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Research article

Severity of environmental degradation and the impact on quality of life in Africa

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ABSTRACT

Considering the mounting impacts of environmental degradation on the global ecosystem, this study offers an empirical contribution to the debate on whether there exists a significant nexus between environmental degradation and quality of life in Africa. Towards this end, we employ several econometric techniques to account for cross-sectional dependence, causality, and also present results based on IV-Lewbel 2SLS regression. Using a sample of African countries, the results indicate cross-sectional dependence due to spill-over effects from common factors in Africa, while the panel cointegration test affirms that environmental degradation have long-term consequences for quality of life only in sub-Saharan African region. Moreover, our results reveal a unidirectional causality between environmental degradation variables and quality of life at both the continent and sub-Saharan African region levels while a bi-directional causality between these variables are revealed for North Africa. On this evidence, our conjecture is that increased mineral extraction, greenhouse gas emissions, and deforestation, amongst other factors, may be driving this result. Hence, improvement in environmental quality in the continent would have an increasingly beneficial effects on the well-being and survival of the populace. The varied impacts across regions also suggest that policy initiatives toward mitigating the effects of environmental degradation should consider regional dynamics of the continent.

1. Introduction

Climate change has emerged as the foremost challenge of the 21st century, necessitating concerted international efforts to address it. Climate risk has ramifications for the growth and development of nations as well as hazards and opportunities for individuals and businesses. One of the dilemmas facing countries with climate risks is how to enhance their human capital and socioeconomic indices in the face of daunting ecological challenges. In this context, mitigation and adaptation strategies have emerged as a prominent approach to improve quality of life and facilitate the transition to net-zero carbon emission. In traversing these complexities, the management of natural resources becomes of utmost importance for nations whose primary source of revenue is derived from the exploration of these resources, thereby having additional effects on humans and the environment.

In this study, we consider a germane issue and investigate the following questions: How does environmental degradation impact quality of life and to what degree? Can regional dynamics and heterogeneous factors explain the nexus between environmental degradation and quality of life? This is crucial, as the effects of climate change may vary based on regional and national characteristics. To answer these pertinent questions, we employ data for Africa and its regions as a point of reference. Importantly, we put the analysis of causation and its direction at the forefront of our discussions. In our analysis, we also account for cross-sectional dependence, panel unit root, long-term cointegration with structural break, and heterogeneous panel causality, among other econometric procedures.

Failure to mitigate climate change, failure of early warning systems,

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natural disasters such as hurricanes, extreme temperatures, ecological imbalance, and habitat destruction are all identified as threats to human well-being in the global risks report (WEF, 2023). Environmental degradation, one of the world's most pressing crises, has far-reaching consequences, including water and food shortages, increased temperatures, storms and floods, loss of livelihood, and even health problems. The direct and indirect effects on human lives also present themselves in a variety of ways, including a decrease in overall quality of life (WEF, 2023) and limited access to critical amenities such as green spaces, clean water, and air. Those who are struck the hardest are frequently vulnerable persons who are already at a disadvantage, whether due to their location, socioeconomic status, or demographic traits.

According to WHO (2021), an estimated 250,000 people each year may lose their lives to climate-related stressors such as hunger, infectious diseases, and overheating. By 2030, it is anticipated that the annual direct health damage costs will range from 2 to 4 billion US dollars, especially in regions with inadequate medical facilities, such as the majority of African countries and other developing nations (Wreford and Topp, 2020). The United Nations has long acknowledged the significant impact that climate change is having and will continue to have on the African continent, especially on the most vulnerable, including adults and children, through increased food poverty, population displacement, farmers-herders land crisis, and stress on natural resources. In 2021, for instance, climate change negatively impacted food security, resulting in 278 million Africans suffering from famine (FAO, 2022; IPCC, 2023). In addition, projections for 2024 indicate that climate change stressors could increase water levels and coastal erosion in large parts of West Africa, cause catastrophic cyclone events in Southern Africa, and cause drought, hunger, and famine in East Africa (WMO, 2022; Sakariyahu et al., 2023).

Indeed, empirical literature considering the impact of climate change is large (see for example Nyiwul, 2021a, 2021b; Wang et al., 2022; Opoku et al., 2022; Gebre et al., 2023; Daka, 2023); the direct and indirect effects on human lives also present themselves in a variety of ways, including limited access to critical amenities such as green spaces, clean water, and air. Those who are struck the hardest are frequently vulnerable persons who are already at a disadvantage, whether due to their location, socioeconomic status, or demographic traits. In essence, increased research in these regions, specifically those in Africa, where six out of ten people become vulnerable due to a lack of early warning signals is essential (IPCC, 2023). Despite contributing less than 3 percent of global greenhouse gas emissions, the African region bears the brunt of climate stressors due to the acute susceptibility of its people and their limited coping mechanisms, as only 40 percent of the African population have access to proactive warning mechanisms against the effects of environmental degradation (IPCC, 2023). Consequently, our investigation focuses on a region that has experienced astounding negative effects of environmental degradation and is predicted to experience even more severe negative effects in the future if responsible multilateral parties do not develop policies and take necessary actions.

From a novel perspective, this study therefore offers an empirical contribution to the debate on the impact of environmental degradation using the African continent and its regional levels. Our empirical investigation reveals the following findings: (i) We find that there is a long-term link between our baseline variables and quality of life in Africa, especially in the SSA region (ii) We further explore the causal association between these variables and findings reveal the existence of a unidirectional causality between the proxies and quality of life (iii) We also apply an instrumental variable (IV) regression analysis and the result confirms the impact of environmental degradation on the main and alternative measures of quality of life. On this evidence, our conjecture is that increased mineral extraction, greenhouse gas emissions, and deforestation, amongst other factors, may be driving this result. Hence, improvement in environmental quality in the continent would have an increasingly beneficial effects on the well-being and survival of the populace.

Considering the mounting impacts of environmental degradation on the global ecosystem, our research complements the growing climate literature in a number of ways. To begin with, we provide empirical support for prior works (Nyiwul, 2021a, 2021b; Opoku et al., 2022; Gebre et al., 2023; Daka, 2023; Sakariyahu et al., 2023) by demonstrating that environmental degradation significantly minimises quality of life in Africa. Additionally, we present new findings on the heterogeneous and long-term causality between the adopted measures and quality of life in Africa and its regions. Finally, by examining the regional dynamics of climate crisis in Africa, our study offers a new perspective to understanding the unique regional solutions to easing the climate calamity.

