



Effects of Climate Change on Population Health in Nigeria

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Abstract. Measures aimed at improving population health in order to enhance individual and overall productivity over time, through the strengthening of physical and mental capacities, are becoming increasingly important for economic growth and development. However, despite efforts to improve healthcare delivery systems in Nigeria, population health has been suboptimal with over 40 out of a hundred of the residents living below the poverty threshold. Statistical data were analysed using the autoregressive distributed lag (ARDL) approach. The results showed that increase in precipitation and in the number of people using at least basic sanitation services reduces infant mortality significantly; while a unit change in precipitation increases life expectancy, improved sanitation and higher secondary school enrolment contribute to increased life expectancy. The study, therefore, recommends policymakers that they invest in climate-resilient health facilities and integrate heat-health intervention into community health extension services.

Keywords: ARDL, infant mortality, life expectancy, temperature

JEL Classification: I15, Q54, C13

1. Introduction

It is becoming increasingly crucial to enhance individual and overall productivity over time by improving physical and mental capacities, achieved via improvement in population health, in order to promote economic growth and development.

Poor population health undermines human capital development, reduces labour productivity, and increases healthcare costs, hindering sustainable development. Empirical evidence suggests that mitigating climate variability in most industrialized economies has resulted in a significant reduction in newborn mortality rates and improved life expectancy. However, this is not the case in developing nations despite all government efforts at improving healthcare delivery systems, as population health, particularly in Nigeria, has remained critically weak. Population health measures the overall health status of a population and incorporates not only individual health outcomes but also the underlying determinants (McCartney et al., 2019; Kindig and Stoddart, 2003). It emphasizes the significance of addressing the root causes of health inequities, promoting policies and interventions that create conditions conducive to good health for all (Emmanuel, 2024). Population health acknowledges that individual health is influenced not only by biological factors but also by the interplay of financial, social, and ecological circumstances in which individuals are born, live, grow, age, and work (Shantz and Elliott, 2021; World Health Organization (WHO), 2008). This recognition of the broader determinants of health is a core tenet of the population wellbeing approach (Kindig and Stoddart, 2003). Social factors, such as education, revenue, employment, and housing conditions, played a decisive role in shaping health behaviours, access to healthcare, and overall well-being (Braveman and Gottlieb, 2014; Gómez et al, 2021). Economic factors, including poverty, inequality, and employment opportunities, influence an individual's ability to access nutritious food, safe living conditions, and quality healthcare services (Adler and Newman, 2002; Lynch et al., 1997). Specifically, environmental determinants, ranging from water and air quality to exposure to pollutants and toxins, can directly impact health outcomes and exacerbate existing disparities.

Nigeria, the country with the largest population in Africa (Onah, 2014), faces a multitude of health challenges exacerbated by the complexities of climate change and various socioeconomic factors despite efforts to enhance agricultural production and address food supply concerns, for instance, Nigeria's Climate Change Act, Agricultural Promotion Policy (2016–2020), Anchor Borrowers' Programme, inauguration of the National Agriculture and Food Security Council. Many of these initiatives have failed to mitigate climate variability, owing to persistent economic, security, and infrastructural obstacles (Olayinka et al., 2024).

This can be attributed to factors such as climate change, poverty, conflict, increasing population, and post-harvest losses, with over 40 percent of the population living below the poverty threshold. Moreover, Nigeria is experiencing the adverse effects of climate change, manifested in escalating heat stress, unpredictable rainfall patterns, and heightened occurrence of severe weather phenomena.

In fact, the Global Climate Risk Index identifies Nigeria as one of the countries that are greatly impacted by weather extremes caused by climate change (Eckstein

et al., 2021; Ucheje et al., 2024), mostly in areas like the Northeast and Middle Belt, which impedes agricultural operations, displaces populations, and hinders food production and distribution, exacerbating food insecurity United Nations Development Programme (UNDP, 2020). Additionally, Nigeria's rapidly expanding population, projected to surpass 400 million by the year 2050 (Yeboua et al., 2022), places considerable strain on already limited resources, including water and land, thereby affecting farming productivity and food availability (Hossain et al., 2020; Udoinyang, 2024).

