_0 + \sum_{i=1}^{p-1} \beta_{1i} \Delta NMR_{t-i} + \sum_{i=1}^{p-1} \beta_{2i} \Delta CO_{2t-i} + \sum_{i=1}^{p-1} \beta_{3i} \Delta CH_{4t-i} + \sum_{i=1}^{p-1} \beta_{4i} \Delta N_2 O_{t-i} + \sum_{i=1}^{p-1} \beta_{5i} \Delta LNCSP_{t-i} + \Omega_1 ECM_{t-1} + \varepsilon_{1t} \quad (14)$$

$$\Delta N_2 O_{4t} = \beta_0 + \sum_{i=1}^{p-1} \beta_{1i} \Delta NMR_{t-i} + \sum_{i=1}^{p-1} \beta_{2i} \Delta CO_{2t-i} + \sum_{i=1}^{p-1} \beta_{3i} \Delta CH_{4t-i} + \sum_{i=1}^{p-1} \beta_{4i} \Delta N_2 O_{t-i} + \sum_{i=1}^{p-1} \beta_{5i} \Delta LNCSP_{t-i} + \Omega_1 ECM_{t-1} + \varepsilon_{1t} \quad (15)$$

$$\Delta LNCSP_t = \beta_0 + \sum_{i=1}^{p-1} \beta_{1i} \Delta NMR_{t-i} + \sum_{i=1}^{p-1} \beta_{2i} \Delta CO_{2t-i} + \sum_{i=1}^{p-1} \beta_{3i} \Delta CH_{4t-i} + \sum_{i=1}^{p-1} \beta_{4i} \Delta N_2 O_{t-i} + \sum_{i=1}^{p-1} \beta_{5i} \Delta LNCSP_{t-i} + \Omega_1 ECM_{t-1} + \varepsilon_{1t} \quad (16)$$

The post estimation tests were carried out to ascertain the reliability of the result. The post estimation tests used are Heteroskedasticity, Breusch–Godfrey test for serial correlation, normality test was used to determine residual normality, and the AR Characteristic Polynomial test was used to examine how stable the variables entered the VECM model.

Results and Discussion

The Augmented Dicker–fuller (ADF) and Philip Peron (PP) unit roots was used to check for the stationarity of the data. The result is presented in Table 1.

Table 1: Unit Root Test Result

Variable	Level	Critical Value @5%	1 st Difference	Critical Value @5%	Order of Integration
ADF t-statistic					
NMR	0.101654	-2.938987	-3.820882	-2.941145	I(1)
CO ₂	-0.963499	-2.933158	-6.209478	-2.936942	I(1)
CH ₄	-0.868090	-2.933158	-5.476412	-2.935001	I(1)
N ₂ O	3.659082	-3.935001	-6.512132	-2.935001	I(1)

Variable	Level	Critical Value @5%	1 st Difference	Critical Value @5%	Order of Integration
LNCSP	-0.477919	-2.933158	-7.230457	-2.935001	I(1)
Phillips-Perron test statistic					
NMR	0.026601	-2.933158	-4.029575	-2.948886	I(1)
CO ₂	-0.963499	-2.933158	-7.568278	-2.935001	I(1)
CH ₄	-0.868090	-2.933158	-5.444478	-2.935001	I(1)
N ₂ O	5.059636	-5.933158	-6.549942	-2.935001	I(1)
LNCSP	-3.463222	-3.520787	-7.800465	-2.935001	I(1)

Source: Authors' Computation from Eviews

The ARDL and PP unit root testes shows that neonatal mortality, carbon emission, methane, nitrous oxide and household consumption are integrated of order one [I(1)]. This is because their respective ADF t-statistics values are greater than 0.05 critical level (significant) after differencing. Based on the unit root results, the vector error correction mechanism is utilized for data analysis given that all the variables are stationary after differencing. The result of the lag selection criteria which identifies the optimal lag order for efficient estimates is presented in Table 2.

Table 2: Lag Order Length Criteria Result

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-505.9482	NA	85654.37	25.54741	25.75852	25.62374
1	-264.7211	410.0861	1.747302	14.73605	16.00271	15.19404
2	-195.9159	99.76748*	0.207850*	12.54580	14.86801*	13.38543*
3	-170.4770	30.52674	0.239537	12.52385*	15.90161	13.74514

Source: Authors' Computation from Eviews

The asterisk sign (*) indicates lag order selection by the information criterion.

