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Revisiting the forecasting power of public health expenditure and climate change impact on life expectancy in Nigeria: A scenario analysis.

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Abstract

In this study, we investigate the forecasting power of public health expenditure and the impact of climate change on life expectancy in Nigeria. This study relies on time-series data covering a period of 35 years (1988 to 2022) and uses a bias-adjusted ordinary least squares (OLS) method to predict the relationship and ARMSE to forecast with 8 policy options (scenarios) for 5 years. The analysis is based on data sourced from FAO, 2025, and WDI, 2025 databases. The results reveal a positive impact of both climate change (CC) and public health expenditure (PHE) on life expectancy (LE). In a single predictor model, for every one-degree Celsius rise (or fall) in CC and a percentage rise (or fall) in PHE, LE will rise (or fall) by 52.3 and 2.82, respectively. However, in a multiple predictor equation, the responses of LE to a change in CC and PHE are 15.14 and 2.12, respectively. We also reveal the 3rd scenario as the best option for policymaking. Given these positive impact results, the study concludes that climate change has led to an improvement in healthcare investment in Nigeria to mitigate the effects of climate-induced health challenges. We thus advise the government to sustain its improvement in the health sector through budgetary allocation and implementation.

Keywords: Bias-adjusted OLS, Climate change, Forecasting power, In-sample forecast, Life expectancy, Nigeria, Out-of-sample forecast, Prediction, Public health expenditure, Scenario analysis.
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Contents

Contribution of this paper to the literature
The contributions of this study lie in the analysis of eight scenarios to forecast the impact of public health expenditure and climate change on life expectancy over five years. Additionally, the application of ARMSE for both in-sample and out-of-sample forecasts is utilized in a study that integrates public health expenditure and climate change in a single study in Nigeria.

1. Introduction

Public expenditure on health and climate change are critical determinants of life expectancy of people, particularly in low- and middle-income countries like Nigeria. The interplay of these factors significantly impacts the quality of life, socio-economic progress, and overall well-being of the population. Understanding this relationship is essential for formulating effective policies that promote health equity and resilience to climate change.

Public expenditure on health is a critical driver of improved healthcare delivery and population health outcomes. However, in Nigeria, the allocation of public resources to the health sector has consistently fallen short of expectations. According to World Bank (2023) Nigeria allocates less than 5% of its gross domestic products (GDP) to healthcare, significantly below the 15% target set by the Abuja Declaration. Also, out-of-pocket healthcare expenditures account for over 70% of total health spending, leaving vulnerable populations at risk (World Health Organization (WHO), 2023). Nigeria's life expectancy is among the lowest globally, at approximately 55 years in 2022, compared to a global average of 73 years (World Bank, 2023). Life expectancy in Nigeria lags behind regional peers such as Ghana (64 years) and South Africa (65 years), reflecting disparities in health investments and outcomes. Though, Women in Nigeria generally live longer than men, with female life expectancy at 57 years compared to 55 years for men. This aligns with global trends but highlights the need for targeted male health interventions (National Bureau of Statistics, 2023). This under-funding has resulted in inadequate healthcare infrastructure, limited access to essential services, and a disproportionate burden of diseases, particularly among vulnerable populations.

Simultaneously, Nigeria faces significant challenges from climate change, which exacerbates health risks and disrupts socio-economic activities. Rising temperatures, unpredictable rainfall, and increased frequency of extreme weather events have led to the proliferation of climate-sensitive diseases such as malaria, cholera, and respiratory illnesses (Intergovernmental Panel on Climate Change (IPCC), 2022). Climate change exacerbates food insecurity, and malnutrition, thereby reduces life expectancy in affected regions (Akinbobola & Saibu, 2021). Integrated health system and climate adaptation policies remain scarce, leading to missed opportunities for improving resilience and life expectancy (United Nations Development Programme (UNDP), 2020). Though, investments in climate-resilient health systems mitigate these effects, but such measures are largely underdeveloped in Nigeria (World Health Organization (WHO), 2021). These health impacts are particularly pronounced in rural and underserved areas, where healthcare systems are already overstretched.

