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Climate change and health outcomes in Sub-Saharan African countries

Uche Okirie[1]
Ahmed Adefemi Adesete[2+]

[1]*Department of International Development, University of East Anglia, Norwich Research Park, United Kingdom.*
Email: uche.okirie@yahoo.com
[2]*Department of Economics, University of Lagos, Nigeria.*
Email: adeseteahmed@gmail.com
(+ Corresponding author)

ABSTRACT

This paper examines the effect of climate change on health outcomes in sub-Saharan Africa (SSA). Greenhouse gas emission was used as the measure of climate change, while life expectancy rate was used as the measure of health outcomes. This paper's significant contribution is how the interaction of climate change and government effectiveness index influence health outcomes in SSA. We estimated the impact of climate change on health outcomes using the panel system generalized method of moments (GMM) method. Our empirical result show that there is a negative and significant relationship between climate change and life expectancy in the short and long run. In addition, we find that if effective government policy is interacted with climate change, this mutes the negative impact of climate change on health outcomes in SSA. This implies that, with effective government policies targeted toward achieving net zero carbon emission, climate change is not expected to have a significant impact on health outcomes in SSA.

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Contribution/ Originality: We contribute to existing literature by examining the interactive role of the effectiveness of government policy on the relationship between climate change and health outcomes. In addition, we motivate the relationship between climate change and health outcomes by augmenting the Grossman model with Environmental Kuznets curve in our theoretical framework.

1. INTRODUCTION

Issues regarding climate change are mostly understudied from the perspective of the deteriorating environment and its relationship to sustainability. (Abiodun et al., 2017; Bekaert, Ruyssen, & Salomone, 2021). Changes in the environment can be identified from some of the ecological components of climate change, like greenhouse gas emissions, rising sea levels, drought, and water & environmental pollution. Even though Africa contributes less to the global carbon footprint relative to the rest of the world, climate change severely impacts Africa (most especially sub-Saharan Africa (SSA)). Sub-Saharan Africa contributes approximately 5.15% to global greenhouse emissions (WDI, 2022) relative to emissions from Europe (33%) and Asia (29%).

Generally, Africa is the most vulnerable to the effects of climate change, and more than 100 million Africans are exposed to the impact (World Meteorological Organization (WMO), 2021). Increasing CO2 levels, rising sea levels, rising temperatures and extreme weather events weigh on health outcomes by reducing air quality, heat stress, lowering water quality and food insecurity (United Nations Framework Convention on Climate Change (UNFCCC), 2021). Hence, the devastating effect of climate change on health and other socio-economic outcomes has triggered some policy changes, especially in vulnerable countries. For example, the Alliance for Transformative Action on Climate and Health (ATACH) was launched at Conference of the Parties 26 (COP26) (the annual climate change conference organized by the United Nations (UN) (in 2021) in order to strengthen the health sector response of mostly African countries to climate change. Additionally, at the recently organized United Nations (UN) climate change conference in 2023 (COP28), 151 countries reinstated their commitment to mitigating the impact of climate change on health outcomes. This policy changes over time and the concerns over the impact of climate change on health outcomes necessitate answering the research question in this paper: What is the effect of climate change on health outcomes in Sub-Saharan Africa?

There are limited studies on the impact of climate change on health outcomes, as papers have used different indicators for climate change, such as heat stress, CO2 emission and level of precipitation. Hence, there is no consensus from empirical works. Most studies argue that climate change has a negative impact on the health outcomes of particularly developing countries. For instance, Thiede, Ronnkvist, Armao, and Burka (2022) understudied the relationship between birth histories and climate change anomalies in 23 sub-Saharan African countries and found that climate change reduces women's fertility. On the other hand, other empirical evidence from the literature reveals that climate change measured with heat stress, does not have a significant effect on health outcomes in the short run. (Jagarnath, Thambiran, & Gebreslasie, 2020). However, most of these papers focus more on the direct effect of climate change indicators on health outcomes, whilst little attention has been paid to an important variable: government effectiveness score. According to the World Bank, the government effectiveness index measures "the quality of public services, civil service, policy formulation and implementation, and the credibility of a government's commitment to improving or maintaining these aspects". The role of government effectiveness specifically encompasses how the quality of policy formulation and implementation can be improved to achieve the best economic outcomes. Broadly, it includes improving the quality of all levels of governance. Hence, this implies that the interaction of government effectiveness and the effort to reduce climate change should limit or eradicate the effect of climate change on socio-economic outcomes, including health outcomes. This highlights the need for higher quality of governance, especially for the most vulnerable country or region to climate change and contributes towards achieving sustainable development goal (SDG) 13, especially in SSA.

The objective of this paper is to investigate the effect of climate change on health outcomes in SSA. First, this paper posits that climate change influences health outcomes via greenhouse gas emissions, which is a key indicator of climate change. Burning fossil fuels and deforestation are part of the human activities that increase greenhouse gas emissions. This results in climate change by trapping heat in the atmosphere, which in turn affects health outcomes by affecting air quality, leading to respiratory and cardiovascular disease as well as premature deaths. Second, we hypothesise that, with the interaction of climate change indicator and government effectiveness, climate change could have limited or no impact on health outcomes. With a good quality of governance across all areas, climate change or environment-related policies have a more significant impact on socio-economic outcomes, such that climate change has a muted effect on health outcomes. This aids most countries or regions in order to meet their climate change-related targets like the SDG13. The primary objectives of SDG 13 are to "strengthen resilience and adaptive capacity to climate-related disasters, integrate climate change measures into policies and planning, build knowledge and capacity to meet climate change, implement the UN framework convention on climate change, and promote mechanisms to raise capacity for planning and management" (UN-SDGs, 2015).