Concurrently, socioeconomic factors and malnutrition, exacerbated by climate change, market forces, and other factors, directly impact population health, especially among vulnerable groups (Phalkey et al., 2015; Headey and Martin, 2016). Poor population health undermines human capital development, reduces labour productivity, and increases healthcare costs, impeding economic growth and sustainable development. Several studies specifically examine the direct effects of weather modification on food nutrition and security. Consequently, determining the effect of climate changes on population health is critical. Based on the above, this study looked into the influence of climate change on population health in Nigeria from 2000 to 2024.

The subsequent sections of the study are structured as follows: Section 2 summarizes the literature review, Section 3 describes the methodology and sources of data, Section 4 presents and analyses the results, and Section 5 states the conclusions and policy recommendations.

2. Literature Review

The academic literature incorporates an increasing body of research that examines the relationship between climate change and population health. These studies reveal numerous issues that transcend national boundaries. To begin with, Kelly and Wassou (2025), using the Driscoll–Kraay fixed-effects and two-step system generalized method of moments regressions, examine the impact of climate variability on the health status of sub-Saharan African nations between 2004 and 2019. The findings demonstrate that climate alteration considerably impairs health consequences. Specifically, many climate change indicators have a significant and adverse effect on the prevalence of malnutrition, infant mortality, and malaria. Conversely, a rise in surface temperature has an undesirable and substantial consequence on life expectancy at birth, reducing it by 0.129 years. This implies that if changes in weather patterns become more severe, health hazards will grow significantly, resulting in a decline in life expectancy.

In another study, Roy (2024) evaluates the effect of climate change on life expectancy from 1940 to 2020, using cross-national data from 191 nations by

employing the fixed-effects technique. The study found that an increase in the mean annual temperature reduces life expectancy at birth by 0.44 years. Furthermore, rises in temperature reduced life expectancy by interfering with the rainfall cycle. If the composite climate change index, which includes temperature and rainfall, rises by 10 points, life expectancy at birth is reduced by 0.50 years. This result also indicates that climate change will shorten women's life expectancy more than men's.

Ogunbode et al. (2023) investigated how adverse psychological responses to climate change affect mental health and sleep in a diverse, non-representative sample of individuals from 25 nations. The questionnaire, which measured adverse weather-related experiences, symptoms, of sleeping disorders as well as self-rated mental health, was completed by participants. A 7-item scale, adapted from the state anxiety component of the State-Trait Anxiety Inventory, was used to measure weather-related emotions. The relationships between adverse emotions associated with climate change, sleep disturbance symptoms, and mental health were examined across the sample nations using correlation analysis. Given the interconnectedness of the data (individuals within the particular nations), linear multilevel regression models with random intercepts were estimated by employing the R package lme4. Results indicate that, in most countries, adverse weather-related reactions are negatively linked with self-rated psychological health and positively correlated with signs of insomnia.

Babalola et al. (2018) examined the impact of temperature fluctuations on infant mortality in Bangladesh from 1982 to 2008. The study used a regression model with autoregressive integrated moving average (ARIMA) and revealed that higher temperatures were associated with lower infant mortality in Bangladesh. Each one-degree Celsius increase in average monthly temperature reduced monthly mortality by 3.672. The beneficial effects of maximum monthly temperature ranged from 0.623 to 0.712 and were statistically significant for both girls and boys. Mean monthly temperature had a greater effect on neonates than post-neonates in terms of mortality reduction per degree.

Furthermore, Foye (2018) investigated the dynamic relationship between climate variability, human health, and fiscal expansion in Nigeria between 1960 and 2015. Using the structural vector auto regression (VAR) technique, results demonstrate that economic growth, climate variability, and social health are the main predictors of each other over time in both global and local climate models. However, global climate is a better predictor of human health and economic growth than local climate. This study found that climate change shocks are associated with negative human health outcomes in Nigeria, whereas economic growth shocks had a minor impact on human health status, resulting in reduced man-hours, labour productivity, and economic growth.