Table 2 shows the optimal lag order selection and the Final prediction error (FPE), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ) selected two (2) as the maximum or optimal lag, while Akaike information criterion (AIC) selected lag 3 as the optimal lag. Thus, lag 2 has been used all through in the study for estimation given that most of the criteria choose lag 2.

Johansen Cointegration

The trace statistic and Max-Eigen statistic for Johansen are estimated and the obtained results is presented in Table 3.

Table 3: Johansen Cointegration Test Result

<i>Hypothesized No. of CE(s)</i>	<i>Eigenvalue</i>	<i>Trace Statistic</i>	<i>0.05 Critical Value</i>	<i>Prob.**</i>
Trace Statistic				
None *	0.654596	110.5844	69.81889	0.0000
At most 1 *	0.589995	68.06276	47.85613	0.0002
At most 2 *	0.461801	32.39928	29.79707	0.0245
At most 3	0.159674	7.618222	15.49471	0.5071
At most 4	0.016355	0.659602	3.841466	0.4167
Max-Eigen Statistic				
Hypothesized		Max-Eigen	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.654596	42.52166	33.87687	0.0037
At most 1 *	0.589995	35.66348	27.58434	0.0037
At most 2 *	0.461801	24.78106	21.13162	0.0146
At most 3	0.159674	6.958620	14.26460	0.4940
At most 4	0.016355	0.659602	3.841466	0.4167

* denotes rejection of the hypothesis at the 0.05 level

Source: Authors' Computation from Eviews

The Johansen Cointegration test result reveals the presence of three cointegrating equations in the model based on the Trace Statistic and Max-Eigen Statistic as indicated by the asterisk sign.

Long run impact of greenhouse gas emission on neonatal mortality rate in Nigeria

The long run impact of greenhouse gas emission on neonatal mortality rate is considered in this section using the normalised Johansen cointegrating and the result is shown in the Table 4.

Table 4: Long run Coefficient (Dependent Variable: NMR)

<i>Variables</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-statistic</i>
CO ₂	-0.942393	0.20075	-4.69436
CH ₄	0.090930	0.03918	2.32058
N ₂ O	5.041980	1.04183	4.83953
LNCSP	-3.978006	7.39467	-0.53796

Source: Authors' Computation from Eviews

The result in Table 4 shows that carbon emission (CO_2) has negative impact on neonatal mortality rate in Nigeria and the coefficient is significant at 5% level. This means 94% of neonatal mortality reduces even as carbon emission increases which is not theoretically expected. The negative impact of carbon emissions on neonatal mortality in Nigeria likely reflects development and health-system improvements that co-move with emissions, rather than a protective effect of pollution. The result further implies that carbon emissions is not the toxic pollutant driving neonate deaths in Nigeria. The negative impact of carbon emission on neonatal mortality rate is similar to the result of Rasoulinezhad et al. (2020) who revealed an inverse relationship between CO_2 emissions and health outcome.

However, the study found that methane (CH_4) has positive and significant impact on neonatal mortality at 5% level of statistical significance. The result means that neonatal mortality rate increased by 9.1% due to increase in methane in Nigeria during the study period. It implies that neonatal mortality rate rises due to the increasing consequences of methane which can worsens air quality. The positive impact of methane on neonatal mortality rate is theoretically expected given that exposure to indoor air pollution caused by methane can affect pregnancy as well as new-born babies. This finding is in line with the study of Adeleye and Tiwari (2023) who found that increase in methane emissions increases infant mortality rate. Findings also reveal that nitrous oxide (N_2O) affect neonatal mortality positively and significantly at 5% level. The result means that nitrous oxide accounted for about 5% increase in neonatal mortality rate in Nigeria during the study period. A positive coefficient of nitrous oxide means that higher nitrous oxide emissions are associated with higher neonatal deaths. It suggests that new-borns exposed to pollutant from nitrous oxide faces high death risks. Result further shows that household consumption negatively affects neonatal mortality rate in Nigeria. The result signifies that a unit increase in household consumption leads to 3.9% decrease in neonatal mortality rate in Nigeria. The negative impact of household consumption on neonatal mortality implies that improved household welfare enhances new born survival chances. Higher consumption enables better nutrition and living conditions, reducing preventable neonatal deaths. The negative impact of household consumption on neonatal mortality rate in Nigeria is theoretically expected.