In this paper, we contribute to existing literature in the following ways. First, this paper contributes to existing literature by broadly investigating the determinants of health outcomes in Sub-Saharan Africa and specifically examining the relationship between climate change and health outcomes in SSA. Second, we aim to examine the interactive role of the effectiveness of government policy on the relationship between climate change and health outcomes, which is a significant contribution relative to other literature on this subject matter. This was necessitated by the increasing call by different international organizations and authors on the role of the effectiveness of government policies in SSA in combating climate change and its impact on the health outcomes of the region. Understanding this from the empirical evidence of this paper helps SSA countries know how to effectively structure their policies to achieve their greenhouse emission target and douse the impact of climate change. Lastly, this paper uses the panel GMM to uncover the dynamic relationship between climate change and health outcomes, with data spanning 21 years and 40 SSA countries. This helps to provide a more comprehensive and up-to-date analysis relative to other related papers.

Here is a brief preview of our results. We found a negative significant relationship between climate change and life expectancy in both the short and long run. More importantly, we found that if effective government policy is interacted with climate change, this mutes the impact of climate change on health outcomes in SSA.

The rest of this paper is structured as follows. Section two comprises the existing works of literature. Section three focuses on the methodology of the research analysis. Section four discusses the empirical findings of the analysis, while section five includes the conclusion and policy recommendations.

2. BRIEF REVIEW OF RELATED LITERATURES

The study of climate change is an important socioeconomic issue that has attracted diverse studies from academics. However, it did not get the necessary attention it deserved in the past decade because of the inconspicuous short-run effect on the environment. This is because the effects of greenhouse gas emissions, global warming, and rising sea levels are not easily identifiable by non-scientists or non-academic scholars. This is one of the arguments for its lack of popularity at the micro-level of society. A second argument is as bleak as the first; it is just not true. As important as the knowledge of the effect of climate change is on our environment, it is still debatable amongst political commentators. Nevertheless, the impact of climate change has become of scientific importance in various regions of the world. There is evidence of rising heat waves in the United Kingdom and most parts of Europe. Also, sea levels are rising in Asia, as evidenced by flooding in Pakistan and tropical West African regions. All these have potential adverse effects on the earth and, more importantly, the people of the earth.

Thiede et al. (2022) examined the effect of climate change on health outcomes. Their study reviewed issues of fertility in SSA using birth histories from 1982 – 2017 and climate change variability within these periods. They revealed that climate change has a significant effect on fertility in SSA in the short run. They proposed that climate change has an indirect but significant relationship with population growth. Furthermore, weather shocks affect the transition of adolescents into adults through its effect on health outcomes. Also, Yeboah (2021) used (randomized controlled trials) RCTs to examine the impact of climate change on health outcomes in Burkina Faso and Kenya. Their model captured the combined effect of the impact of agro-biodiversification on undernutrition amongst children in the rural communities of both countries (examined 600 children), the impact of sunlight on household health outcomes (300 households in Burkina Faso), and an Index-Based Weather Insurance (IBWI). Their study revealed that climate change has a strong negative impact on the health outcomes of Burkina Faso and Kenya and recommends that local adaptive transformative projects will enable developing countries like Burkina Faso and Kenya to adapt and combat major health issues posed by climate change.

Hui-Min, Xue-Chun, Xiao-Fan, and Ye (2021) conducted a study on the systematic risks of climate change from a dynamic perspective. Systematic risk is an induced type of risk derived from the combination of several single risk factors caused by climate change. The impact of their systematic risk study of climate change cuts across health outcomes, the economy, society, homeland security, and living conditions. Their study discovered that an increase in greenhouse gas emissions leads to vulnerability in the socioeconomy.

Abiodun et al. (2017) streamlined their study to the effect of environmental precipitation on four coastal cities in Africa; Cape Town, Lagos, Maputo, and Port Said. They used future climate index RCP scenarios (4.5 & 8.5) and 16 multi-model simulation datasets from the Coordinated Regional Climate Downscaling Experiment to analyse the effect of extreme precipitation on these cities. They find that the environmental impact of extreme precipitation has a direct effect on health outcomes. Their model predicted increased aridity in these cities and decrease humidity in the long term. However, this result was more consistent with Lagos, Maputo, and Port Said. They recommended that adequate measures should be taken to reduce the impact of future precipitation in these cities.

Adeola et al. (2017) conducted a time series analysis on the effect of climate change on malaria morbidity and mortality in South Africa. They used monthly time series data from 1998 – 2017 and Spearman's autocorrelation technique to develop a seasonal autoregressive integrated moving average (SARIMA) model for monthly malaria cases and seasonal climatic variations. Their result revealed a significant relationship between seasonal data and malaria morbidity. The study recommends that understanding variations in climate aids in understanding their effect on health outcomes in tropical regions like South Africa.

3. RESEARCH METHODOLOGY

3.1. Theoretical Framework

The Grossman model identifies the benefits of good health, which is more for high-wage workers, so they demand higher optimal health stock. Hence, workers who receive more wages have the capability to demand higher optimal health stock (which translates to better health outcomes). Thus, this implies that health outcomes should be higher for a more productive economy and health outcomes should be lower for a less productive economy. This shows that there should be a positive relationship between health outcomes and economic growth.

Additionally, the effect of economic growth on environmental degradation can be motivated by the environmental Kuznets curve (EKC). The intuition behind this is that, as the economy experiences growth from industrialization, the effect is felt in the environment (due to higher greenhouse gas emissions) at the early stages of development. However, as the economy develops, industrialization and emissions slow down (Gangadharan & Valenzuela, 2001).

The model used in this paper is motivated by the Environmental Kuznets Curve, Grossman model and the argument made by Gangadharan and Valenzuela (2001):

$$\mathrm{ED} = \mathrm{f(Y)} \qquad (1)$$

According to EKC, environmental degradation is a function of economic growth as shown in Equation 1. Environmental degradation is a function of economic growth and greenhouse gas emissions (Gangadharan & Valenzuela, 2001). Hence, Equation 1 is augmented with CO2 emission as an additional explanatory factor, resulting in Equation 2:

$$\mathrm{ED} = \mathrm{f[Y, CO_2]} \qquad (2)$$

From the Grossman model, income is a key determinant of health outcomes. Hence, environmental degradation and other factors are added as other determinants of health outcomes. Environmental degradation is added due to the objective of this paper while the inclusion of controls like population growth and government expenditure on healthcare is motivated by income (Suzman & Beard, 2011).

$$\mathrm{H_1} = \mathrm{f[Y, ED_t, Z]} \qquad (3)$$

$$Z = [POPGR, GE] \qquad (4)$$

Equations 2 and 3 suggest that an economy's health status depends on its level of growth (Y), environmental degradation (ED), and other control factors.