Yang and Liu (2018) used hierarchical linear regression techniques to assess the influence of ecological pollution on residents' wellbeing and investigate the

underlying mechanisms through which economic and environmental factors are involved in China's growing health disparities. The key findings imply that pollution poses serious health hazards, while personal income and life satisfaction are strongly positively associated, as are health and income. Furthermore, the influence of environmental contamination strengthens this relationship. The data show that health inequities exist throughout China, and they are most prominent in rural areas. Pollution exacerbates health inequities to varying degrees across income groups and amplifies the impact of income inequality on health outcomes.

Grace et al. (2015) examine the link between precipitation, temperature, and birth weight in 19 African nations. The study combined birth weight data derived from population surveys conducted from 1986 to 2010 with monthly temperature and precipitation data collected from satellite- and ground-based meteorological stations. Climate trends recorded at different phases of conception were also examined to determine the effects of precipitation and temperature on birth weight. The experimental model considers changes in the impact of climatic circumstances depending on the primary food production technique (livelihood zone) in a certain area, together with household income, the mother's educational background, and the time of birth. The findings demonstrated that environmental factors had an impact on birth weight, in some cases comparable to the effects of household electrification or women's education.

Barbieri et al. (2010) investigated the link between migration, economic effects, and climate change by modelling the long-term interaction between migration and demographic changes during a projected period of up to 45 years, which is influenced by shifts in the structure of Northeastern Brazil's economy caused by climate change. This study employed IMAGEM-B (Integrated Multi-Regional Advanced General Equilibrium Model for Brazil), which revealed that the integrated model generated migration scenarios at the municipal levels based on how climate variability affects the major economic segments and how those effects interact with one another. According to the findings, the projected climate changes will have a detrimental influence on the region's agricultural business, potentially driving migration to other regions of the country.

3. Methodology and Sources of Data

3.1. Data

This study investigates the effects of climate change on population health. The study utilizes annual time series data between 2000 and 2024 in Nigeria, owing to its status as the continent's largest economy and most densely populated black country, as well as the accessibility of trustworthy data. The dimension of climate

change is denoted by annual mean temperature and precipitation. Population health is estimated using infant mortality and life expectancy, as earlier used by Murray (1988) and Xu et al. (2014). Per capita health expenditure, secondary school enrolment, and improved sanitation were introduced as exogeneous variables, as widely used in existing studies such as Liang and Tussing (2019) or Singh (2014). To streamline estimation, statistics for annual mean temperature and precipitation were transformed into natural logarithmic form to guarantee variance stationarity. Table 1 presents the sources and explanation of the variables utilized in the study.

Table 1. *Description of variables*

Variables	Description	Measurements	Source
LE	Life expectancy	Life expectancy	World Development Indicator (WDI) 2024
IMR	Population Health	Mortality rate, infant (per 1,000 live births)	World Development Indicator (WDI) 2024
LMTEMP	Temperature	Mean Annual Temperature	Climate Change Knowledge Portal
LPRECP	Precipitation	Precipitation Level	Climate Change Knowledge Portal
GOVHEXP	Per capita Health expenditure	Government health expenditure	World Development Indicator (WDI) 2024
SAN	Sanitation	People using at least basic sanitation services (% of population)	World Development Indicator (WDI)2024
SSE	Secondary School Enrolment	School enrolment, secondary (% gross)	World Development Indicator (WDI)2024

Source: authors' compilation (2025)

Model Specification

The model used to estimate the effects of climate change on population health is stated as

$$IMR = \beta_0 + \beta_1 lmtemp + \beta_2 lprecip + \beta_3 Govhexp + \beta_4 San + \beta_5 Sse + \mu_t$$

$$LE = \beta_0 + \beta_1 lmtemp + \beta_2 lprecip + \beta_3 Govhexp + \beta_4 San + \beta_5 Sse + \mu_t,$$

where IMR is the infant mortality rate, LE is life expectancy (a proxy for population health), lmtemp denotes annual mean temperature, lprecip is a measure of precipitation, β_0 is the constant term, β_1 , β_2 , β_3 , β_4 , and β_5 denote the coefficients of the model, μ_t stands for error term, GOVHEXP denotes per capita health expenditure, and SAN proxy stands for sanitation and SSE proxy for secondary school enrolment. The equation is estimated using the ARDL process as part of