Short run impact of greenhouse gas emission on neonatal mortality rate in Nigeria

The short run impact of greenhouse gas emission on neonatal mortality rate in Nigeria is shown in Table 5.

Table 5: Vector Error Correction results

<i>Variables</i>	<i>Coefficients</i>	<i>Std. Error</i>	<i>t-statistic</i>
ECM(-1)	-0.511704	0.00327	-2.52113
D(CO ₂)	0.000116	0.00471	0.02459
D(CH ₄)	0.076511	0.00187	2.01472
D(N ₂ O)	0.081322	0.00423	2.26609
D(LNCSP)	-0.016203	0.00731	-2.37442

Adj. R-squared = 0.887289

Source: Authors' Computation from Eviews

The result reveals that the error correction coefficient is negative (-0.51) and statistically significant at 5% level. It means deviations from the long-run equilibrium are corrected or reverted back with an adjusted speed of 51%. Short-run shocks (sudden increase in emissions) does not permanently displace neonatal mortality from its long-run path instead, the system gradually returns to equilibrium. The short run result shows that carbon emission affect neonatal mortality positively even though, the coefficient is not significant at 5% level, suggesting weak impact of carbon emission. The study also found a positive and significant impact of methane and nitrous oxide on neonatal mortality rate in Nigeria at 5% level of statistical significance. It means that neonatal increased by 0.1% and 7.6% due to immediate rise in methane and nitrous oxide in Nigeria. The positive short-run (immediate) impact means that a rise in CH₄ and N₂O emissions instantly increases neonatal deaths in Nigeria. This reflects the direct health hazards of exposure to polluted air, particularly for new-borns. On the other hand, household consumption affect neonatal mortality negatively and significantly at 5% level in the short run. It means neonatal mortality rate reduced by approximately 2% due to increase in the level of consumption. The model fit as reveals by Adjusted R-squared value of 0.89 implies that greenhouse gas emissions and consumption accounted for 89% variation in neonatal mortality rate in Nigeria.

Response of Neonatal Mortality Rate to greenhouse gas emissions in Nigeria

The response of neonatal mortality rate to greenhouse gas emissions in Nigeria is examined using impulse response as presented Figure 1.

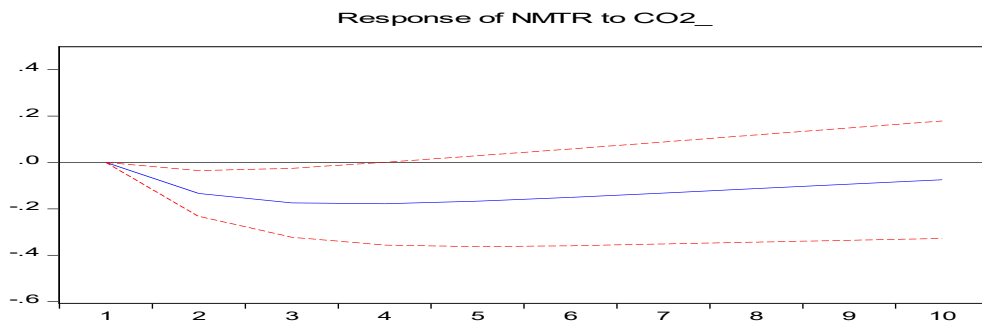


Figure 1: Response of Neonatal Mortality Rate to Carbon Emission

Source: Authors' Computation from Eviews

The straight and continues black line reveals how neonatal mortality adjusts over the horizon as a result of changes in greenhouse gas emissions. Also, the dashed two line are critical region plots that replicates the difference between positive and negative changes, while the line in-between the critical region is the response line. The impulse response result in Figure 1 shows that the response of neonatal mortality rate to carbon emission is not noticed in period 1, however, neonatal mortality responded negatively to carbon emission from period 2 to the 10th period. The response of neonatal mortality rate to methane is shown in Figure 2.