The intersection of insufficient public health investment and climate-induced health challenges exacerbates this situation, highlighting the urgent need for comprehensive policy responses. In the past, Nigeria has developed several health policies, such as the National Health Policy and Basic Health Care Provision Fund, but implementation gaps remain significant (Olaniyan, Oladeji, & Adepoju, 2022).

There is wealth of knowledge in this area of research, for instance, the work of Ilori, Olalere, and Babatola (2017) and Odhiambo Sewe et al. (2018) separately investigated the relationship of public health expenditure on life expectancy and temperature on years of life lost respectively. Ilori et al. (2017) revealed a long-run association between public health expenditure and life expectancy while Odhiambo Sewe et al. (2018) found mixed result across low-, middle-, and high-income countries. Kewalani and Saifudeen (2021) also explored the climate change and life expectancy in 172 countries and found that life of human living in cold region is elongated than those living in temperate region. Empirical studies consistently show that increased public health expenditure positively impacts life expectancy, while climate change poses significant risks to health outcomes, particularly in low-income and vulnerable regions like Nigeria. Despite the wealth of research, there is limited integration of public health expenditure and climate change in a single analytical framework, particularly in Nigeria.

It is evident from the literature that most studies focused on county-specific and cross-countries analysis and concentrated on the impact analysis. However, this study seeks to investigate the relationship between public expenditure on health and climate change, on life expectancy in Nigeria. By examining these interdependencies, the research aims to provide actionable insights for policymakers to optimize health spending, enhance resilience to climate change, and ultimately improve life expectancy. This, we proffer a scenario analysis to help policy making easier after forecasting for five years. The bias-adjusted ordinary least squares (OLS) and the ARMSE in-sample and out-of-sample forecast (developed by adjusting the traditional RMSE) methodology deployed also signifies the novelty of this study over others.

2. Literature Review

To conceptualize this study, we start from public health expenditure which refers to government spending on healthcare infrastructure, services, and programs aimed at improving the health of the population (Anyanwu & Erhijakpor, 2009). However, in Nigeria, public health expenditure remains below international benchmarks, which undermines its ability to significantly impact health outcomes (World Health Organization (WHO), 2023). Climate change on the other hand is a global challenge that has direct and indirect impacts on health. The ecological framework of health highlights how environmental factors, including temperature, precipitation, and extreme weather events, influence the spread of vector-borne diseases, heat-related illnesses, and food insecurity (McMichael, Woodruff, & Hales, 2006). Nigeria, being highly vulnerable to climate change, faces rising incidences of diseases such as malaria, cholera, and respiratory infections, particularly in rural areas where adaptive capacities are limited (Intergovernmental Panel on Climate Change (IPCC), 2022). These climate-induced health risks disproportionately affect the most vulnerable populations, exacerbating existing health inequities.

Finally, Life expectancy, the average number of years an individual is expected to live, serves as a critical indicator of a population's overall health and well-being. Factors influencing life expectancy include healthcare access, socioeconomic conditions, environmental quality, and government policies. The capability approach, as proposed by Sen (1999) emphasizes that life expectancy is not only a measure of biological survival but also a reflection of the broader socio-economic and environmental context. In Nigeria, low life expectancy is driven by high infant and maternal mortality rates, prevalence of communicable diseases, and insufficient public health investment.

Therefore, the implications of the interaction between public expenditure on health and climate change significantly affects life expectancy. Inadequate health funding limits the capacity to address climate-sensitive diseases, while the impacts of climate change strain already underfunded healthcare systems. The concept of climate-resilient health systems (World Health Organization (WHO), 2021) emphasizes the need for integrated policies that enhance health system capacity to adapt to climate change while improving health outcomes. Studies suggest that targeted investments in healthcare, coupled with climate adaptation strategies, can mitigate the adverse impacts of climate change and improve life expectancy (Ebi, Campbell-Lendrum, & Wyns, 2018).