the selected empirical approach. For a long time, the area of econometrics has made extensive use of ARDL approaches. In recent years, their use has grown in popularity, especially when it comes to cointegrating connection analysis (Odusanya et al., 2014). The studies of Pesaran, Shin, and PSS (2001) make two important contributions in this regard. According to the authors, ARDL methods have clear benefits since they can handle cointegration and show resistance when integration orders of relevant variables are misrepresented. The ARDL framework is particularly suitable because it accommodates variables integrated of order $I(0)$ and $I(1)$, and it provides robust estimates even with small sample sizes.

Further, the ARDL ($p, q_1, q_2, q_3, q_4, q_5$) specification for IMR is expressed as

$$\begin{aligned} IMR_t = & \alpha_0 + \sum_{i=1}^p \phi_i IMR_{t-i} + \sum_{j=0}^{q_1} \beta_{1j} Lmtemp_{t-j} + \sum_{j=0}^{q_2} \beta_{2j} Lprec_{t-j} \\ & + \sum_{j=0}^{q_3} \beta_{3j} Govhexp_{t-j} + \sum_{j=0}^{q_4} \beta_{4j} San_{t-j} + \sum_{j=0}^{q_5} \beta_{5j} Sse_{t-j} + \varepsilon_t \end{aligned}$$

However, a similar ARDL specification is estimated for life expectancy (LE_t) as

$$\begin{aligned} \Delta LE_t = & \alpha_0 + \sum_{i=1}^{p-1} \phi_i \Delta IMR_{t-i} + \sum_{j=0}^{q_1-1} \beta_{1j} \Delta Lmtemp_{t-j} + \sum_{j=0}^{q_2-1} \beta_{2j} \Delta Lprec_{t-j} + \\ & \sum_{j=0}^{q_3-1} \beta_{3j} \Delta Govhexp_{t-j} + \sum_{j=0}^{q_4-1} \beta_{4j} \Delta San_{t-j} + \sum_{j=0}^{q_5-1} \beta_{5j} \Delta Sse_{t-j} + \varepsilon_t \end{aligned}$$

Further, the study sought to analyse the effects of climate change on population health in Nigeria. Descriptive statistics were utilized to efficiently display and summarize the data. Data regularity was further established by assessing mean and Jarque–Bera standards (Gujarati and Porter, 2010). To evaluate stationarity, the study performed unit root tests employing the Philips–Perron techniques and ADF.

4. Results and Discussion

Descriptive Statistics

The findings of the descriptive statistical analysis are shown in *Table 2*. The descriptive statistics explain the dataset, and they explicitly do so by describing the mean, standard deviation, kurtosis, and skewness of the variables employed. The results indicate that all the variables' median and mean values are within the bounds of their lowest and maximum standards.

Table 2. *Descriptive statistics*

	IMR	LE	LMTEMP	LPRECP	SSE	GOVHEXP	SAN
Mean	84.587	50.966	1.438	3.072	36.752	10.948	36.823
Median	81.800	51.497	1.438	3.074	40.910	10.657	36.430
Maximum	109.600	53.633	1.444	3.112	54.882	15.834	46.570
Minimum	68.500	47.193	1.430	3.021	4.637	3.232	27.994
Std. Dev.	11.961	1.889	0.003	0.024	11.889	3.291	6.161
Skewness	0.604	-0.555	-0.287	-0.478	-1.432	-0.867	0.093
Kurtosis	2.308	2.128	3.484	2.603	4.930	3.297	1.653
Jarque–Bera	2.022	2.078	0.589	1.117	12.432	3.228	1.925
Probability	0.363	0.353	0.744	0.571	0.001	0.199	0.381
Sum	2114.681	1274.172	35.958	76.800	918.805	273.720	920.581
Sum Sq. Dev.	3433.780	85.695	0.000	0.014	3392.409	260.042	911.120
Observations	25	25	25	25	25	25	25