Apriori expectations of the variables are such that an increase in economic growth leads to an increase in environmental degradation, an increase in environmental degradation leads to a decrease in health outcomes, an increase in population growth (POPGR) leads to a decrease in health outcomes, while an increase in public expenditure on healthcare or increase in overall government expenditure (GE) leads to an increase in health outcomes (Gangadharan & Valenzuela, 2001).

Converting Equations 2 and 3 to functional forms:

$$ED = u - \theta_1 Y + \theta_2 CO_2 \quad (5)$$

$$H_t = \alpha + \beta_1 Y - \beta_2 ED + \beta_3 Z \quad (6)$$

Substituting Equation 7 in 8

$$H_t = \alpha + \beta_1 Y - \beta_2[u - \theta_1 Y + \theta_2 CO_2] + \beta_3 Z$$

$$H_t = \alpha + \beta_1 Y - \beta_2 u + \beta_2 \theta_1 Y - \theta_2\beta_2 CO_2 + \beta_3 Z \quad (7)$$

$$H_t = [\alpha - \beta_2 u] + \beta_1 Y + \beta_2 \theta_1 Y - \theta_2\beta_2 CO_2 + \beta_3 Z$$

$$H_t = [\alpha - \beta_2 u] + Y[\beta_1 + \beta_2 \theta_1] - \theta_2\beta_2[CO_2] + \beta_3 Z \quad (8)$$

Let $\delta = \alpha - \beta_2 u$ ≫ Constant

$b_1 = \beta_1 + \beta_2 \theta_1$

$b_2 = -\theta_2\beta_2$

From Equation 8

$$H = \delta + b_1 Y + b_2 CO_2 + \beta_3 Z \quad (9)$$

Breaking down the vector of Z from Equation 4 whereby Z is a function of [POPGR, GE]

$$H = \delta + b_1 Y + b_2 CO_2 + \beta_3[POPGR, GE]$$

$$H = \delta + b_1 Y + b_2 CO_2 + b_3 POPGR + b_4 GE + \mu \quad (10)$$

Whereby,

$b_1 > 0$

$b_2 < 0$

$b_3 < 0$

$b_4 > 0$

μ : Error term.

Equation 10 implies that the health outcome is determined by economic growth, CO_2 emission, population growth rate, and public health expenditure.

Table 1. Description of variables.

SN	Label	Description	Apriori Expectation	Source
1	LER	LER, life expectancy rate at birth in years as a proxy for health outcome.		WDI
2	GHG	GHG, greenhouse gas emission in kilo tonnes of CO_2 equivalent.	Negative	WDI
3	GNE	GNE, gross national expenditure in US $.	Positive	WDI
4	INCOME	GDPPC, (gross domestic product per capita) in US $ as a proxy for income	Positive	WDI
5	POPGR	POPGR. population growth rate (%)	Negative	WDI

Note: WDI – World Bank's World Development Indicators database.

3.2. Measurement and Description of Variables

Table 1 depicts the variables that are to be considered in this paper. All data was obtained from the World Bank's WDI for 40 sub-Saharan African countries from 2000 to 2020. The breakdown of the sub-Saharan African countries is as follows: 15 countries from West Africa, nine countries from East Africa, eight countries from South Africa, and eight countries from Central Africa. These countries were selected for the panel data analysis due to the availability of data and the best fit in the representation of sub-Sahara Africa. GHG was used as a proxy for climate change as used in other related papers (McMichael, Woodruff, & Hales, 2006) GNE is a proxy for government expenditure, and life expectancy rate is a proxy for health outcomes.

3.3. Analytical Technique

First, we provide the descriptive statistics of each variable and try to observe the trend analysis of the data for the selected countries. This is necessary to observe the distribution of the variables and make adjustments for any estimation bias in the model. Graphical analysis of the data set is also conducted, and this is necessary as a pre-estimation technique to give a snapshot analysis.

Next, given the micro panel cross-sectional data of 39 countries for 21 years, we test for cross-sectional dependence to observe the effect of spillovers in climate change between countries in sub-Saharan Africa. Checking for cross-sectional dependence also idealizes the specific choice of the unit root test we employ in this paper.

The Generalized Method of Moments (GMM) estimation technique is employed for the panel data estimation. Some of the reasons why this technique was used include;

(1) GMM estimators are used to address heteroskedasticity and autocorrelation within individual cross sections.

(2) GMM accounts for the problem of endogeneity.

(3) GMM is effective for micro panel data analysis, which is when the number of cross sections (N = 40) is greater than the period for each cross-section (T = 21).

We estimated two variants of the GMM, the difference GMM proposed by Arellano and Bond (1991) and the system GMM developed by Blundell and Bond (1998). After estimating the two variants, we used the Bond (2002) procedure to choose the most preferred model.

According to Bond (2002) if the lagged dependent variable estimate from the difference GMM is less than the upper bound estimate, the difference GMM is downward biased because of weak instrumentation. This will then mean that system GMM is the most preferred. If otherwise, a difference in GMM is preferred. The coefficient of the dynamic or lagged dependent variable of the pooled OLS is considered the upper bound estimate, while that of the fixed effects model is the lower bound estimate.

3.4. Model Specification

Following the EKC, Grossman model and the theoretical framework of this paper, the model to be estimated is as follows:

$$LER_{it} = \beta_0 + \beta_1 GHG_{it} + \beta_2 GNE_{it} + \beta_3 INCOME_{it} + \beta_4 POPGRE_{it} + \mu_{it}$$

Whereby,

LER_{it} - Life expectancy rate for each cross-section of each country over 20 years.

GHG_{it} – Greenhouse Gas Emissions for each cross-section over 20 years.