While some studies have explored these issues individually, there is a paucity of research examining their interrelationships in the Nigerian context, leaving a critical gap in understanding and policy-making. Several theoretical postulations have sought to explain the relationship between public health expenditure, climate change and life expectancy. Starting with the health production function theory which posits that health is both a consumption and an investment good. That is, individuals and government invest in health to improve their quality of life, productivity, and societal well-being. The suitability of this theory in our study is that, it contributes to improved healthcare services, reduced morbidity, and increased life expectancy (Grossman, 1972).

Empirically, the validity or otherwise of this theory rests on the outcomes of studies that links Public Expenditure on Health and Life Expectancy. For example, the studies of Bokhari, Gai, and Gottret (2007); Anyanwu and Erhijakpor (2009); Novignon, Olakojo, and Nonvignon (2015) and Olaniyan et al. (2022) found that increased public health expenditure significantly improves life expectancy and reduces infant mortality rates in Africa, including Nigeria, and other Sub-Saharan African countries. However, the efficacy of the impact rests on governance quality and the efficiency of resource allocation. This theory underscores the importance of adequate health funding in achieving better health outcomes. In the Nigerian context, where public health expenditure is significantly low, the theory provides a basis for analyzing its impact on life expectancy.

Concerning the Bronfenbrenner (1979)'s ecological systems theory which emphasizes the interplay between individuals and their environment, highlighting how external factors influence health outcomes. Climate change, as a macro-level environmental factor, affects human health through extreme weather events, temperature changes, and the spread of vector-borne diseases. This theory is particularly relevant for understanding the impacts of climate change on health in Nigeria, where vulnerabilities to climate-related risks are high, especially in rural areas with limited adaptive capacities. Empirical evidences have shown direct and indirect negative impact of climate change on life expectancy. Directly, it was argued by Ebi et al. (2018) that low-income countries are disproportionately affected by climate change on global health. Their outcome was not surprising as other investigations revealed an indirect effect of climate change on life expectancy through malarial prevalence, food insecurity and malnutrition, increased disease burden, and migration (Abidemi, Alabi, & Olatunji, 2018; Akinbobola & Saibu, 2021; Dell, Jones, & Olken, 2012). These studies highlighted the role of climate adaptation strategies, such as improved healthcare infrastructure and disease surveillance systems, in mitigating the negative impacts on life expectancy.

Other frameworks that explain these relationships are the capability approach and Climate-Resilient Health Systems Framework. Where capability approach focuses on the freedom individuals have to achieve well-being and live a long and healthy life, Climate-Resilient Health Systems Framework emphasizes the need for health systems to adapt and respond to the challenges posed by climate change. It highlights the integration of climate adaptation measures into health policies, infrastructure, and services (World Health Organization (WHO), 2021). These approaches underscore the role of public health expenditure in enhancing individuals' capabilities and mitigating the effects of socio-economic and environmental constraints, such as climate change. It should be understood that in Nigeria, where healthcare systems are already strained, this framework provides a lens to explore how public health funding can be optimized to build resilience against climate-related health risks and improve life expectancy. Empirical studies that focused on the impacts of public health expenditure and climate change on life expectancy to validate or otherwise the postulation of these frameworks suggested that countries with higher investments in health and adaptive infrastructure experienced fewer climate-induced health crises and higher life expectancy gains (Ogunleye, Balogun, & Abayomi, 2020; United Nations Development Programme (UNDP), 2020; World Health Organization (WHO), 2021). They concluded that integrated policies addressing both health and climate resilience are essential for improving life expectancy in vulnerable regions.

3. Methodology and Data

Based on the multi-theoretical postulations this study is underpinned, we follow the Ilori et al. (2017) procedure to express life expectancy as a function of government health expenditure and climate change as follows.

$$LE = f(PHE, CC) \qquad (1)$$

The term LE is the Life expectancy and is measured as the average number of years a newborn is expected to live, based on current mortality trends. PHE is public health expenditure as a percentage of gross domestic products (GDP) and per capita health spending. CC is Climate change indicators and is captured by average temperature at time. Although, the common approach in the literature is to measure the climate change using CO_2 emissions (see for example (Opoku & Boachie, 2020; Tang & Tan, 2015)). The CO_2 despite representing a major source of climate change is not the only sources. In other not to undermine the accuracy of the measure of climate change in this study, preference was given to temperature which is a better indicator of climatic condition and global warming irrespective of the varying sources of climate change. All the variables are annual time-series spanning between 1988 to 2022 totaling 34 number of observations. The data were sourced from two main online databases namely, Food and Agricultural Organization (FAO) (Climate change) and World Development Indicators (WDI) (public health expenditure and Life expectancy) databases.