Source: authors' compilation, 2025

Test of Multicollinearity

A correlation matrix was generated to test the presence of multicollinearity among the predictor variables (annual mean temperature, precipitation, health expenditure, sanitation, and secondary school enrolment). *Table 3* lists the correlation matrices. The analysis indicates that there is no link between the variables, suggesting that the study's conclusions are highly reliable. *Table 3* likewise offers the results of the correlation matrix, indicating that the factors yield both positive and negative correlation coefficients. The association between annual mean temperature and precipitation was positive, with a coefficient of 0.034; secondary school enrolment is positively associated with annual mean temperature (0.355), health expenditure is positively linked with annual mean temperature (0.345) and secondary school enrolment (0.483), and annual mean temperature is positively linked with sanitation (0.370).

Table 3. *Correlation matrix*

	LMTEMP	LPRECP	SSE	GOVHEXP	SAN
LMTEMP	1				
LPRECP	0.034	1			
SSE	0.355	-0.229	1		
GOVHEXP	0.345	-0.140	0.483	1	
SAN	0.370	0.193	0.432	0.285	1

Source: authors' compilation, 2025

Table 4 presents the outcomes of the PP and ADF confirmatory tests. The results illustrate that the variables exhibit stationarity at level, that is, $I(0)$ except for the per capita health expenditure, which demonstrates stationarity only at first difference, $I(1)$. The empirical findings indicated the non-stationarity of the variables as well as the analysed dataset's covariance structure. We adopted an ARDL model to evaluate the connection between the variables under consideration. In this study, the estimation technique is chosen to align with the observed data patterns. Choosing a suitable lag duration for every underlying variable in the ARDL model is critical to ensuring the presence of Gaussian error terms.

Table 4. *Unit root test*

Variables	Level		First Difference		Order of Integration
	ADF	PP	ADF	PP	
	Intercept {Trend& Intercept}	Intercept {Trend& Intercept}	Intercept {Trend& Intercept}	Intercept {Trend& Intercept}	
IMR	-4.885** 1.659	-4.885** -1.404	-2.868 -4.750**	-2.868 -4.435**	$I(0)$
LE	-4.780** -1.139	-9.037** -0.506	-1.194 -5.510**	-5.972** -22.188**	$I(0)$
LMTEMP	-4.199** -4.200**	-5.074** -4.824**	-4.866** -4.368**	-10.061** -12.282**	$I(0)$
LPRECP	-5.741** -5.827**	-5.676** -5.748**	-11.281** -11.009**	-25.368 -24.366**	$I(0)$
GOVHEXP	-2.704 -2.236	-2.701 -2.193	-4.226** -4.427**	-4.232** -4.416**	$I(1)$
SSE	3.611** -4.101**	-3.614** -4.094**	-8.208** -8.017**	-10.868** -10.707	$I(0)$
SAN	0.845** -2.221	0.239** -2.712			$I(0)$

Source: authors' compilation, 2025

4.1. Results of the Impact of Climate Change on Population Health in Nigeria

Lag Length Selection

Determining the optimal lag time for every underlying variable in the ARDL model is critical given the need to obtain Gaussian error terms. For optimal lag length selection, we rely on the Akaike Information Criterion (AIC) to determine

the lag length value that optimizes the information criterion while ensuring the model is free from autocorrelation.

Table 5. *Lag length selection for model 1*

Lag Length	AIC
1	11.408
2	2.420*

Source: authors' compilation, 2025

Notes: * $P < 0.01$, ** $P < 0.05$.

The findings in *Table 5* reveal that lag 1 minimizes AIC and thus represents our utmost lag length. We then test for the long-term link among the variables.

The findings in *Table 6* reveal that lag 1 minimizes AIC and thus represents our utmost lag length. We then test for the long-run link between the variables.

Table 6. *Lag length selection for Model 2*

Lag Length	AIC
1	7.976
2	0.150*

Source: authors' compilation, 2025

Notes: * $P < 0.01$, ** $P < 0.05$.