GNE_{it} – Gross National Expenditure for each cross-section over time.

$INCOME_{it}$ – Per Capita GDP for each cross-section over time.

$POPGRE_{it}$ – Population Growth Rate for each cross-section over 20 years.

μ_{it} – Error term for each cross-section over time.

β_i – Unknown intercept for each country.

4. RESULTS AND DISCUSSIONS

This section contains descriptive statistics, pre-estimation tests, graphical analysis, as well as equation estimation and interpretation.

4.1. Descriptive Statistics

Section 4.1 presents the descriptive statistics for all the variables that we use in this paper (as shown in Table 2) and the list of all the countries that we use for our analysis (as shown in Table 3).

Table 2. Descriptive statistics for dependent and independent variables.

	GHG	GNE	INCOME	LER	POPGR
Mean	47,650.08	3.18E+10	2074.44	57.48	2.54
Median	23,723.60	1.08E+10	879.04	57.71	2.67
Maximum	541,945	5.14E+11	22942.61	75.01	5.60
Minimum	320	4.15E+08	111.93	39.44	-2.63
Std. dev.	83964.94	7.35E+10	3140.22	6.67	0.86
Skewness	3.88	4.37	3.22	0.12	-1.01
Kurtosis	19.50	22.66	15.30	2.87	5.97
Jarque-Bera	11347.62	15797.95	6573.84	2.55	438.70
Probability	0.00	0.00	0.00	0.28	0.00
Observations	819	819	819	819	819

Table 3. Broad classification of the countries used for analysis.

Sub-Saharan Africa			
West Africa	**Eastern Africa**	**Southern Africa**	**Central Africa**
Cabo Verde	Seychelles	Botswana	Gabon
Senegal	Sudan	South Africa	Congo, Rep.
Mauritania	Comoros	Namibia	Congo, Dem. Rep.
Ghana	Rwanda	Zambia	Equatorial Guinea
The Gambia	Ethiopia	Angola	Cameroon
Benin	Kenya	Mozambique	Chad
Togo	Tanzania	Zimbabwe	Central Africa Republic
Niger	Burundi	Lesotho	
Burkina Faso	Uganda		
Guinea			
Mali			
Guinea-Bissau			
Cote d'Ivoire			
Nigeria			
Sierra Leone			

Table 1 presents the descriptive statistics for the series on greenhouse gas emission (GHG) in kilo tons of CO_2 equivalent, gross national expenditure (GNE) in US dollars, real GDP per capita in US dollars (proxy to INCOME), life expectancy rate at birth (LER) in years and population growth rate (POPGR) in percentage (%). All the series were collected for 40 African countries across West Africa (15), Eastern Africa (9), Southern Africa (8), and Central Africa (7), ranging between 2000 and 2020 for each country. The combination of these four sub-regions makes up Sub-Saharan Africa (SSA). The countries that we use for our analysis are listed in Table 3. The selection of the countries in each region was based on the UN classification of each Sub-region in Africa.

Between the years 2000 and 2020, the average volume of greenhouse gas emission in Africa was 47,650.08 kilo tons (kt), the maximum is 541,945.0 kilo tons (kt) (South Africa in the year 2020) while the lowest was 320kt (by Comoros in the year 2000). The mean value life expectancy rate within the specified period and across the 40 African countries was 57.48 years, compared to other continents like Europe and Asia, whose life expectancy rate is more than 70 years. This makes Africa the continent with the lowest life expectancy in the world. Across the 40 African countries, Seychelles has the highest life expectancy rate (75.01 years) in 2020 while Sierra Leone has the least life expectancy rate (39.44 years) in the year 2000.

All the series were positively skewed except the population growth rate, which was skewed to the left (negative skewness). The kurtosis statistic indicates that the GHG, GNE, INCOME, and POPGR data are Leptokurtic because the kurtosis value is greater than three, while the data on life expectancy rate (LER) is Platykurtic. All the series are not normally distributed because the probability value of the Jarque Bera statistic is less than 5%.

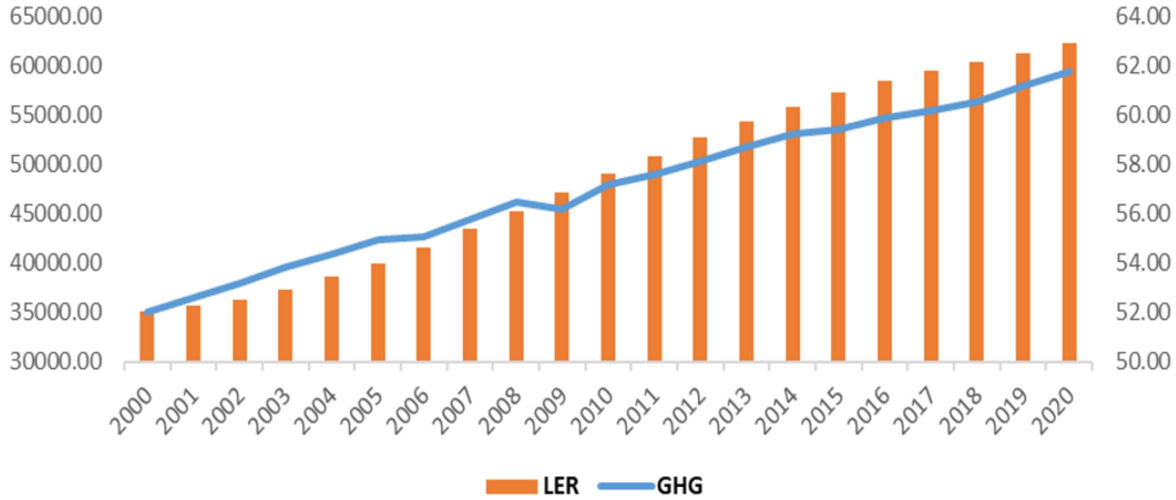

Figure 1. Trend of average life expectancy rate and greenhouse gas emission for the 39 selected SSA countries (2000-2020).