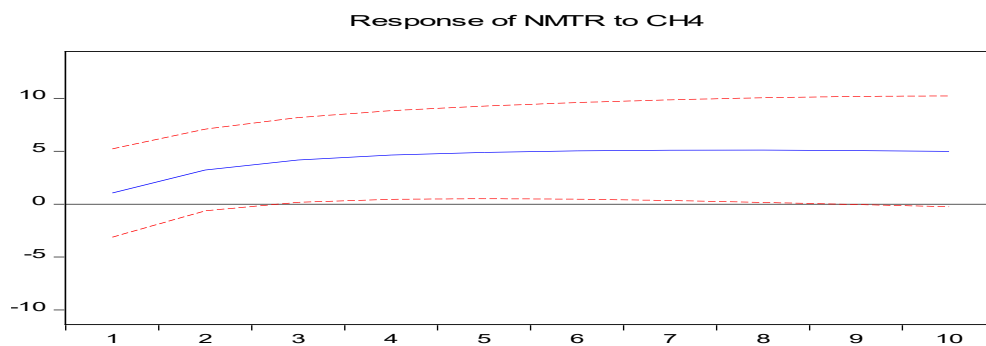


Figure 2: Response of neonatal mortality rate to methane

Source: Authors' Computation from Eviews

The response of neonatal mortality rate to methane as indicated in Figure 2 shows that neonatal mortality rate increase from period 1 to the 10th period. This implies that neonatal mortality rate rises as methane increases in Nigeria in the short run and long run. How neonatal mortality responded to nitrous oxide is also considered and the impulse response function is shown in Figure 3.

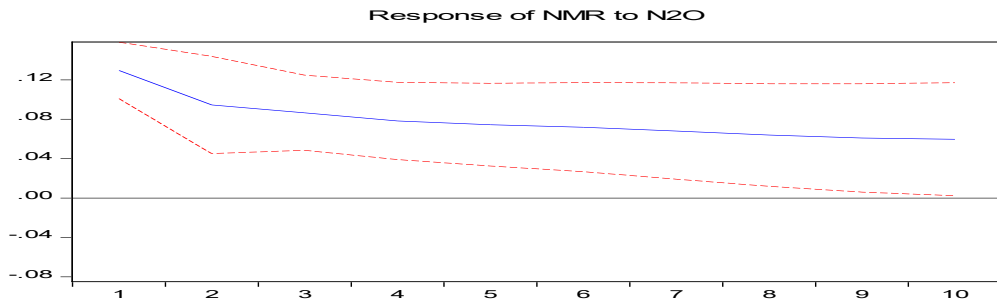


Figure 3: Response of neonatal mortality rate to Nitrous Oxide

Source: Authors' Computation from Eviews

The impulse response function in Figure 3 indicates a positive but downward response of neonatal mortality rate to nitrous oxide in Nigeria. The result shows that neonatal mortality positively and highly responded to nitrous oxide in period 1. From period 2 to 10, the response of neonatal remains positive but with a downward movement. The result implies that neonatal mortality rate respond positive to nitrous oxide in Nigeria both in the short run and long run. The forecasted impact of Neonatal Mortality Rate on greenhouse gas emissions in Nigeria is carried out for the period of ten years. The result is presented in Table 6.

Table 6: Result of Forecast Variance Decomposition of Neonatal Mortality Rate

Period	S.E.	NMR	CO2	CH4	N2O	LNCSP
1	0.089666	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.194197	95.53157	1.350806	0.225107	2.762676	0.129843
3	0.318178	91.34189	2.951877	0.138765	4.942742	0.624723
4	0.467348	85.02983	4.525159	0.848484	7.167975	2.428552
5	0.639492	77.85969	5.246422	2.276776	9.382686	5.234429
6	0.834880	70.24263	5.268232	4.109853	11.61603	8.763250
7	1.050250	62.84085	4.877017	6.005669	13.73157	12.54490
8	1.280721	56.03881	4.329964	7.740699	15.64402	16.24650
9	1.519834	50.03026	3.767339	9.205975	17.32348	19.67294
10	1.760841	44.84528	3.250965	10.36859	18.78880	22.74636

Source: Authors' Computation from Eviews

The result in Table 6 shows that at period 1 (short run), 100% variation in neonatal mortality rate is explained by own shocks. Over longer horizons, the share of variance explained by greenhouse gas emissions shocks increases. The result implies that in the short run (1 year), 100% of neonatal mortality variance is explained by its own shocks, but after 10 years, only 44.8% is self-explained, while 32.5% comes from greenhouse gas emissions and 22.7% is from household consumption. The implication of the result is that shocks in greenhouse gas emissions and household consumption account for an increasing proportion of its variance, underscoring the growing influence of environmental and economic factors on neonatal outcomes.