In sum, we submit that policymakers should be keenly interested in the above-stated findings. Hence, we offer policy implications that grant considerable scope for global stakeholders on how to foster new alliances for resolving one of the great challenges of our times. In particular, our results have shown that environmental degradation has a deleterious effect on quality of life in Africa. Being aware of this, a key policy prescription is that legislation and legal sanctions should be put in place to ensure reductions in the level of environmental degradation. Furthermore, policy efforts to mitigate the effects of environmental degradation on quality of life has to consider regional dynamics of the continent. On this basis, we recommend that policymakers focus on tailor-made sustainable climate strategies, as a one-size-fits-all approach may not provide the desired solutions to Africa's climate crises.

2. Literature review

2.1. Theoretical framework

Numerous studies have shown that an increase in temperature, often brought on by climate change, would have various unfavourable effects. From a theoretical perspective, diverse theories have been put forward to explain the connections between climate change and socioeconomic indices of a nation. Firstly, the ecopsychology theory connects climate change to psychological and emotional problems in people's lives and ties it to the subjective quality of life approach (Bechtoldt et al., 2020). The positive psychological and emotional effects on human existence may motivate people to take action to slow down climate change, while adverse effects can cause depression or encourage indifference and denial of reality (Tam et al., 2021). Secondly, the physical causation theory holds that natural changes caused by climate degradation negatively impact people, plants, and societal structures. According to Zhang et al. (2011) massive human calamity can be directly attributed to climate change throughout the pre-industrial age in Europe and the North Hemisphere. Thirdly, the environmental justice theory states that vulnerable low income countries could be subjected to uneven effects of climate change. This can further deteriorate after experiencing inequality, poverty, food shortages, heightened health risks, poor productivity, and other consequences of climate change that can affect people's quality of life (Miranda et al., 2011; Islam and Winkel, 2017). Furthermore, Adger et al. (2014) use the human security theory from the issue of conflicts, shortages in basic infrastructure, human displacements, and migrations to establish the relationship between climate change and quality of life. The theory advances the inability of government to provide the needed minimum infrastructure requirement for survival, as may be imposed by climate change challenges on human security.

2.2. Review of past studies

2.2.1. Climate change and quality of life

Climate change is one of the many factors rapidly disrupting and affecting natural and living environment, which ultimately affects the quality of human lives (Santhakumari and Sagar, 2020; Timlin et al., 2021). Several studies have used various parameters to measure the quality of life, and these studies can be divided into two groups: Firstly, those studies that focus on subjective well-being indicators such as happiness, and those that focus on objective well-being indicators, such as life expectancy and gross domestic product (Ambrey and Daniels, 2017). Researchers have found that sustainability is generally associated with improvements in subjective well-being (Ambrey and Daniels, 2017; Cloutier et al., 2014). This is because much of the research on sustainability and well-being has focused on subjective well-being. Additionally, the subjective method often relies on opinions that are gleaned through surveys or questionnaires, such as those that measure stress, happiness, and well-being (Sączewska-Piotrowska, 2022; Wang and Zhou, 2023).

However, the study of Noll (2013) and Jahedi and Méndez (2014) argue that there are some drawbacks to the subjective measures of quality of life, including soft information compared to statistical data, lengthy gathering process, and difficulties in interpreting the results. Consequently, the objective well-being method upholds the idea that a group of people's well-being can be assessed using the outputs and services provided by institutions (Lawton et al., 1999). Therefore, it makes sense that the quality of life be evaluated objectively using social and economic indicators. These variables are free from human judgments and are uninfluenced by opinions (Boelhouwer and Noll, 2014).

A series of studies have demonstrated that both subjective and objective methods applied individually have their respective drawbacks, and as such, the United Nations Development Program (UNDP) usually releases the Human Development Index (HDI), which is a composite social indicator index built upon necessary measures of developments related to human advancement, education, the standard of living, and health (Urda et al., 2017; O'Connor, 2022). The integration of both approaches into a single set of quality-of-life indicators results in an improved, composite, and multi-diverse measurement of the quality of life known as the human development index (Soltes & Novakova, 2015; Ghislandi et al., 2019). In addition, the human development index is regarded as a leading, and most cited social indicator in policy and research (Yang, 2018). For example, in assessing the quality of life for economically advanced nations, Šoltés and Nováková (2015) utilized the human development index to provide a position on quantifying the quality of life. In the same vein, the study of Pinar et al. (2022) applied the human development index as a base index for well-being with other governance metrics using stochastic dominance techniques. In this study, we align with extant studies and also adopt the human development index as a proxy for quality of life.

2.2.2. Climate change susceptibility, carbon emission, and quality of life

The study of Bosello et al. (2012) claim that one of the dangers of climate change is the increase in sea levels, and this menace is considered the worst, as it tends to boost the chances of occurrence of dangerous thunderstorms and downpours, increased corrosion and jeopardizes the availability of freshwater, with its negative impact on global economy. Other studies, such as Sheng et al. (2022) and Sakariyahu et al. (2023), also reveal that climate change harms economic growth and development. Several studies have also shown that carbon emission is the primary cause of climate change, and this is because when carbon dioxide and other greenhouse gases are released into the atmosphere, they trap heat from the sun and cause the Earth's temperature to rise. This leads to the melting of glaciers, rising sea levels, more frequent and intense heatwaves, droughts, floods, and extreme weather events such as hurricanes, cyclones, and typhoons, and this ultimately reduces the people's quality of life (Alexander et al., 2012; McGranahan et al., 2007). Similarly, Carbon emissions contribute to air pollution, leading to respiratory problems and other health issues. Particulate matter, such as soot and smog, can cause lung cancer, heart disease, and stroke (Arias-Maldonado, 2015)

Furthermore, Aluko et al. (2021) argue that carbon emissions could lead to ocean acidification, which can have detrimental effects on marine life, including coral reefs, shellfish, and other organisms that rely on calcium carbonate to build their shells and skeletons. In the same vein, Quinn et al. (2019) state that carbon emissions could lead to the loss of habitats and ecosystems, and as such, this can reduce the biodiversity of plants and animals. Moreover, carbon emissions can also lead to social and political unrest as people compete for scarce resources or are displaced from their homes due to extreme weather events or rising sea levels. This can exacerbate existing conflicts and lead to instability in vulnerable regions of the world, especially African countries (Hino et al., 2017).