However, in order to explore functional representation in Equation 1 as our predictive model, we transform it to an estimable empirical model and in reduced form to include the predictors only, namely; government health expenditure and climate change.

$$le_t = \beta_0 + \beta_1 phe_t + \beta_2 cci_t + \varepsilon_t \qquad (2)$$

Equation 2 is our estimable predictive model which is a reduced form of the functional representation in Equation 1. According to Liu, Reed, and Girard (2017) having too many predictors in a predictive model often lead to inclusion of irrelevant variables likely to result into an in-sample over fitting problem. To address this concern, we follow the Westerlund and Narayan (2015) estimation techniques to account for possible endogeneity bias that may result from the omission of an important variable(s) in Equation 2. While the estimated coefficients attached to each predictor series, for instance β_1 and β_2 can be positive or negative depending on which of the three hypotheses earlier mentioned is under consideration, we further rewrite Equation 2 in a more compact form and in line with the Westerlund and Narayan procedure as shown below.

$$LE_t = \propto + \beta^{Adj} x_{t-1} + \eta(x_t - \rho x_{t-1}) + \vartheta_t \qquad (3)$$

The predicting series for instance, le_t in Equation 3 remain as earlier defined while x_t is potential predictor of life expectancy (LE) which will be captured singly for climate change (CC) and public health expenditure (PHE) when the predictive model in Equation 3 is expressed in bivariate form, and jointly in a multivariate form to simultaneously include CC and PHE in a single framework. The parameter β in Equation 3 measures the first order autocorrelation coefficient, while the inclusion of the second term $(x_t - \rho x_{t-1})$ is meant to address any presence of persistence effect in the predictive model. The term η on the other hand is meant to capture the likelihood of the presence of endogeneity effect in the model (see (Lewellen, 2004)). In particular, accounting for endogeneity via the Lewellen approach has the potential to help address bias that would have arisen due to omission of any important variable(s) in the predictive model. Hence, estimating Equation 3 with ordinary least squares (OLS) method having corrected for the potential presence of persistence and endogeneity is expected to yield a bias-adjusted OLS estimator for β described as:

$$\beta^{Adj} = \beta^\wedge - \delta(\rho^\wedge - \rho) \qquad (4)$$

For the purpose of our analysis and the quest to have a robust comparison regarding which matter most between public health expenditure (PHE) and climate change (CC) in forecasting of life expectancy, we consider the following pair of predictors:

$$le_t = \propto + \beta cc_{t-1} + \eta(cc_t - \rho cc_{t-1}) + \vartheta_t \qquad (5)$$

$$le_t = \propto + \beta phe_{t-1} + \eta(phe_t - \rho phe_{t-1}) + \vartheta_t \qquad (6)$$

The bivariate predictive model presented in Equations 5 and 6 captured CC and PHE singly in each equation to evaluate and compared their respective forecasting power in the predictability of climate change. For easy identification and representation of results in the subsequent section we named the equations as CC_Model and PHE_Model, respectively. Furthermore, Equation 7 are a multivariate predictive model that captured the combine forecasting power of CC and PHE in a single framework and tagged "CC_PHE_Model".

$$le_t = \propto + \beta_{cc} cc_{t-1} + \beta_{phe} phe_{t-1} + \eta_{cc}(cc_t - \rho_{cc} cc_{t-1}) + \eta_{phe}\big(phe_t - \rho_{phe} phe_{t-1}\big) + \vartheta_t \qquad (7)$$

The in-sample forecastability of the predictive models will be assessed to determine which variant of the predictive models is the most suitable for our out-of-sample forecast and scenario analysis. Essentially, the predictability of life expectancy is evaluated using alternative forecast performance measures, viz: Root Mean Square Error (RMSE) and it adjusted variant (i.e. ARMSE) developed by Moosa and Burns (2012). The outcomes of each of the measures is expected to be consistent so as to ascertain the robustness of our findings.