Table 4. Average yearly life expectancy rate and greenhouse gas emission in SSA between 2000 and 2020.

Year	LER	GHG
2000	52.05	35063.08
2001	52.28	36422.31
2002	52.53	37993.33
2003	52.93	39610.26
2004	53.45	40942.05
2005	54.00	42424.36
2006	54.64	42638.97
2007	55.37	44357.69
2008	56.11	46167.44
2009	56.87	45433.08
2010	57.63	47917.69
2011	58.35	48999.74
2012	59.09	50308.46
2013	59.72	51821.28
2014	60.33	53097.18
2015	60.90	53492.56
2016	61.38	54713.33
2017	61.80	55498.46
2018	62.14	56390.51
2019	62.51	57956.65
2020	62.93	59403.16

4.2 Health Outcome and Climate Change in SSA (2000-2020)

Figure 1 shows the trend of the average life expectancy rate and greenhouse gas emissions in the selected 40 SSA countries between the years 2000 and 2022. This is also broadly illustrated in Table 4. It is evident from the figure that the average life expectancy rate and greenhouse gas emissions were on an upward trend between 2000 and 2020.

Within these years, the average life expectancy rate increased by 20.90% to 62.93 years in 2020 from 52.05 years in 2000, and greenhouse gas emissions rose by 69.42% to 59,403.16 kilo tons (kt) from 35,063.08 kt in 2000. Hence, between 2000 and 2020, average greenhouse gas emissions increased at a faster rate relative to the life expectancy rate. This is primarily attributed to increased efforts towards industrialization in some African countries like Ethiopia, South Africa, and Ghana as well as higher oil exploration activities in some African countries like Angola and Nigeria. These activities contribute immensely to the spike in greenhouse gas emissions in SSA and weigh heavily on health outcomes in the region. This could be the reason for the minimal increase in life expectancy rate between 2000 and 2020.

Table 5. Regional comparison of the average of LER and GHG (2000-2020).

Region	LER	GHG
Eastern Africa	61.17	46687.05
Western Africa	57.72	32282.20
Central Africa	55.33	39993.59
Southern Africa	54.75	84247.68
Overall average	57.48	47650.08

According to Table 5, between 2000 and 2020, Eastern Africa has the highest average life expectancy rate (61.17 years) in Sub-Saharan Africa (SSA). This was followed by West Africa (57.72), Central Africa (55.33), and Southern Africa (54.78). Only the LER for Central and Southern Africa were lower than the overall SSA average (57.48). Interestingly, the regions with high greenhouse gas emissions have low LER except for Eastern Africa. For instance, Southern Africa, with the lowest average LER (54.75), has the highest volume of GHG (84,248kt), while Eastern Africa, with the highest LER (61.17), has a low GHG (46,687kt). Seychelles has the uppermost value of LER in Eastern Africa (73.13 years) and has the second-lowest average greenhouse gas emission (695.89 kt) in Sub-Saharan Africa. On the other hand, Lesotho has the lowest average LER (47.51 years), and it is situated in Southern Africa with the bottommost mean LER in SSA.

Table 6. Year-by-year average of LER and GHG in each sub-region (2000-2022).

Years	Central Africa		Eastern Africa		Southern Africa		West Africa	
	LER	GHG	LER	GHG	LER	GHG	LER	GHG
2000	50.94	31612.86	54.26	31205.56	48.83	62583.75	52.95	24310.00
2001	51.12	31225.71	54.87	31461.11	48.49	67765.00	53.29	25108.00
2002	51.37	32671.43	55.24	33887.78	48.32	70216.25	53.70	25754.67
2003	51.70	35120.00	55.91	34875.56	48.32	73362.50	54.16	26545.33
2004	52.11	35951.43	56.84	35847.78	48.51	77206.25	54.67	26986.67
2005	52.57	37642.86	57.60	37454.44	48.93	77862.50	55.21	28737.33
2006	53.08	38064.29	58.46	37892.22	49.60	78146.25	55.77	28684.67
2007	53.62	38035.71	59.43	42203.33	50.51	81553.75	56.34	28762.67
2008	54.19	38982.86	60.29	44176.67	51.61	86580.00	56.91	29161.33
2009	54.76	38710.00	61.09	45258.89	52.86	83457.50	57.46	28395.33
2010	55.33	39911.43	61.86	46642.22	54.20	89075.00	57.98	30468.67
2011	55.90	40735.71	62.51	47802.22	55.56	88937.50	58.48	32274.67
2012	56.46	41092.86	63.32	50034.44	56.88	90675.00	58.95	33244.67
2013	57.00	42345.71	63.77	51891.11	58.11	91758.75	59.41	34901.33
2014	57.53	42938.57	64.31	53861.11	59.20	93206.25	59.84	35988.00
2015	58.03	43950.00	64.90	56126.67	60.13	90828.75	60.25	36452.67
2016	58.49	44818.57	65.32	58363.33	60.88	90595.00	60.64	38004.00
2017	58.91	45122.86	65.68	58484.44	61.48	92348.75	61.00	38895.33
2018	59.28	45744.29	65.84	59333.33	61.98	91770.00	61.35	40724.00
2019	59.61	47026.19	66.26	61099.39	62.39	94443.57	61.68	41712.21
2020	59.99	48162.07	66.72	62526.41	62.85	96829.02	62.06	42814.58

Table 6 shows the average GHG and LER for each year across the four sub-regions (Central Africa, Eastern Africa, Southern Africa, and West Africa).

In 2020, each sub-region has an average LER of – West Africa (62.06 years), Eastern Africa (66.72 years), Southern Africa (62.85 years), and Central Africa (55.99 years). Between 2000 and 2020, Central Africa's LER rose by 17.76%, Eastern Africa by 22.96%, Southern Africa by 28.71%, and Western Africa by 17.20%. Southern Africa's LER improved by the highest magnitude. The overall average life expectancy rate in 2020 for SSA was 62.93 years. For greenhouse gas emissions, in 2020, each sub-region has an average of – Southern Africa (96829.02 kt), Eastern Africa (62526.41 kt), Central Africa (48162.07 kt), and West Africa (42814.58 kt). The overall average of GHG in

2020 for SSA was 59403.16 kt. Between 2000 and 2020, greenhouse gas emissions rose by – 52.35% in Central Africa, 100.37% in Eastern Africa, 54.72% in Southern Africa, and 76.12% in West Africa. In percentage terms, greenhouse gas emissions rose the highest in Eastern Africa.