2.2.3. Ecological footprint and quality of life

The study of Rees and Wackernagel (1996) popularised the concept of on ecological footprint, referring to it as a technique for assessing how much impact people have on the environment. The concept has gained considerable academic acceptance and application due to its novel point of view in assessing regional sustainable development. According to some researchers, ecological footprint is a valuable indicator of the ecosystem's overall health since it demonstrates how the environment is deteriorating, directly affecting people's lives and livelihood. Ecological footprint is also a way of assessing the sustainability of human activities and their impact on the planet. The term incorporates the land needed to produce goods from plants, animals, and forests; the space needed to absorb atmospheric CO2 emissions, which are mainly brought on by the burning of fossil fuels; and the acreage needed to meet nuclear energy demand (Wackernagel et al., 2002). In a geographic setting, such as at the level of countries, regions, or cities, ecological footprint has often been employed to quantify how human pressure on the atmosphere impacts their survival (Wackernagel et al., 2002; Nijkamp et al., 2004).

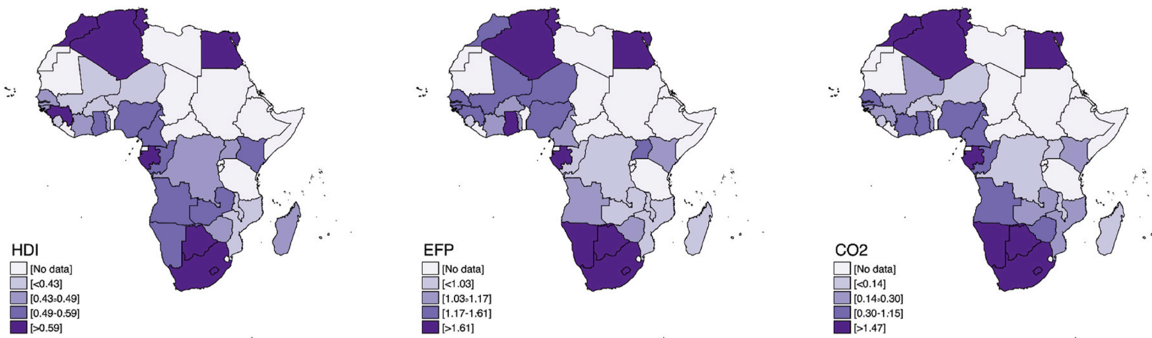
3. Methodology

3.1. Data

In this study, we use data for 31 African countries[1] covering the period 2000 to 2018 due to the availability of data. We also classify these African countries into two regions: Northern Africa (NA) and sub-Saharan Africa (SSA). For empirical purpose, our dependent variable is the quality of life measured using human development index (HDI) following Nikolaev (2014). The HDI data was obtained from the United Nations Development Programme (UNDP) database. As alternative measures of quality of life, we follow the approach of Nyiwul (2021a) and use food production index, access to electricity, basic drinking water services, and Gini index, all sourced from World Bank database. In contrast to Nyiwul's (2021a) study which computed composite index from these variables, we employed their individual data in our analysis. For the main explanatory variables, we follow the approach of Aluko et al. (2021) by using data for ecological footprint (EFP) and carbon emissions (CO_2) at the aggregate and regional levels. Data for both EFP and CO_2 were respectively sourced from the Global Footprint Network (GFN) and World Development Indicators (WDI).

Fig. 1 depicts the distribution of the three main variables in maps. Fig. 1a plots human development index for each of the 31 countries in our sample, over the period 2000 to 2018. Covering the same number of countries and sample period, Fig. 1b and c displays the ecological footprint and carbon emissions, respectively. For Fig. 1a–c, darker regions indicate higher values, with the lightest shades signifying countries with missing data. As can be seen in Fig. 1, there exists substantial variations in each of human development index, ecological footprint,

[1] African countries included in the analysis include Algeria, Angola, Botswana, Burkina Faso, Cameroon, Congo, Cote d'Ivoire, Democratic Republic of Congo, Egypt, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Madagascar, Malawi, Mali, Morocco, Mozambique, Namibia, Niger, Nigeria, Senegal, Sierra Leone, South Africa, Togo, Tunisia, Uganda, Zambia, and Zimbabwe.



(a) Human development index (HDI) (b) Ecological footprint (EFP) (c) Carbon emissions (CO_2)

Fig. 1. Distribution of human development index, ecological footprint, and carbon emissions in Africa.
Notes: This figure plots the mean human development index, ecological footprint, and carbon emissions for the 31 African countries in our sample.

and carbon emissions across the 31 countries represented in our sample.

Following prior studies in the literature (see Acheampong et al., 2019; Aluko et al., 2021), we reduce the propensity of omitted variables by controlling for country-specific economic and development (E&D) factors such as renewable energy consumption, GDP per capita, FDI, trade openness, inflation, and population growth. Furthermore, we account for political, governance and institutional (PGI) factors that may influence a country's HDI. These measures include control of corruption, political stability, regulatory quality, rule of law, and government effectiveness. The PGI variables were gathered from the World Governance Indicators (WGI) database. Table 1 shows all the variables adopted in the study, their definitions, and sources.

3.2. Descriptives

Table 2 shows the descriptive statistics of the variables used in our study. The results indicate that the average quality of life, ecological footprint, and carbon emissions within the African continent are 0.51, 1.45, and 1.05, respectively. For the regions, Northern Africa appears to have higher average quality of life (0.67) than the SSA region (0.49). This is not surprising given the level of infrastructural development, educational attainment, and other socio-economic indices of the countries in North-African region compared to other countries in Africa. Meanwhile, Table 2 also reveals that the average carbon emissions (2.36) and ecological footprint (1.88) in the North-African region are much higher than the counterpart values in the SSA region (0.85; 1.38). We infer that these observations are due to the level of manufacturing and heavy industrial activities witnessed by the countries in the Northern region. More specifically, 5 out of the top 10 largest and most industrialised economies in Africa are situated in the North of Africa.

Table 1
Definitions of variables and data sources.

Variable	Definition	Source
Dependent variable		
HDI	Human development index, used to proxy quality of life.	UNDP
Climate change measures		
EFP	Ecological footprint per capita global hectares.	GFN
CO_2	Carbon emissions per capita.	WDI
Economic and development (E&D) indicators		
Renewable	Renewable energy consumption (% of totalenergy consumed).	WDI
GDP per capita	Log of GDP per capita.	WDI
FDI	Net inflows of foreign direct investment(% of GDP)	WDI
Trade openness	Trade as a percentage of GDP.	WDI
Inflation	Percentage change in the consumer price index.	WDI
Population growth	Annual growth rate of population.	WDI
Political, governance, and institutional (PGI) factors		
Control of corruption	Control of corruption score.	WGI
Political stability	Political stability and absence of violence/ terrorism score.	WGI
Regulatory quality	Regulatory quality score.	WGI
Rule of law	Rule of law score.	WGI
Voice and accountability	Voice and accountability score.	WGI
Government effectiveness	Government effectiveness score.	WGI

Notes: UNDP: United Nations Development Program; GFN: Global Footprint Network; WDI: World Development Indicators; HF: Heritage Foundation; WGI: World Governance Indicators.