If the full-sample period is $t = n + 1, \ldots, n + k,$ such that n is the in-sample period while k is the forecast horizon, hence the RMSE for the in-sample and out-of-sample forecasts can be expressed as follows:

$$\text{In-Sample:} \quad RMSE = \sqrt{\frac{1}{\mathrm{n}} \sum_{t=1}^{\mathrm{n}} (le_t - le_t)^\wedge 2} \qquad (8)$$

$$\text{Out-of-Sample:} \quad RMSE = \sqrt{\frac{1}{\mathrm{k}} \sum_{t=1}^{\mathrm{k}} (le_t - le_t)^\wedge 2} \qquad (9)$$

For the sake of consistency and robustness of the forecasts, we compliment the RMSE method with its adjusted variant following the Moosa and Burns (2012) approach (see also, (Ali, Awe, Mohammed, & Isah, 2024; Salisu, Isah, & Ademuyiwa, 2017)). The ARMSE is developed by adjusting the traditional RMSE to take into consideration the potential of the model to predict the direction of change. In line with the Salisu et al. (2017) procedure, the ARMSE can be calculated using the following formula:

$$\text{In-Sample:} \quad ARMSE = \sqrt{\frac{CR}{\mathrm{n}} \sum_{t=1}^{\mathrm{n}} (le_t - le_t)^\wedge 2} \qquad (10)$$

$$\text{Out-of-Sample:} \quad ARMSE = \sqrt{\frac{CR}{\mathrm{k}} \sum_{t=1}^{\mathrm{k}} (le_t - le_t)^\wedge 2} \qquad (11)$$

The term CR is often described as the confusion rate calculated as $CR = 1 - DA$, where the DA is the direction accuracy computed correspondingly for the in-sample and out-of-sample as:

$$\text{In-Sample:} \quad DA = \frac{1}{m} \sum_{t=1}^{m} a_t \qquad (12)$$

$$\text{Out-of-Sample:} \quad DA = \frac{1}{k} \sum_{t=1}^{k} a_t \qquad (13)$$

Intuitively, the predictive model which in-sample and out-of-sample forecasts has the least RMSE values would be considered the most accurate to carry out scenario analysis. With respect to the ARSME, however, it is posited that where two models have equal RMSE values, the model with a higher CR should have a higher ARMSE (Moosa & Burns, 2012). One of the attractive features of the ARMSE as represented in Equations 10 & 11, is that it is not sensitive to the measures of either magnitude (i.e. values of RMSE) or direction (i.e. CR).

Table 1. Descriptive and/or summary statistics.

Statistics	Life expectancy (LE)	Climate change (CC)	Public health expenditure (PHE)
Mean	49.1	0.80	16.6
Std. dev.	2.81	0.42	4.21
Skewness	0.02	-0.69	0.75
Kurtosis	1.44	3.76	3.64
JB Stat.	3.55 (0.17)	3.59 (0.17)	3.84 (0.15)

Note: The values in parenthesis are probability values associated with the Jaque-Bera (JB) statistic.

4. Results and Discussion of Findings

Table 1 shows the descriptive statistics of the data deploy. the essence is to provide some background information about the variables of interest. The variables; LE, CC, and PHE have different mean values of 49.1, 0.79, and 16.57 respectively. This suggests that, the variables are influenced by different factors. The standard deviation, the skewness, and the kurtosis largely suggest that the variables under consideration are well behaved. The Jaque-Bera (JB) statistics, which takes into consideration the skewness and kurtosis, for all variables are insignificance suggesting they are normally distributed. The kurtosis for LE is less than 3 while that of CC and PHE are greater than 3. This means that the skewness for LE platykurtic while that of CC and PHE are leptokurtic.

Table 2. Unit root, autocorrelation, persistence and endogeneity tests results.