Table 7. Sub-regional average of LER and GHG for Central African countries.

Countries	LER	GHG
Gabon	61.73	6894.41
Congo, Rep.	59.29	8771.23
Congo, Dem. Rep.	56.33	51196.66
Equatorial Guinea	55.92	21419.76
Cameroon	55.19	85406.99
Chad	50.91	58023.96
Central Africa Republic	47.97	48242.11
Overall average	55.33	39993.59

Table 7 presents the sub-regional average life expectancy rate (LER) and greenhouse gas emission (GHG) for some central African countries.

In Central Africa, Gabon has the highest average life expectancy rate (61.73 years) between 2020 and 2020. Also, Gabon has the lowest GHG (6,894 kt) in the sub-region. On the other hand, the Central African Republic has a minimum life expectancy rate (47.97 years) with a high GHG (48,242 kt). It is important to note that Cameroon has the uppermost average greenhouse gas emission in Central Africa. This implies that climate change action is more prevalent in Cameroon in Central Africa, and this is expected to weigh on the country's health outcome as it has an average LER of 55.19. The average LER in Central Africa is 55.33 years, which is below the SSA average of 57.48 years. Similarly, the average greenhouse gas emission in the sub-region (39,993 kt) was lower than the SSA average (47,650 kt). With this, Central Africa has the second-lowest average GHG in SSA, which means that the magnitude of climate change in Central Africa is still minimal.

Table 8. Sub-regional average of LER and GHG for Eastern African countries.

Countries	LER	GHG
Seychelles	73.13	695.89
Sudan	62.43	95491.42
Comoros	61.86	451.67
Rwanda	61.27	5060.52
Ethiopia	60.56	132020.80
Kenya	59.80	61459.05
Tanzania	58.61	80741.47
Burundi	56.55	3967.39
Uganda	56.28	40295.24
Overall average	61.17	46687.05

Table 8 shows the subregional average life expectancy rate (LER) and greenhouse gas emission (GHG) for some east African countries.

Between 2000 and 2020, Seychelles has the highest life expectancy rate (73.13 years) and lowest greenhouse gas emission (695.89 kt) in Eastern Africa and Sub-Saharan Africa generally. In Eastern Africa, Uganda has the minimum average LER (56.28), while Ethiopia has the uppermost GHG (132,020 kt). The average LER in Eastern Africa is 61.17 years, 6.42% above the SSA average (57.48 years). Meanwhile, the average GHG in CA is 2.02% higher than the average of 47,650 kt.

Table 9. Sub-regional average of LER and GHG for Southern African countries.

Countries	LER	GHG
Botswana	59.93	15860.67
South Africa	58.46	472794.53
Namibia	56.90	12494.43
Zambia	54.98	34023.44
Angola	54.71	76440.29
Mozambique	53.84	28516.89
Zimbabwe	51.64	28952.91
Lesotho	47.51	4898.31
Overall average	54.75	84247.68

Table 9 shows the sub-regional average life expectancy rate (LER) and greenhouse gas emission (GHG) for some southern African countries.

Botswana has the highest average life expectancy rate (59.93 years) in Southern Africa, while Lesotho has the lowest LER (47.51 years) in the subregion. Meanwhile, South Africa emits the highest greenhouse gas (472,794 kt) in Southern Africa and has the second-highest average life expectancy rate (58.46 years) in the subregion.

Table 10. Sub-regional average of LER and GHG for West African countries.

Countries	LER	GHG
Cabo Verde	71.15	680.50
Senegal	63.64	24628.11
Mauritania	62.69	11359.56
Ghana	60.78	31919.88
Gambia, the	59.41	2357.49
Benin	58.99	12284.50
Togo	57.33	7046.86
Niger	56.94	32155.00
Burkina Faso	56.62	24535.85
Guinea	56.54	21515.33
Mali	54.67	32392.71
Guinea-Bissau	54.60	2357.70
Cote d'Ivoire	53.24	23843.36
Nigeria	50.71	251080.93
Sierra Leone	48.51	6075.17
Overall average	57.72	32282.20

Table 10 shows the sub-regional average of life expectancy rate (LER) and greenhouse gas emission (GHG) for some west African countries.

In West Africa, Cabo Verde has the highest life expectancy rate (71.15 years) between 2000 and 2020, with the lowest greenhouse gas emission (680.50 kt) in the sub-region. On the other hand, Sierra Leone has the lowest LER (48.51). This is followed by Nigeria (50.71 years), which emits the highest greenhouse gas (251,080 kt) in West Africa.

Table 11. Pesaran, Frees, and Friedman cross-sectional dependence test results.

Cross-sectional dependence (CSD) test	Fixed effects	Random effects
Pesaran CSD	6. 679 (0.000)	15.278 (0.000)
Frees	9.488	10.371
Friedman	58.046 (0.0197)	110.273 (0.000)

Note: Critical values from Frees' Q distribution
Alpha = 0.10: 0.1294
Alpha = 0.05: 0.1695
Alpha = 0.01: 0.2468

4.3. Cross Dependence Test

Table 11 indicates the Peseran, Frees and Friedman cross-sectional dependence test result.

One of the essential steps to be taken under panel data modelling is checking for cross-sectional dependence. According to Tugcu (2018) cross-sectional dependence is the most important diagnostic that should be conducted before embarking on panel data analysis. This helps establish if there is any spillover impact of changes in any of the variables considered for analysis. For instance, the incidence of climate change in one country may not affect the health income of that country alone but spill over to other neighbouring or close ties countries. Additionally, checking for cross-section dependence determines the choice of unit root test we will use, whether first or second-generation tests. If the test confirms that there is cross-sectional dependence, the second or third-generation unit root test is recommended.