3.3. Empirical strategy

To achieve the objectives of this study, we first specify quality of life as a function of environmental degradation variables for both Africa and its regions as shown below:

$$HDI_{i,t} = \beta_1 EFP_{i,t} + \beta_2 CO_{2i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

$$HDINA_{i,t} = \gamma_1 EFPNA_{i,t} + \gamma_2 CO_2NA_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t} \quad (1)$$

$$HDISSA_{i,t} = \delta_1 EFPSSA_{i,t} + \delta_2 CO_2SSA_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

where HDI is human development index (a proxy for quality of life) at the aggregate African level while HDINA and HDISSA represent human development index for Northern African region and sub-Saharan African region, respectively. EFP, EFPNA, EFPSSA, CO_2, CO_2NA, and CO_2SSA are the environmental degradation measures, which refer to the ecological footprint and carbon emissions at the aggregate level and regions (Northern and sub-Saharan African), respectively. Country and time are shown by the subscripts i and t, respectively. β_1, β_2, γ_1, γ_2, δ_1, and δ_2 represent the slopes of the climate change proxies. The fixed effects for country and year are denoted by α_i and α_t, respectively. $\varepsilon_{i,t}$ is the stochastic error term.

3.4. Estimation methods

We employ a number of steps in the estimation procedure. First, we explain the unit root and cross-sectional dependence of the variables. Second, we analyse long-run cointegration relationship of the variables. Next, we check for heterogeneous causality amongst the variables. Finally, we conduct series of regression analyses by investigating the magnitude of impact of the environmental degradation proxies on the quality of life. Details of the analytical procedures are discussed in the next section.

3.4.1. Accounting for cross-sectional dependence and unit root in the panel

In empirical economics, it is common to assume the presence of unit root and cross-sectional dependence among the individual series in a

Table 2
Descriptive statistics.

Variable	Panel A: Full sample				Panel B: SSA countries				Panel C: Northern countries			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
HDI	0.51	0.11	0.25	0.75	0.49	0.10	0.25	0.72	0.67	0.05	0.53	0.75
EFP	1.45	0.63	0.66	3.82	1.38	0.64	0.66	3.82	1.88	0.31	1.22	2.65
CO_2	1.05	1.59	0.03	8.57	0.85	1.59	0.03	8.57	2.36	0.68	1.14	3.93
Renewable	63.50	28.96	0.06	98.34	71.44	21.29	10.19	98.34	9.92	11.72	0.06	95.22
LogGDP	3.05	0.42	2.14	4.03	2.99	0.42	2.14	4.03	3.42	0.21	2.38	3.74
FDI	3.77	5.17	−10.72	39.81	3.94	5.42	−10.72	39.81	2.59	2.72	−2.54	18.82
Trade openness	66.81	23.80	20.72	156.86	66.40	24.43	20.72	156.86	69.61	18.90	30.25	114.34
Inflation	9.44	30.52	−3.5	513.91	10.11	32.6	−3.50	513.91	4.87	4.61	0.34	29.51
Population growth	2.53	0.76	0.39	5.79	2.67	0.68	0.39	5.79	1.53	0.43	0.91	2.34
Control of corruption	−0.63	0.64	−1.85	1.42	−0.83	0.54	−1.67	1.38	0.47	0.32	−0.45	1.62
Political stability	−0.55	0.92	−3.31	1.28	−0.65	0.71	−3.22	1.53	−0.67	1.49	−2.46	3.18
Regulatory quality	−0.71	0.64	−2.55	1.20	−0.73	0.53	−2.45	1.37	−0.55	0.74	−1.42	2.30
Rule of law	−0.712	0.66	−2.59	1.02	−0.51	0.65	−2.51	1.04	−0.23	0.95	−3.61	2.87
Government effectiveness	−0.78	0.63	−2.45	1.16	−0.81	0.59	−2.41	1.32	−0.59	0.76	−2.32	2.70

Notes: This table presents descriptive statistics of all the variables used in the analysis. Our base sample consists of 31 countries in Africa, further separated into North and sub-Saharan Africa.

panel data. Unit root in panel data tests for the stationarity (or otherwise) of the series, while cross-sectional dependence of series may occur due to unobserved shocks. Over the years, econometricians have had to contend with these in heterogeneous panel data structures. If present in a series, it poses a problem to the validity of results generated as they may be biased. Hence, it is pertinent to investigate these situations before embarking on the main analysis (Afonso and Jalles, 2015; Tiwari et al., 2021).

Recognising these issues, we cater for cross-sectional dependence (CD) in the series by employing the test developed by Pesaran (2004). More specifically, we account for unit root at both the level and first-difference forms, using three different techniques. We start with the tests proposed by Pesaran (2007) and Pesaran and Yamagata (2008) called Cross-sectionally Augmented Dickey-Fuller (CADF) test and Cross-sectionally Augmented Im-Pesaran-Shin (CIPS) unit root test. Then, we use Hadri (2002) test to further confirm the validity of the two models.

Given the possibility of a conflicting outcome amongst the three methods, we follow the approach of Nazlioglu and Karul (2017) panel stationarity test, which captures structural break. We are conscious of the existence of structural breaks in the series because its presence could affect the reliability of results. Hence, we allow the date of the break to be endogenously determined using a simple Monte-Carlo experiment. Should our variables be integrated at level form, then there may be no need to proceed to differencing the variables; otherwise, stationarity may be achieved in the first-order difference [$I(1)$]. The latter case would, therefore, require further investigation of long-run relationships using cross-sectional dependence cointegration (CDC) test. The CADF and CIPS equations are shown below, where $t_i(N, T)$ denotes the CADF and CIPS ADF-statistic for the aggregate and regional observations:

$$\Delta y_{it} = \alpha_i + b_i\, y_{i,t-1} + \varepsilon - i\, y_{t-1} + d_i \, \underset{\Delta y_t}{\bar{}} + \varepsilon_{it} \tag{2}$$

$$CIPS(N,T) = N^{-1} \sum_{i=1}^{N} t_i\,(N,T\,) \tag{3}$$

3.4.2. Accounting for long-run relationship: panel cointegration tests

The use of long-run cointegration test is warranted when the relationship between environmental degradation and quality of life is established to be cointegrated at order one (that is, $I(1)$). In this study, we use two different cointegration tests to substantiate our conjecture. First, we use the Westerlund (2006, 2007) test for cointegration and panel cointegration test developed by Westerlund and Edgerton (2008). The latter test has superiority over the former because it eliminates the proposition of a unique restriction. Besides, it is designed to handle the specific intercept of individual series and situations where the residuals, gradients, and trends are autocorrelated. Additionally, it accounts for unknown structural breaks and cross-sectional dependence.