The Bound Test

We use the bound testing approach to determine the extended-term link between the variables. The bound testing approach is built on the F-test, as described in Pesaran et al. (2001). The F-test is predicated on an assumption of no co-integration among the variables versus the evidence of its presence, as indicated by:

$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$, i.e. there is no co-integration among the variables.

$H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq \beta_7 \neq 0$, i.e. there is co-integration among the variables.

The bound test results in *tables 7–8* show an F-statistic of 26.898 for model 1 and 4.222 for model 2 respectively. We reject the null hypothesis since the upper bound critical value is greater, and we infer that all the variables in the model exhibit co-movements in Nigeria over time. The values are in the range of 1.99–2.94 at a 10% level of significance, 2.27–3.28 at a 5% level of significance, and 2.88–3.99 at

a 1% level of significance. Hence, given the results, we can estimate the long-term relationship between climate change and population health.

Table 7. *Bound test results for Model 1*

F-Statistic	1%		5%		10%	
26.898	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
	2.88	3.99	2.27	3.28	1.99	2.94

Source: authors' compilation, 2025

Notes: * $P < 0.01$, ** $P < 0.05$.

Table 8. *Bound test results for Model 2*

F-Statistic	1%		5%		10%	
4.222	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
	2.88	3.99	2.27	3.28	1.99	2.94

Source: authors' compilation, 2025

Notes: * $P < 0.01$, ** $P < 0.05$.

In the evaluation of the climate change–population health relationship, as revealed in *Table 9*, the adjusted R-square indicates that the model's explanatory variables explained 99% of the variance in the dependent variable, and about 1% remained unexplained. The value of the F-statistic (2367.389) was statistically significant at the 1% level, demonstrating the model's significance. The Durbin–Watson statistic (1.196) indicates that the model does not have a serial correlation issue because it falls within the acceptable range of 1.5–2.5 (for references, see Dufour and Dagenais, 1985; Durbin, 1960).

Table 9. *Results on the impact of climate change on population health outcomes in Nigeria (dependent variable IMR)*

Variable	Coefficient	Std. err.	t-Statistic	Prob.
LMTEMP	-0.117	0.502	-0.233	0.819
LPRECP	-0.003	0.001	-2.725	0.017
LPRECP (-1)	-0.003	0.001	-2.925	0.011
SSE	-0.005	0.008	-0.661	0.519
SAN	-1.461	0.139	-10.477	0.000
SAN(-1)	1.350	0.157	8.580	0.000
GOVHEXP	-0.033	0.049	-0.683	0.506
C	29.401	19.752	1.488	0.160

Variable	Coefficient	Std. err.	t-Statistic	Prob.
R-squared	0.999		—	—
Adjusted R-squared	0.999		—	—
F-statistic	2367.389		Durbin–Watson Stat.	1.196
(Prob.)	(0.000*)			

Sources: authors' compilation, 2025

Climate Change

Temperature: the coefficient of annual mean temperature, the proxy for climate change, was negative and not statistically significant at the 5% level of significance. The data reveals that an increase in the yearly mean temperature correlates with a 0.117% decrease in infant mortality. This suggests that there are no meaningful long-term relationships between annual mean temperature and infant mortality in this model. This unexpected result suggests that its effects may be context-specific, indirect, or obscured by other structural factors, highlighting the need for more disaggregated and mechanism-focused analyses.

Precipitation: The coefficient for precipitation as an indicator of climate change was negative and statistically significant at the 5% level, suggesting that a unit change in precipitation correlates with a 0.035 unit decrease in infant mortality rate, suggesting that alterations in rainfall patterns exert a consistent effect on infant mortality.

Secondary School Enrolment: The coefficient of secondary school enrolment is negative and not statistically significant at the 5% level of significance, demonstrating that there is no long-term link between secondary school enrolment and infant mortality.

People using at least basic sanitation services: improved sanitation reduces exposure to diseases that contribute to infant mortality. This is indicated by the fact that a unit change in SAN (people using at least basic sanitation services) results in a decrease of 1.461 in infant mortality rate (IMR), and this decrease is statistically significant at a 5% level of significance.