The cross-sectional dependence test proposed by Pesaran (2004) was employed as it is effective for micropanel data with large N (39) and small T (21). The result of this test was corroborated by other tests such as Friedman (1937), Frees (1995) and Frees (2004). All these tests were conducted under the assumption of fixed and random effects, as used by De Hoyos and Sarafidis (2006) in their paper "Testing for cross-sectional dependence in panel data models".

According to Pesaran's CSD test result in Table 11, the null hypothesis of cross-sectional independence is rejected under the assumption of the fixed and random effects models. This is because the probability value of the test statistic is less than the 5% significance level, which implies the presence of cross-sectional dependence.

Also, the Frees (1995); Frees (2004) and Friedman (1937) tests in Table 11 corroborate this result, confirming the rejection of the null hypothesis. The Frees test statistic is greater than its critical values from the Free's Q distribution. This means there is a strong evidence of -cross-sectional dependence under the assumption of fixed and random effects.

Table 12. Pesaran CADF test result.

Variables	Probability values	First difference	Remark
	Level		
LFER	0.000	0.000	I(0) and I(1)
LCC	0.029	0.001	I(0) and I(1)
LINCOME	0.133	0.000	I(1)
LGE	0.080	0.000	I(1)
POPGR	0.000	0.000	I(0) and I(1)

4.4. Unit Root Test

As proposed by Pesaran (2003) the Pesaran CADF is a panel unit root test that can be used in the presence of cross-sectional dependence. This is why the Pesaran cross-sectionally Augmented Dickey Fuller (CADF) panel unit root test (a second-generation test) was used.

The natural logarithm of life expectancy rate (LFER), logarithm of climate change (LCC) proxy by natural logarithm of total greenhouse gas emission (GHG), income (LINCOME), and logarithm of government national expenditure (LGE) was used for analysis in this paper. The population growth rate was used in its level form because taking the natural logarithm results in the loss of information about the negative growth rates.

According to Table 12, LINCOME and LGE were stationary at the first difference, leading to the rejection of the null hypothesis of non-stationarity at I(1). This is because the probability value of these series at first difference was less than 5% significance level. Meanwhile, LFER, LCC, and POPGR were stationary at the level and first difference.

4.5. Durbin-Hausman Panel Cointegration Test

DH_g group statistics = 12.327.

DH_p panel statistics = 2.741.

Critical values

1% 2.33.

5% 1.645.

10% 1.28.

The Durbin-Hausman (DH) test was developed by Westerlund (2007). It accounts for the mixture of I(0) and I(1) variables as well as cross-sectional dependence. This makes the DH test appropriate for this paper since the pre-estimation tests show the presence of cross-sectional dependence and a mixture of variables stationary at the level and first difference.

The DH test result shows that the DH group statistics were greater than the table critical values, which implies that the null hypothesis of no cointegration is rejected. This means that there is a presence of a long-run relationship between life expectancy rate (LER), climate change (LCC), and other variables (LINCOME, LGE, and POPGR) used in this paper.

Table 13. Variance inflation factors (VIF) for explanatory variables.

Variables	R squared	A	VIF	Decision
INCOME	0.318	0.682	1.467	Low degree of multicollinearity
LCC	0.785	0.215	4.657	Low degree of multicollinearity
LGE	0.797	0.203	4.915	Low degree of multicollinearity
POPGR	0.077	0.923	1.084	Low degree of multicollinearity

4.6. Multicollinearity Test

The variance inflation factor (VIF) is used to check for multicollinearity in this paper. The rule of thumb is that if VIF is greater than 5, then there is a high degree of multicollinearity but if otherwise, there is a low degree of multicollinearity.

In Table 13, the values of the VIF for the explanatory variables (LINCOME, LCC, LGE, and POPGR) were all less than 5, which implies a low degree of multicollinearity.

Table 14. GMM model selection.

Model	Coefficient of LFER (-1)	Probability values
Pooled OLS	0.978	0.000
Fixed Effects	0.960	0.000
Two-step system GMM	0.901	0.000
Two-step difference GMM	0.787	0.000

4.7. Equations Estimation and Discussion

The coefficient of the lagged dependent variable (life expectancy rate) is presented in Table 14. We used this as the benchmark to select the appropriate model between the pooled OLS, fixed effects, two step system GMM or two-step difference GMM.

We estimated the two variants of the GMM (system and difference), as discussed in section 3.3. The GMM estimators are designed for dynamic panel data with "small-T and large-N", which makes them suitable for this paper (T = 21, N = 39).

From Table 14, the coefficient of the lagged dependent variable (LFER (-1)) from the two-step difference GMM was less than that of the fixed effects (0.960) models. This justifies the choice of the two-step system GMM model in this paper.

Table 15. System GMM results without interaction of governance indicator.

Variables	Coefficients	Prob values
LFER (-1)	0.902	0.000**
LCC	-0.008	0.094*
LINCOME	-0.005	0.336
LGE	0.008	0.070*
POPGR	0.003	0.445
CONS	-1.599	0.139
Year dummies	Yes	
No of observations	780	
F-statistics (Prob)	1.83e+07 (0.000)	
Group/Instruments	39/27	
AR(2)	0.562	
Hansen statistics	0.591	

Note: * implies significance at 10% level only, ** implies significance at 5% and 10%.

Table 15 shows the LFER two-step system GMM result. It was estimated using the xtabond2 syntax developed by Roodman (2009) using STATA. Options included in the estimation are robust, two-step, nodiffsargan, pca, and orthogonal. The two-step robust requests Windmeijer's finite-sample correction for the two-step covariance matrix. The robust option helps generate standard error estimates that account for heteroskedasticity and autocorrelation within panels. The PCA option was used to reduce the number of instruments to 27 from 44 by reducing "GMM-style" instruments with their principal components (Bai & Ng, 2010; Kapetanios & Marcellino, 2010; Mehrhoff, 2009).