Using four specific parameters at both panel and group forms, the Westerlund and Edgerton (2008) cointegration test explains how the panel can be integrated as a group rather than individual series. It also indicates the possibility of regime, level, and endogenous structural changes in a longitudinal data. Importantly, Westerlund and Edgerton (2008) test allows us to understand the heterogeneity within the regions and the propensity for macroeconomic factors to influence the relationship between quality of life and environmental degradation. The equation for the cointegration test is specified below:

$$y_{i,t} = \alpha_i + \delta_{i,t} + \beta_1 x_{1i,t} + \beta_2 x_{2i,t} + \ldots + \beta_k x_{ki,t} + \varepsilon_{i,t} \tag{4}$$

In Eq. (4) above, we expect x and y to cointegrate at order $I(1)$, where α is a constant term, β denotes the slope, t represents observations, ε is the residual term, and the number of explanatory variables are denoted by k. From Eq. (4), we further derive the residuals of cointegration since they ought to be cointegrated at order $I(1)$:

$$e_{it} = \rho_i\, e_{it-1} + \sum_{j=1}^{\rho i} \varphi_{ij} \Delta e_{it-1} + v_{it} \tag{5}$$

Next, we specify the cointegration test that accounts for cross-sectional homogeneity in the intercept and slopes. Here, our null hypothesis is equally specified as no cointegration as shown below:

$$y_{i,t} = \alpha_i + \beta x_{i,t} + \varepsilon_{i,t}, i = 1, 2, \ldots, N\,;\ t = 1, 2, \ldots, T \tag{6}$$

where y, x, and ε are the HDI proxy, matrix of explanatory variables, and residuals, respectively, for each country.

3.4.3. Accounting for causality in heterogeneous panels

Econometric modelling assumes that the presence of a causal relationship between two or more time series variables can further be efficiently extended to panel observations, whilst simultaneously considering the individual differences (heterogeneity) in the panel. The existence of a long-term relationship does not translate to causality. Although cointegration tests deal with the former, the latter is best handled using causality tests. Most studies have used Granger (1969) causality test to explain the direction of causality between variables. The drawback with the use of this approach is its inability to cater for causality and heterogeneity in a panel context. Hence, in this study, we ascertain the direction of causality between environmental degradation and quality of life using the heterogeneous panel causality test developed by Dumitrescu and Hurlin (2012), which is basically an extension of Granger (1969).

Indeed, both approaches are similar in the sense that they check if the present observation of the dependent variable y can be significantly explained by the past observations of the explanatory variable/s X. However, in contrast to Granger (1969), the method of Dumitrescu and Hurlin (2012) is specifically designed to detect causality in panel models. Moreover, it uses both bootstrap and Monte Carlo simulations to show that the Wald statistic is adequate to detect causality at panel levels given independent, identical, and standard normal distribution of observations. We compute the mean of the Wald statistics to ascertain the panel test value.

Furthermore, the Dumitrescu and Hurlin (2012) model breaks a specific group into subgroups, such that it accounts for the possibility of the existence of causal relationship in subgroups, whilst absent in other subgroups. This implies that two variables may have causality at the aggregate level, but at the individual levels, they may not. This is particularly important given the dynamics of short- and long-term causal relationships between variables in a panel. Equation (7) below describes the causality test proposed by Dumitrescu and Hurlin (2012):

$$y_{i,t} = a_i + \sum_{k=1}^{K} \gamma_{ik} y_{i,t-k} + \sum_{k=1}^{K} \beta_{ik} x_{i,t-k} + \varepsilon_{i,t} \quad (7)$$

In the above equation, $x_{i,t}$ and $y_{i,t}$ are the series of both environmental degradation and quality of life for each country/region at a given period, respectively. The i subscript for each coefficient indicates that the coefficients remain the same for each period but can vary across countries. Essentially, this model works for a panel where the lag order K remains the same for each country. Although this could pose an empirical obstacle, it is nevertheless resolved by choosing the appropriate lags using one of the information criteria of AIC, BIC or HQIC, thereby allowing estimations to have a common nested sample.

3.4.4. Main estimation: IV-Lewbel 2SLS regression

In explaining the severity of climate change on quality of life in Africa, we apply an instrumental variable (IV) approach using Lewbel (2012) two-stage least squares (IV-Lewbel 2SLS). In the face of weak or few instruments and identification problems, the Lewbel (2012) approach is designed to overcome model specifications as it generates internal instruments like those constructed in the model. Moreover, this approach overcomes issues associated with autocorrelation, endogeneity, missing data points, and panel heteroscedasticity. This approach is also suitable for both balanced and unbalanced panel data. The model is specified below:

$$\text{HDI}_{i,t} = \alpha_0 + \beta_1 \text{EFP}_{i,t} + \beta_2 \text{CO}_{2i,t} + \beta_3 Controls_{i,t} + \varepsilon_{i,t} \quad (8)$$

where HDI is human development index (a proxy for quality of life) at the aggregate African level, Northern African region and sub-Saharan African region, respectively. EFP and CO_2 are the environmental degradation measures, which refer to the ecological footprint and carbon emissions of Africa at the aggregate level and by regions, respectively. $X_{i,t}$ represents a matrix of control variables included in the empirical model to prevent omitted variable bias (see Table 1 for the data description).