Post estimation Result

The study carried out heteroskedasticity test to check if variance of the error term is constant (homoskedasticity) and to ensure validity of the estimates. The result of heteroskedasticity and VEC Residual Serial Correlation LM Tests is shown in Table 7.

Table 7: Heteroskedasticity and Serial Correlation LM Tests result

Chi-sq		Df	Prob.			
343.1361		330	0.2979			
VEC Residual Serial Correlation LM Tests						
Lag	LRE* stat	Df	Prob.	Rao F-stat	Df	Prob.
1	18.14944	25	0.8360	0.699267	(25, 72.1)	0.8408
2	30.75703	25	0.1972	1.282546	(25, 72.1)	0.2057

Source: Authors' Computation from Eviews

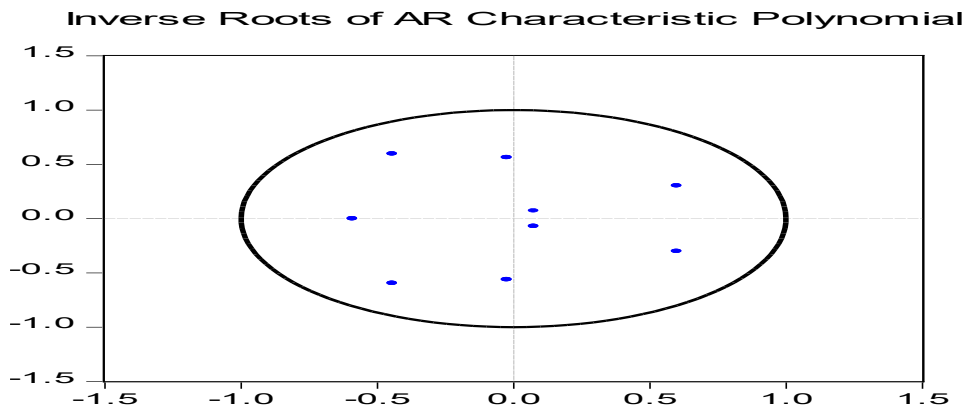
The VEC residual Heteroskedasticity result reveals that there is absence of heteroskedasticity in the model implying that the residuals are homoscedastic. Therefore, the regression residuals maintained constant variance and the result is considered valid. The VEC Residual Serial Correlation LM Tests is also carried out to ensure whether residuals are serially uncorrelated. The VEC Serial Correlation LM Test result reveals the absence of serial correlation among the study variables given that the probability values are greater than 0.05 critical level. It means the residuals of the model are serially independent.

Table 8: VEC Normality Tests

<i>Component</i>	<i>Jarque-Bera</i>	<i>Df</i>	<i>Prob.</i>
1	1.618095	2	0.4453
2	0.241741	2	0.8861
3	1.301525	2	0.5216
4	0.682744	2	0.7108
5	4.145405	2	0.1258
Joint	7.989510	10	0.6299

Source: Authors' Computation from Eviews

The Skewness, Kurtosis and Jarque-Bera statistics test result in Table 8 indicates that residuals are normally distributed and the model does not suffer from misspecification issue as evidenced by high p-values. In terms of stability test results for the model, the study used the inverse roots of AR characteristics polynomial test. The results are presented in Figure 4.

**Figure 4: Stability Test Results**

Source: Authors' Extract from Eviews

The Inverse Roots of AR Characteristic Polynomial test was used to examine how stable the variables entered the SVAR model. Results satisfy the VAR stability condition since all the roots lied within the unit circle shown in Figure 4, thus stable.