The number of instruments (27) was less than the group (39) used for analysis. The probability value of the AR(2) statistic was greater than the 5% significance level, which means the absence of second-order serial correlation. The Hansen statistics show that instruments are valid because their probability value (0.591) exceeds the 5% significance level. All these align with the primary conditions of system GMM that must be met.

From Table 15, greenhouse gas emission (LCC) negatively impacts the life expectancy rate (LFER) at a 10% significance level in the short run. This implies that there is a negative and significant relationship between climate change and health outcomes in Sub-Saharan Africa (SSA). This corroborates the findings of Yeboah (2021) that climate change strongly affects the health of persons in SSA. A 1% increase in greenhouse gas emission results in a 0.0077% decrease in life expectancy rate ceteris paribus. On the other hand, government expenditure (LGE) positively affects the life expectancy rate in SSA in the short run. This is consistent with the result of Makuta and O'Hare (2015). This means that if government expenditure on the health sector increases, this is expected to boost the life expectancy rate in the short run and improve health outcomes. If government expenditure increases by 1%, the life expectancy is expected to rise by 0.008%.

Table 16. Long run coefficients for significant variables.

Variables	Coefficients	Prob values
LCC	-0.0778	0.069*
LGE	0.0828	0.176

Note: * implies significance at 10% level only, ** implies significance at 5% and 10%.

Table 16 shows the long-run coefficients for the significant variables in the two-step GMM model. The long-run coefficients were only estimated for the significant system GMM variables (LCC and LGE). This was computed via:

$$L_R = \frac{\_b([\text{significant explanatory variable}])}{1 - \_b([\text{endogenous variable}])}$$

In the long run, climate change (LCC) has a higher negative significant impact (0.0778) on the life expectancy rate (LFER) compared to the short-run impact (0.0077). The magnitude of the negative impact of climate change on health outcomes is 10 times higher in the long run compared to the short run. A 1% increase in greenhouse gas emission leads to a 0.0778% decrease in life expectancy rate (LFER). Meanwhile, government expenditure (LGE) does not significantly impact health outcomes in the long run.

Table 17. System GMM coefficients (Interaction with governance indicator).

Variables	Interaction of climate change with government policy effectiveness
LFER (-1)	0.894 (0.000) **
LCC*GE	0.0004 (0.165)
LINCOME	-0.001 (0.067) *
LGE	0.0004 (0.416)
POPGR	0.002 (0.162)
CONS	-2.103
Year dummies	Yes
No. of observations	780
F-statistics (Prob.)	5.95e+07 (0.000)
Group/Instruments	39/27
AR(2)	0. 668
Hansen statistic`s	0.158

Note: * implies significance at 10% level only, ** implies significance at 5% and 10%.

Table 17 shows the two-step GMM equation, which examines the role of the effectiveness of government policy on the relationship between climate change and health outcomes. The interaction of government effectiveness indicators and climate change was used to achieve this objective. Government effectiveness from World Governance Indicators (WGI) was used as the indicator for the effectiveness of government policy. This was used because of its broad definition and its relevance. Government effectiveness encompasses "perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies" (Kaufmann, Kraay, & Mastruzzi, 2008).

With the interaction of greenhouse gas emissions and government effectiveness, climate change does not significantly impact the life expectancy rate in Sub-Saharan Africa at 5% and 10% significance levels. This means that if government policies toward reducing greenhouse gas emissions are effective, climate change did not significantly affect health outcomes in SSA. In other words, this implies that the effectiveness of government policies has a vital role to play in neutralizing the impact of climate change on health outcomes in Sub-Saharan Africa. If climate change is controlled with the support of government policies, this is expected to boost the life expectancy rate in SSA.

5. SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1. Summary

This paper's main objective was to examine the relationship between climate change and health outcomes in Sub-Saharan Africa (SSA). The key contribution of this paper is that it investigated whether the effectiveness of government policy plays a role in the relationship between climate change and health outcomes in SSA. The data on greenhouse gas emissions was used as a proxy for climate change, while the life expectancy rate was used as a proxy for a health outcome. The series used for this paper were collected across 39 African countries from Central Africa, Eastern Africa, West Africa, and Southern Africa. These four sub-regions make up Sub-Saharan Africa. All the series have a time frame from 2000 to 2020. The two-step generalized method of moments (GMM) was used as the estimation technique to achieve the objective of this paper.

5.2. Conclusion

The findings from the analysis of this paper show that:

(1) Findings from the two-step GMM equation revealed that there is a negative significant relationship between life expectancy rate (LER) and climate change (LCC), while government expenditure (LGE) has a positive significant impact on life expectancy rate in Sub-Saharan Africa in the short run. Meanwhile, it is only climate change that has a negative and significant impact on the life expectancy rate in the long run.

(2) With the introduction of government effectiveness as an interactive term with climate change, it was observed that greenhouse gas emissions do not have a significant impact on the life expectancy rate in SSA. This implies that, with effective government policies targeted toward achieving net zero carbon emission, climate change does not have a significant impact on the life expectancy rate in SSA. The resulting impact of this is the improvement of health outcomes in the region.

5.3. Recommendations

Based on the findings of this paper, we recommend that:

(1) The implementation of effective government policy toward the eradication or reduction of greenhouse gas emissions. One such policy is the improvement of the generation and distribution of electricity across both rural and urban areas. This reduces the incidence of using brown energy to generate power, which contributes to a large proportion of climate change in SSA. As a result, this positively impact health outcomes in SSA countries.

(2) The government should create an enabling and secure environment, which helps attract more companies and investors into the renewable energy sector. This in turn, increases the supply of renewable energy and make it more affordable to the general population.

(3) An incentive system can be created to encourage SSA countries to preserve their forests, particularly those that are highly dependent on timber export. This helps buffer the impact of the loss of revenue from the reduction in tree felling and timber export. The forests help absorb CO_2 emissions, which have a positive impact on life expectancy rate and health outcomes broadly.

(4) The government in SSA countries should increase expenditure allocation to the health sector. This improves the efficiency and effectiveness of the sector. As a result, this in turn boost the region's life expectancy rate and improve its health outcome in the short to medium term.

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