4. Findings

4.1. Results of cross-sectional dependence and unit root tests

We report the output of the cross-sectional dependence (CD) test in Tables 3 and 4. Table 3 specifically shows the output of the Breusch and Pagan (1980) test and the Pesaran (2004) CD test for individual variables. Table 4 shows the CD tests for the entire panel model. The results in both tables reveal that the data series of the variables in our study exhibit strong cross-sectional dependence, thus leading to the rejection of the null hypothesis at high significance levels. We opine that the sampled regions show cross-sectional dependence due to spill-over effects from common factors, including macroeconomic conditions, geographical location, and political climate (Śmiech and Papież, 2014; Shahbaz et al., 2017). For example, the quality of life across countries within a region can be affected by underlying factors such as migration due to climate change, social unrest, and terrorism. Other factors may include poverty, infrastructure decay, and lack of access to basic amenities.

Table 3
The Breusch-Pagan and Pesaran CD tests for individual variables.

Variable	Breusch-Pagan	Pesaran LM	Bias-corrected LM	Pesaran CD
HDI	2665.19**	301.19**	301.55**	71.09**
HDINA	511.30**	188.01**	211.90**	69.15**
HDISSA	2011.00**	160.59**	301.56**	71.65**
EFP	3318.51**	194.27**	175.03**	78.91**
EFPNA	209.04**	255.78**	188.30**	75.03**
EFPSSA	1981.323**	180.33**	195.22**	68.20**
CO_2	1706.209**	209.16**	203.67**	74.11**
CO_2NA	154.77**	177.30**	134.09**	65.09**
CO_2SSA	1330.67**	205.64**	186.45**	93.22**

Notes: This table shows the Breusch-Pagan LM and Pesaran CD tests for the individual variables. H0: The variable is not dependent (not correlated) across the cross-sections. H0 is rejected if the coefficient is significant.

Table 4
Cross-sectional dependence tests for the entire model.

Test	T -statistic	p-value
Model 1: $\text{HDI}_{i,t} = f\,(\text{EFP}_{i,t}, \text{CO}_{2i,t})$		
Breusch and Pagan (1980)	394.10***	0.000
Pesaran and Yamagata (2008)	251.06***	0.000
Pesaran (2004)	21.39***	0.000
Model 2: $\text{HDINA}_{i,t} = f\,(\text{EFPNA}_{i,t}, \text{CO}_2\text{NA}_{i,t})$		
Breusch and Pagan (1980)	151.00***	0.000
Pesaran and Yamagata (2008)	135.21***	0.000
Pesaran (2004)	13.19***	0.000
Model 3: $\text{HDISSA}_{i,t} = f\,(\text{EFPSSA}_{i,t}, \text{CO}_2\text{SSA}_{i,t})$		
Breusch and Pagan (1980)	311.20***	0.000
Pesaran and Yamagata (2008)	231.11***	0.000
Pesaran (2004)	25.44***	0.000

Notes: This table shows the cross-sectional dependence tests for the entire model using fixed-effect model. H0: Model is not dependent (not correlated) across the cross-sections. H0 is rejected if the test statistic is significant.

Additionally, countries could witness spill-over impact of climate change due to geography and resource-sharing. For instance, recent evidence suggests that countries in the West of Africa have continued to experience acute displacement due to severe flooding arising from climate change (Avom et al., 2020), while countries in the North are ravaged with persistent wildfires. There is also an unprecedented cycle of clones in the South and countries in the Horn of Africa are facing acute famine (Sakariyahu et al., 2023). These incidences may appear sequestered; however, they are interwoven due to environmental degradation. The fact that it is peculiar to a particular region makes countries in that region and the whole continent more susceptible because of cross-sectional dependence.

With regards to the results of the unit root tests shown in Table 5, the output of the Hadri and CIPS tests suggests the presence of unit root in the variables. On the other hand, the output of CADF reveals evidence of stationarity. The contradictory position of these methods can best be resolved using the output of the Nazlioglu and Karul (2017) stationarity test, as already discussed in the previous section. The output from this test shows strong evidence to reject the null hypothesis of stationarity. This implies that the variables, in their level form, exhibit unit root.

4.2. Results of panel cointegration tests for time-varying relationship

We report the results of both the Westerlund (2006, 2007) and Westerlund and Edgerton (2008) heterogeneous panel cointegration

Table 5
Panel unit root test.

Variables	CADF	CIPS	Hadri	NK level shift	NK level and trend shift
HDI	−1.59	−3.19*	15.35*	310.59*	1367.09*
HDINA	−1.03	−1.88*	11.29*	215.11*	2218.33*
HDISSA	−2.11	−2.60	13.25*	236.45*	2019.45*
EFP	−1.85	−1.94*	15.43*	187.10*	1187.10*
EFPNA	−2.00	−2.57*	13.40*	425.43*	3301.45*
EFPSSA	−1.83	−1.83	15.29*	120.68*	1924.11*
CO_2	−1.76	−2.01	23.34*	345.09*	2201.69*
CO_2NA	−1.57	−1.77*	14.91*	254.33*	1925.18*
CO_2SSA	−2.06	−2.05	16.50*	123.02*	1655.01*

Notes: This table shows the output for the stationarity tests using CADF, CIPS, Hadri and NK. H0 is rejected if the test statistic is significant·

tests in Tables 6 and 7, respectively. In Table 6, our results suggest the presence of cointegrating relationship between environmental degradation and quality of life in SSA. For this reason, the null hypothesis of no cointegration is rejected. However, this result does not hold for the whole of Africa and the North African region, as there appears to be no cointegrating relationship in the long run. Furthermore, using panel cointegration level and regime change approaches provided by Westerlund and Edgerton (2008), as shown in Table 7, we consider the likelihood of structural breaks in the output. Our findings further confirm the absence of long run cointegrating relationship in the aggregate for Africa and the Northern region, whilst affirming its presence for the SSA.

Overall, our findings indicate that environmental degradation effects have long term consequences on the quality of life in Africa, particularly the SSA region. This is not surprising considering the heavy reliance of countries in this region on incomes from mineral extraction, deforestation, and land cultivation, which constitute part of the climate crises. A large population of African citizens live in rural areas, with agriculture being the predominant occupation. The effect of environmental degradation on their development has worsened over the years due to increased mineral extraction and industrialisation, which contribute significantly to global warming. The ripple effect also includes loss of fertile land, farmers-herders conflict, and low quantity and quality of harvests.

In the absence of modern agricultural mechanisms, farmers have had to abandon their farms and migrate to urban areas for low paying jobs, such as factory workers, commercial bus drivers, and tricycle operators, as well as site labourers. The lack of decent wages aggravates their living standards and undermines their quality of life in the long run. Furthermore, the migration of people from rural to urban areas, in search of a better life, puts pressure on the population density and infrastructural facilities in the urban ecosystem. For example, access to quality health care, which is a key measure of human development, may become outstretched in such situations due to the poor living conditions of the populace.