Variable	ADF unit root test results	Ljung-box autocorrelation test results	Persistence test results	Endogeneity test results
LE	-3.01^{**F} (0.05)	49.1*** (0.00)	-	-
CC	-3.37^{**L} (0.02)	0.80*** (0.00)	0.49*** (0.00)	0.50*** (0.00)
PHE	-3.16^{**L} (0.03)	16.6*** (0.00)	0.55*** (0.00)	1.02*** (0.00)

Note: *** and ** implies significant at 1%, and 5% levels of significance. The unit root test is performed using the Augmented Dickey-Fuller test with the subscript L suggesting that a variable is stationary at level test while F means that a series is a difference series. The autocorrelation test is performed using Ljung-Box test and the values reported are the Q-statistics associated with the test. The persistence test is performed by regressing each of the predictor on its first lag: $x_t = \alpha + \delta x_{t-1} + v_t$ using the OLS estimator. The first order coefficient, for instance (α) captures the persistence effect and the null is that there is no presence of the effect. The closer the value of $\alpha$to one, the higher the degree of persistence. Regarding the endogeneity test, the procedure follows a three steps approach as follows: (i) we ran a predictive regression, for instance, $z_t = \alpha + \lambda x_{t-1} + \varepsilon_{z,t}$with OLS as the estimator, where z_t denotes the life expectancy and x_{t-1} is the predictor variables such as CC and PHE; (ii) we follows the Westerlund and Narayan (2015) model of the predictor variable as follows: $x_t = \mu(1-\delta) + \delta x_{t-1} + \varepsilon_t$and in the third and final step (iii) the relationship between the two error terms ($\varepsilon_{z,t}$ and $\varepsilon_{x,t}$) is captured using $\varepsilon_{z,t} = \rho\varepsilon_{x,t} + \psi_t$. If the coefficient ρ is statistically different from zero, then the predictor variable is considered to be endogenous and strictly exogenous if otherwise.

Table 2 clearly shows that LE is stationary at first difference while CC and PHE are stationary at level. The evidence of mixed order of integration denotes that the stochastic behaviour of both the predicting variable (i.e., LE) and the predictor series (CC & PHE) aligns with the chosen methodology. Ljung-Box autocorrelation test indicates that there is overwhelming evidence of autocorrelation in the series. Also, we observe the series are significant hence, suggesting high degree of persistence and endogeneity bias in the predictor series. Due to the presence of autocorrelation, persistence and endogeneity in the series which could undermine the forecasting power of life expectancy, LE, preference is given to the Lewellen (2004) estimator as appropriate to capture and accommodate any bias.

Table 3. Predictability results.

Dependent variable LE	Coef.	t-stat.	p-value
Single predictor case			
CC	52.3***	14.2	0.00
PHE	2.82***	24.8	0.00
Multiple predictor case CC_PHE			
CC	15.14***	3.25	0.00
PHE	2.12***	8.85	0.00

Note: The in-sample predictability results were obtained by estimating the predictive model in Equation 3, for instance, $LE_t = \alpha + \beta^{Adj} x_{t-1} + \eta(x_t - \rho x_{t-1}) + \vartheta_t$ where $\hat{\beta}$'s denoting coefficient for the individual predictor across the bivariate and multivariate models, respectively. The values reported in parentheses are standard errors while *** implies 1% levels of significance, respectively.

The main aim of this study is to examine the forecasting power of climate change (CC) and public health expenditure (PHE) in predicting life expectancy and thereafter perform a scenario analysis that will enable us arrive at the most appropriate policy option that will improve life expectancy of Nigerians. Therefore, Table 3 shows the bias-adjusted OLS estimates for each of the predictors across both the single–factor and multiple–factor predictive models. The single-factor predictive model indicates that CC and PHE in the individual models are positive and statistically significant. Also, in a multiple-factor based predictive model that jointly reflects the relationship of CC and PHE on LE, the study reveals a positive and significant effect of the predictors (CC and PHE) on the regresand (LE). What this means is that, both CC and PHE induce life expectancy (LE) in Nigeria and this evidence finds support in some of the recent studies (Abidemi et al., 2018; Ilori et al., 2017; Odhiambo, Bunker, Ingole, Egondi, & Oudin Åström, 2018). Though, the impact of CC which is captured by temperature does not conform with the general expectation of negative relationship (that is, increase in temperature is expected to reduce life expectancy). This result could demonstrate the fact that impact of climate change in Nigeria has led to improvement in mitigation strategy.