Per Capita Health Expenditure: the coefficient of per capita health expenditure is negative and not statistically significant at the 5% level of significance, which indicates that there is no long-term link between GOVHEXP and IMR.

In the evaluation of climate change–population health relationship, as shown in *Table 10*, the adjusted R-square indicates that the model's explanatory variables explained 99% of the variance in the dependent variable, and about 1% remained unexplained. The value of the F-statistic (291.66) was statistically significant at the 1% level, demonstrating the model's significance.

Table 10. *Dependent variable: LE*

	Coefficient	Std. err	t-Statistic	Prob.
LMTEMP	0.165	0.230	0.716	0.489
LPRECP	0.001	0.000	2.347	0.040
LPRECP (-1)	0.001	0.001	2.721	0.021
SSE	0.013	0.004	2.748	0.020
SAN	0.402	0.063	6.299	0.000
SAN(-1)	-0.230	0.072	-3.189	0.009
GOVHEXP	0.005	0.027	0.203	0.843
C	12.927	7.592	1.702	0.119
R-squared	0.997		—	—
Adjusted R-squared	0.993		—	—
F-statistic	291.660		Durbin-Watson	2.364
(Prob)	(0.000*)		Stat	

Sources: authors' compilation, 2025

Temperature: The coefficient of annual mean temperature as a proxy for climate change was positive and not statistically significant at the 5% level of significance. The data reveals that an increase in the yearly mean temperature correlates with an increase in life expectancy. This result signifies that there is no tangible long-term connection between annual mean temperature and life expectancy in this model.

Precipitation: The coefficient for precipitation as an indicator of climate change was positive and statistically significant at the 5% level, denoting that a unit variation in precipitation correlates with a 0.013-unit increase in life expectancy, suggesting that alterations in rainfall patterns exert a consistent effect on life expectancy.

Secondary School Enrolment: The coefficient of secondary school enrolment shows a positive and statistically significant relationship at the 5% level of significance, indicating that a unit increase in SSE would lead to 0.013 increase in life expectancy, signifying that there is a long-term link between secondary school enrolment and life expectancy because education improved health awareness and the related outcomes.

People using at least basic sanitation services: better sanitation shows a positive and statistically significant relationship with life expectancy, and improved sanitation reduces exposure to diseases that contribute to low life expectancy. This is indicated by the fact that a unit change in SAN (people using at least basic sanitation services) results in an increment of 0.402 in life expectancy.

Per Capita Health Expenditure: the coefficient of per capita health expenditure is positive but not statistically significant at the 5% level of significance, which indicates that there is no long-term link between GOVHEXP and life expectancy in the model.

Discussion of Results

Climate change plays an essential role in determining population health because it influences the environmental and socioeconomic setting in which people live. Through their effects on disease exposure, water accessibility, and health system stress, rising temperatures, rainfall variation patterns, and growing climatic extremes have an impact on infant mortality and life expectancy (Campbell-Lendrum et al., 2023). School enrolment, healthcare access, and public health capacity all play a major role in how well populations can adapt to these climate shocks.

According to this study, the association between climate change and population health shows that value increase in the mean annual temperature change is associated with decrease in infant mortality rate (Babalola et al., 2018; Kudamatsu et al., 2012) and reduced life expectancy (Roy, 2024), albeit neither relationship was statistically significant.

The link between precipitation and infant mortality has attracted the attention of researchers. For example, this study found a very strong link with infant mortality, suggesting that alterations in rainfall patterns exert a consistent effect on infant mortality, which is in line with the findings of Heft-Neal et al. (2018). This is empirically confirmed for Nigeria, as variations in rainfall patterns are found to have a strong and negative correlation with infant mortality rates, implying that an increase in rainfall affects infant mortality. This suggests that climate change may reduce infant mortality through water availability and improvement in agricultural yield. In addition, rainfall patterns were also found to exhibit strong and positive correlation with life expectancy in Nigeria, in line with Kewalani and Saifudeen (2021) and Dore (2005). Consequently, we may claim that variations in rainfall patterns exert a consistent effect on life expectancy. This implies that an increase in rainfall may result in improved agricultural productivity, improved nutrition, increased water supply and hence food security, which may eventually lead to better health and improvement in life expectancy in Nigeria.