Table 6
Panel cointegration results using Westerlund (2007) approach.

Statistics	Value	*Z*-value	*p*-value	Robust *p*-value
Model 1: $HDI_{i,t} = f(EFP_{i,t}, CO_{2i,t})$				
G_t	−4.259	1.08	0.4	0.37
G_a	−4.33	2.14	0.32	0.28
P_t	−6.17	1.18	0.2	0.25
P_a	−3.1	1.09	0.65	0.61
Model 2: $HDINA_{i,t} = f(EFPNA_{i,t}, CO_2NA_{i,t})$				
G_t	−11.51	−1.06	0.45	0.49
G_a	−23.34	0.54	0.61	0.58
P_t	−15.69	0.99	0.19	0.3
P_a	−10.38	0.23	0.38	0.45
Model 3: $HDISSA_{i,t} = f(EFPSSA_{i,t}, CO_2SSA_{i,t})$				
G_t	−1.51	−2.16*	0.00	0.01
G_a	−3.24	−1.04**	0.00	0.04
P_t	−3.9	−1.34*	0.00	0.01
P_a	−5.66	−1.09*	0.00	0.05

Notes: This table shows the panel cointegration test of long-run relationship for the entire model. H0: Model is not cointegrated in the long run. H0 is rejected if the *p*-value is less than 0.01, indicating the presence of long-run cointegration.

Table 7
Panel cointegration results using Westerlund and Edgerton (2008) approach.

Level shift			Regime shift		
Statistics	Estimate	P-value	Estimate	P-value	Cointegrated
Model 1: $HDI_{i,t} = f(EFP_{i,t}, CO_{2i,t})$					
$Z_t(N)$	0.39	0.18	0.15	0.10	No
$Z_a(N)$	−0.27	0.11	0.26	0.22	No
Model 2: $HDINA_{i,t} = f(EFPNA_{i,t}, CO_2NA_{i,t})$					
$Z_t(N)$	−1.41	0.26	−0.51	0.11	No
$Z_a(N)$	−1.33	0.12	−1.23	0.19	No
Model 3: $HDISSA_{i,t} = f(EFPSSA_{i,t}, CO_2SSA_{i,t})$					
$Z_t(N)$	−0.76*	0.00	−0.68	0.02	Yes
$Z_a(N)$	−0.43*	0.04	−0.50	0.00	Yes

Notes: This table shows the Westerlund and Edgerton (2008) panel cointegration test of long-run relationship for the entire model. H0: Model is not cointegrated in the long run. H0 is rejected if the *p*-value of the estimate is less than 0.01, thus indicating the presence of cointegration.

4.3. Results of the heterogeneous panel causality test

In Table 8, we present the results of the heterogeneous panel causality test based on Dumitrescu and Hurlin (2012). Our results at the aggregate level denote the existence of a unidirectional causality between both environmental degradation variables and quality of life. Specifically, we find that HDI has a one-way causal relationship with EFP and CO_2, with no reverse causality. This suggests that an increase in human development index causes a depletion in the atmospheric condition in Africa. Similar unidirectional causality results are also shown for the SSA region. At first, the results for this region reveal that human development does not homogenously cause ecological footprint, implying that environmental degradation in the region is not due to an increase in human development. Surprisingly, this finding is dampened by the next result, which shows that HDI does have a one-way causality on carbon emissions, thus reaffirming the earlier position for the whole region.

Interestingly, in the North African region, there is a bi-directional causality between the environmental degradation variables and HDI. The direction of causality implies that an increase in climate crisis affects human development, while an increase in human development can also stimulate climate-related problems. The findings of the causality

Table 8
Pairwise panel causality test using Dumitrescu-Hurlin (2012) method.

Null hypothesis	W-stat	Zbar-stat	*p*-value
Model 1: $HDI_{i,t} = f(EFP_{i,t}, CO_{2i,t})$			
HDI does not homogenously cause EFP	1.94	3.38	0.08
EFP does not homogenously cause HDI	3.25	1.07	0.20
HDI does not homogenously cause CO_2	2.89	2.44	0.04
CO_2 does not homogenously cause HDI	1.65	1.73	0.19
Model 2: $HDINA_{i,t} = f(EFPNA_{i,t}, CO_2NA_{i,t})$			
HDINA does not homogenously cause EFPNA	2.40	2.19	0.00
EFPNA does not homogenously cause HDINA	1.37	1.36	0.02
HDINA does not homogenously cause CO_2NA	1.60	2.45	0.07
CO_2NA does not homogenously cause HDINA	1.49	1.97	0.00
Model 3: $HDISSA_{i,t} = f(EFPSSA_{i,t}, CO_2SSA_{i,t})$			
HDISSA does not homogenously cause EFPSSA	2.44	2.85	0.11
EFPSSA does not homogenously cause HDISSA	1.90	2.27	0.00
HDISSA does not homogenously cause CO_2NA	1.87	1.99	0.05
CO_2SSA does not homogenously cause HDISSA	2.65	2.07	0.13

Notes: This table shows the Dumitrescu-Hurlin (2012) for the pairwise panel causality test. H0 is no causality in the direction, and this is rejected if the p-value is less than 0.01, suggesting the presence of causality.

substantiate our earlier result that the sampled regions show cross-sectional dependence due to spill-over effects from common factors, such as macroeconomic conditions, geographical location, and political climate.

4.4. Results of regression analyses

Having conducted the above estimations, we now turn our attention to empirical investigations based on regression models. To this end, we generate regression results on the direct impact of environmental degradation proxies and other explanatory variables on the quality of life in Africa by applying the IV-Lewbel 2SLS regression. In Table 9, we show the IV-Lewbel 2SLS regression output and find that environmental degradation significantly affects quality of life in Africa. This finding is supported by the negative and statistically significant coefficients (at the 5% level) of both the ecological footprint and carbon emissions on HDI. Essentially, an increase in carbon emissions leads to a reduction in HDI by 18%. Similarly, a rise in ecological footprint reduces quality of life by 12%. Our results are in tandem with prior studies (Costanza et al., 2007; Ambrey and Daniels, 2017), who also find that the implications of environmental degradation are critical for human existence. In terms of other explanatory variables, the coefficients of economic and development indicators, as well as those of political, governance and institutional factors, are positively signed, except for inflation and population growth. For instance, renewable energy has a positive and statistically significant coefficient at the 1% level, thus suggesting that increases in access to clean cooking fuels and energy-efficient technologies will improve quality of life of the populace because there will be less health-related challenges occurring due to exposure to environmental hazards. In recent studies, Acheampong et al. (2019) and Aluko et al. (2021) also confirm that the use of modern clean technologies can drastically reduce the health-related consequences of climate change.