Conclusion

This study concludes that greenhouses gas emissions, particularly methane and nitrous oxide emissions, is a critical determinant of neonatal health outcomes in Nigeria. Policy interventions aimed at reducing harmful greenhouse gas emissions,

alongside strategies to enhance household welfare, are vital in lowering neonatal mortality and achieving sustainable health improvements. The study recommended that Nigerian government should make or reforms policies aim to sustain neonatal health gains through inclusive economic development and strengthened health services, while simultaneously promoting a transition to clean energy to decouple improved survival outcomes from rising emissions. Nigerian government should integrate health–environment policies that can reduce methane emissions in the country. This can be achieved by promoting and expanding access to clean cooking fuels (biogas, solar stoves, electricity) or by regulating waste burning, open dumpsites, and agricultural burning that emit methane. The study recommended for enforcement of stricter regulations that can control nitrous oxide pollutant and reduce neonates’ deaths. Also, government should provide or improve on neonatal intensive care units (NICUs), immunization, and antenatal care programs to reduce vulnerability to pollution-related risks.

References

- Adeleye, B., Tiwari, A., Shah, M. I., & Ullah, S. (2023). Analyzing the impact of carbon emissions and non-renewable energy use on infant and under-5 mortality rates in Europe: New Evidence Using Panel Quantile Regression. *Environmental Modeling & Assessment*, 28(11), 3-21.
- Adeleye, B.N., Olohunlana, A.O., Ibukun, C.O., Soremi, T., & Suleiman, B. (2022). Mortality rate, carbon emissions, renewable energy and per capita income nexus in Sub-Saharan Africa. *PLoS ONE* 17(9), 1-27. <https://doi.org/10.1371/journal.pone.0274447>
- Adeleye, N. B. & Tiwari, A. K. (2023). Empirical assessment of methane emissions, socioeconomic factors, and infant mortality in Europe. *Finance and Economic Review*, 49(1), 305-331. DOI:10.1111/1477-8947.12385
- Akeem, O. O. (2024). Analysis of the health effect of carbon emission in Nigeria. *Journal of Applied Financial Econometrics*, 5(1), 27-39. <https://doi.org/10.47509/JAFE.2024.v05i01.03>
- Akinyemi, A., Okonkwo, C., & Yusuf, T. (2022). Renewable energy adoption and economic sustainability in sub-Saharan Africa: Evidence from Nigeria. *Journal of Sustainable Development Studies*, 14(3), 45–60. <https://doi.org/10.1111/jsds.2022.01403>
- Anugwom, C. G. (2023). Greenhouse gas emissions and health outcomes in Nigeria. *African Journal of Economics and Sustainable Development* 6(3), 72-88. DOI: 10.52589.
- Benjamin, O., Akinola, G. W., & Asaolu, A. A. (2023). Fossil energy consumption, carbon dioxide emissions, and mortality rates in Nigeria. Available at SSRN: <https://ssrn.com/abstract=4503284> or <http://dx.doi.org/10.2139/ssrn.4503284>

- Bosede, A., & Aviral, K. (2023). Empirical assessment of methane emissions, socioeconomic factors, and infant mortality in Europe. *Sustainable Development Journal*, 3(1), 128–136. <https://doi.org/10.1111/1477-8947.12385>
- Federal Ministry of Environment. (2021). *Nigeria's updated nationally determined contribution*. Federal Government of Nigeria. <https://environment.gov.ng/>
- Federal Ministry of Environment. (2023). *National climate change policy for Nigeria (2021–2030)*. Federal Government of Nigeria. <https://climatechange.gov.ng/doc/NCCP-Nigeria.pdf>
- Food and Agriculture Organization. (2016). *Climate-Smart Agriculture* (Agricultural Development Economics Thematic Brief). FAO. <https://openknowledge.fao.org/items/c9c23d42-6a54-4afe-b558-53c2c706146f>
- Food and Agriculture Organization. (2021). The state of food security and nutrition in the world 2021: Transforming food systems for food security, improved nutrition and affordable healthy diets for all. FAO. <https://www.fao.org/3/cb4474en/cb4474en.pdf>
- Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, 80(2), 223–255. <https://doi.org/10.1086/259880>
- Javanshirova, Z. (2024). The impact of carbon emissions on infant mortality rate in Azerbaijan. *Journal of Sustainable Development Issues*, 2(2), 104–114
- Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 23(12), 231–254.
- Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors. *Journal of Economic Dynamics and Control*, 4(12), 231–254.
- Johansen S., & Julius, K. (1990). Maximum likelihood estimation and inferences on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, 52(2), 162–210.
- National Bureau of Statistics. (2023). *Greenhouse gas emissions account for Kaduna and Nasarawa States: Pilot ecosystem accounts* (Natural Capital Accounts). National Bureau of Statistics.
- Natufe, O. K., & Evbayiro-Osagie, E. I. (2023). The effects of CO₂ and NO₂ emissions on economic growth in Nigeria. *International Journal of Business & Management*, 11(3). <https://doi.org/10.24940/theijbm/2023/v11/i3/BM2303-010>
- Niyi-Odumosu, F., Ozoh, O., Ope, V. O., Ale, B. M., Akinnola, O., & Adeloye, D. (2025). Exploring the impact of climate change on respiratory health in Nigeria: a scoping review of current research, government policies and programs. *Climatic Change*, 25(7), 17–35. <https://doi.org/10.1007/s10584-025-03880-0>.
- Ogunbenle, S., & Rufus, O. O. (2022). Carbon emissions and mortality rate nexus in Nigeria. *The International Journal of Humanities and Social Studies*, 10(3), 18–26.