Furthermore, the link between school enrolment and life expectancy has also attracted researchers' attention (e.g. Bulled and Sosis, 2010; Sede and Ohemeng, 2015; Ali, et al., 2023). The research at hand found a statistically significant positive correlation between school enrolment and life expectancy for the period of the study in Nigeria, which implies that there is a long-term link between secondary school enrolment and life expectancy, as education improved health awareness and related outcomes. Also, the link between school enrolment and infant mortality was found to be negative and not statistically significant.

It is noteworthy that improved sanitation reduces exposure to diseases that contribute to infant mortality. This is indicated by the fact that a unit change in SAN (people using at least basic sanitation services) results in a decrease in infant

mortality rate (Mebrahtom and Gage, 2022; Sriyanto, et al., 2023), while improved sanitation also shows a positive and statistically significant relationship with life expectancy, and better sanitation conditions reduce exposure to diseases that contribute to low life expectancy (Ummalla et al., 2022; Roy, 2025).

This study found that per capita health expenditure is not a strong driver of infant mortality, having found a negative and non-significant link between the two variables, contrary to Anwar et al. (2023). However, per capita health expenditure is positive but not statistically significant at 5% regarding life expectancy, indicating that there is no long-term link between GOVHEXP and life expectancy in the model (Banik et al., 2023).

5. Conclusions and Policy Recommendations

The association between climate change and population health has been widely investigated in the academic discourse, considering elements such as per capita health expenditure, sanitation, and secondary school enrolment. Climate change and its interactions with other factors are not adequately investigated in the current study, indicating a clear gap in the subject. To discuss this, data from the World Bank's World Development Indicator and a climate change knowledge platform were used from 2000 to 2024, also adopting an autoregressive distributed lag estimate technique. The findings of the current investigation indicate a negative link between infant mortality and precipitation, as well as secondary school enrolment and sanitation over an extended period in Nigeria. It is important to keep in mind that this association is statistically significant beyond a certain point. In a similar vein, we have found that annual mean temperature and government health expenditure shows a negative, statistically insignificant impact on infant mortality in Nigeria. These results are in line with Helldén et al. (2021). Moreover, improved sanitation had a significant and negative association with infant mortality rate, and it also showed a positive and statistically significant association with life expectancy, which is the most impactful variable in the model. Therefore, policy makers should prioritize ensuring access to basic sanitation infrastructure by investing in the construction of sewage systems, public toilets, and waste disposal facilities, as well as incorporating sanitation education in the curriculum to ensure elimination of open defecation. Furthermore, a positive and significant relationship was found between life expectancy and precipitation and secondary school enrolment in the long run, while a positive and insignificant result was obtained regarding the relationship between life expectancy and health expenditure. The findings of this study provide novel insights into the complex connections between various variables that influence infant mortality and life expectancy in Nigeria. These implications underline the need for specialized

policy interventions and offer insight into the challenges associated with achieving lower healthcare costs, boosting productivity, increasing workforce participation in order to boost economic growth. Despite the lack of statistical significance concerning the relationship between health expenditures and infant mortality, as well as life expectancy, revealed in this model, this is still an important area that requires further scrutiny given its conceptual relevance. Health expenditure can play a supportive role in reducing infant mortality, but it must be prudently utilized to target high-impact interventions, for instance, providing maternal care or administering vaccines. The relationship between precipitation and infant mortality is negative and significant, while its relationship with life expectancy is positive and significant. Policymakers must therefore ensure water storage in dry areas to improve agriculture through rainfall, invest in irrigation systems, develop a climate-resilient agriculture, and improve clean water access.

It is also critical to have strategies for continuous assessment and monitoring to ensure that healthcare expenditure is targeted at high-impact interventions so that funding is translated into outcomes that effectively reduce infant mortality. The need for comprehensive policy responses is emphasized by the statistically insignificant influence of health expenditure on infant mortality, and future research should explore this further.

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