Table 4. In-sample forecast performance results.

Forecast performance measures	CC_model	PHE_model	CC_PHE_model	Remark (Preferred model)
RMSE	18.2	10.9	9.21	CC_PHE_Model
ARMSE	8.58	5.10	4.14	CC_PHE_Model

Note: The model with the least RMSE and ARMSE values is considered the most accurate to forecast climate change.

The in-sample forecasting power of the predictors is determined to ascertain which of the predictive models is the most accurate and appropriate for our out-of-sample and scenario analysis. Table 4 explains the in-sample forecasts performance of the alternative predictive models under consideration namely CC_Model, PHE_Model and CC_PHE_Model, respectively. The results of the RMSE and ARMSE find that the predictive model that jointly includes both CC and PHE is the most accurate to forecast LE in Nigeria.

Table 5. Out-of-sample forecasts, scenario analysis and ranking of life expectancy.

Scenario								
Year	1	2	3	4	5	6	7	8
2023	50.0	48.9	54.9	54.7	46.3	45.0	45.2	46.2
2024	58.0	55.3	63.0	62.3	44.0	40.5	41.3	43.3
2025	59.8	55.7	70.8	69.6	41.8	36.5	37.7	40.6
2026	62.7	57.5	80.8	79.2	39.7	32.8	34.5	38.1
2027	66.8	60.6	93.2	91.2	37.7	29.6	31.5	35.8
Rank	3rd	4th	1st	2nd	5th	8th	7th	6th

Note: The ranking is based on the life expectance increase impact of the scenario option. Hence, scenario that causes consistent increase in life expectancy across all the five out-of-sample forecast horizons considered is ranked higher and it is in that order that we determine the ranking.

Haven established multiple-equation as the most accurate in the predictability of life expectancy, hence, the need for out-sample forecasts and scenario analysis to determine which policy option is the most suitable for life expectancy improvement in Nigeria. Table 5 presents the result of the out-sample forecast results, scenario analysis and ranking position of the scenarios,

This study considers eight scenarios that could provide guide for policy makers to proffer policies that could increase life expectancy in Nigeria. In the first and second scenario, we allow both CC and PHE to follow their natural path using unequal weight moving average technique. That is, we allow CC to follow its conventional path and reduces PHE by 5% and 10%, respectively. For the sake of just comparison, the third and fourth scenarios are nothing but direct opposite of the first and second scenarios. The fifth and sixth scenarios allow both CC and PHE are reduced by 5% and 10% respectively. We also further check for seventh and eight scenarios where the former allow for CC reduction by 5% and 10% for PHE. The eight scenario reverse the policy option of scenario seven which allows for percentage increase of CC to 10% and reduces the percentage of PHE to 5%. Using each of these scenarios, we projected for the impacts of CC and PHE in the next five years (that is, 2023, 2024, 2025, 2026, and 2027) and observe that scenario three impact increases consistently more on life expectancy (LE), thus, ranked the best for policy makers to improve LE.

5. Conclusion

The relationship between climate change, public health expenditure and life expectancy is what this study examined in the quest to analyse the predictive impact of climate change and public health expenditure on life expectancy. Also, the forecasting power of these predicting variables is examined on life expectancy for five years under eight potential policy options (scenarios) that can be adopted to improve life expectancy in Nigeria. To accurately forecast, the study explored single-predictor and multiple-predictor equation and found that the multiple predictor equation was better, Therefore, it was observed from the results of the chosen model that both climate change and public health expenditure positively impact on life expectancy. The positive impact of climate change suggests possible improvement in health facilities to mitigate its effect. This is suggestive in the result of public health expenditure as it positively impacts on life expectancy. On the forecasting outcome, it was discovered that scenario three was a better option to adopt to improving life expectancy in the next five years given its consistent increase. Based on the aforementioned, the implication is that as climate change (temperature) impact intensified (or increase), the need for the improved healthcare facility to mitigate its accompanied effect like fever, malaria and other related sickness.

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