- Olawale, O. B. (2023). Fossil energy consumption, carbon dioxide emissions and adult mortality rate in Nigeria. *Managing Global Transitions*, 21(4), 353–384
- Oyedele O. (2022). Carbon dioxide emission and health outcomes: is there really a nexus for the Nigerian case? *Environmental Science and Pollution Review*, 29(37):56309-56322. doi: 10.1007/s11356-022-19365-x.
- Oyelade, A. O., Maku, O. E., & Oladimeji, O. (2022). The effect of CO2 emissions on quality of life in Anglophone countries in West Africa. *African Journal of Economic Review*, 10(1), 27-41.
- Pierre, G. P., Gilles, R. M., & Sangco, B. (2025). The impact of economic growth and greenhouse gas emissions on health costs: The East Asia and the Pacific. *International Research Journal of Multidisciplinary Scope*, 6(2), 280-294
- Rani P., & Dhok, A (2023). Effects of pollution on pregnancy and infants. *Cureus* 15(1), 1-7. DOI 10.7759/cureus.33906
- Rasoulinezhad, E., Taghizadeh-Hesary, F., & Taghizadeh-Hesary, F. (2020). How is mortality affected by fossil fuel consumption, CO2 emissions and economic factors in CIS Region? *Energies*, 13(5), 1-17. DOI: 10.3390/en13092255
- United Nations, Department of Economic and Social Affairs, Population Division. (2023). *World Population Prospects 2023* (extended dataset).
- Uvoh, S. M., Osuwo, E., Onokpite, E., Nnamdi, C. N., & Dirime, J. (2025). Impact of gas flares on neonatal weight and health profile in Yenagoa, Bayelsa State, Nigeria. *Journal of Advances in Medicine and Medical Research*, 37(6), 269-276. <https://doi.org/10.9734/jammr/2025/v37i65869>
- Waltona, H., Dajnaka, D., Hollandd, M., Evangelopoulou, D. (2025). Health and associated economic benefits of reduced air pollution and increased physical activity from climate change policies in the UK. *Environment International*, 19(6), 109-128
- WHO. (2022). *Global health observatory: Health facilities in sub-Saharan Africa*. World Health Organization.
- WHO. (2023). *Emission in the Sub-Saharan region*. World Health Organization. <https://www.who.int/news-room>
- WHO. (2023). *Newborn mortality fact sheet*. World Health Organization. <https://www.who.int/news-room/fact-sheets/detail/newborn-mortality>
- Wilkinson, A. K., Radhakrishnan, V., Quint, Q., Maslova, E., Janson, C., Budgen, N. (2024). Greenhouse gas emissions associated with suboptimal asthma care in the UK: the SABINA health care- based environmental cost of treatment (CARBON) stud. *Thorax* 79(15), 412–421. doi:10.1136/thorax-2023-220259 79:412–421.

Zhang, D.; Raghupathi, W.; Raghupathi, V. (2024). Exploring the effects of greenhouse gases and particulate emissions on quality of life: A country-level empirical study. *Climatic Review*, 11(6), 1054- 176. [https:// doi.org/10.3390/cli12110176](https://doi.org/10.3390/cli12110176).