Furthermore, the coefficient of GDP per capita is positive and significant, indicating that a rise in output production of a country, per head, will enhance their living standards as there will be more income in the hands of households. Similar positive and significant signs are shown for the coefficients of FDI, and trade openness. We opine from these results that improving the quality of life would require significant amount of both local and foreign investments in a country. Moreover, the ability of countries to attract these investments through its trade and economic policies is also a vital factor in improving human development. More importantly, the quality of institutions embedded in a country has a direct impact on the rate of investments a country would experience, which in turn can serve as a viable medium to significantly improve quality of life.

Our findings do not differ from prior studies that have also shown how economic and governance indicators improve human development (Aluko and Opoku, 2022; Opoku et al., 2022). Meanwhile, the results of

Table 9
Climate change and quality of life in Africa using IV-Lewbel 2SLS.

DV = HDI	Model 1	Model 2	Model 3	Model 4	Model 5
EFP	−0.120**	−0.330*		−0.235***	−0.334*
	(0.211)	(0.013)		(0.011)	(0.005)
CO_2	−0.181**		−0.225**	−0.040***	−0.229**
	(0.003)		(0.011)	(0.129)	(0.104)
Renewable	0.341***	0.503*	0.331*	0.336*	
	(0.101)	(0.012)	(0.040)	(0.013)	
GDP per capita	0.476***	0.396**	1.153**	1.337**	
	(0.003)	(0.019)	(0.110)	(0.022)	
FDI	0.326*	1.301*	0.445**	1.657*	
	(0.101)	(0.211)	(0.013)	(0.322)	
Trade openness	0.232	0.336***	0.224*	0.995**	
	(0.105)	(0.048)	(0.115)	(0.104)	
Inflation	−0.033*	−0.503	−1.320***	−0.221	
	(0.014)	(0.211)	(0.120)	(0.113)	
Population growth	−0.410***	−1.098***	−0.009	−1.215*	
	(0.161)	(0.220)	(0.103)	(0.101)	
Control of corruption	0.221***	1.335*	0.336**		0.775*
	(0.152)	(0.012)	(0.104)		(0.341)
Political stability	0.390*	0.300***	0.330		0.631**
	(0.216)	(0.220)	(0.008)		(0.011)
Regulatory quality	0.334**	0.501	0.214**		0.440*
	(0.001)	(0.093)	(0.002)		(0.129)
Rule of law	0.226*	0.201**	0.331		0.562**
	(0.005)	(0.103)	(0.023)		(0.008)
Government effectiveness	0.873***	0.401	1.331***		0.102
	(0.224)	(0.113)	(0.016)		(0.015)
Constant	33.902**	12.151**	22.360***	24.654***	19.265***
	(1.335)	(0.310)	(0.295)	(1.005)	(0.143)
R^2	0.402	0.351	0.286	0.341	0.297
K–P LM-statistic	58.23**	50.01***	41.25***	55.19**	51.32**
Cragg-Donald F-stat	60.35***	71.40***	48.33**	51.67***	69.20**
Hansen J-stat	3.20	5.12	3.60	4.35	6.25
Observations	589	589	589	589	589

Notes: This table presents the main regression results for the nexus between climate change and quality of life in Africa. Estimation is performed by IV-Lewbel 2SLS regression, with coefficients computed using standard errors robust to heteroskedasticity. The validity of the 2SLS estimates are assessed by employing the Kleibergen-Paap (K–P) LM statistic, the Hansen J-statistic and Cragg-Donald Wald F-statistic. The probability values of the K–P LM statistic are below the threshold of conventional statistical significance while the probability value of the Hansen J-statistic is found to be greater than the customary thresholds of statistical significance. Standard errors are shown in parentheses. The outcome variable is HDI which is a proxy for quality of life. The key explanatory variables are climate change proxied with carbon emission and ecological footprint. Other explanatory variables are grouped into two: (i) economic and development (E&D) indicators and (ii) political, governance and institutional (PGI) factors. Model 1 includes all variables in the estimation. Model 2 includes all variables except carbon emission (CO2). Model 3 includes all variables except ecological footprint (EFP). Model 4 includes all variables except PGI factors and model 5 captures all variables except E&D factors. All regressions control for country fixed effects, and year fixed effects as well as an intercept term. *, **, and *** denote significance at 10%, 5% and 1%, respectively. Definitions of variables and data sources are provided Table 1.

inflation and population growth appear to have negative coefficients. We deduce from the output of the regression that increases in population and cost of living will trigger a reduction in human development. This does not come as a shock as we opine that inflation affects the purchasing power of money due to erosion of disposable income. Thus, an increase in inflation will ultimately have a devastating effect on the quality of life of the populace, particularly for large households, where there is a high number of people jostling to spend the meagre income. The validity of the 2SLS are assessed by employing the Kleibergen-Paap (K–P) LM statistic, the Hansen J-statistic and Cragg-Donald Wald F-statistic. The probability values of the K–P LM statistic are below the threshold of conventional statistical significance while the probability value of the Hansen J-statistic is found to be greater than the customary thresholds of statistical significance.

4.5. Does the effect of environmental degradation on quality of life differ materially by region?

We now turn attention to answering this question by considering the results obtained for the regions of Africa. The outputs are shown in Tables 10 and 11 for the SSA and North African regions, respectively. In Table 10, we find that carbon emissions and ecological footprint have negative and statistically significant effect on the quality of life in the SSA region. This finding suggests that higher levels of environmental degradation restrict human development in the region. A further implication of this finding is evident in the level of malnutrition, poverty, and forced migration prevalent among the citizens of countries within this region. The coefficients of other explanatory variables such as GDP per capita, and renewable energy are found to be largely positive and statistically significant, confirming earlier results that living standards in the face of environmental degradation can only be improved if there are strong institutional qualities. On the contrary, we find that population growth, inflation and FDI hinder quality of life in sub-Saharan Africa because their coefficients are found to be negative, indicating that an increase in any of these measures does not necessarily translate to improved quality of life in the SSA region.

With respect to the results for the North African region, it is interesting to see strong positive support for the role of environmental degradation on the quality of life in the region. This stems from the positive and statistically significant coefficients (at 1% level) exhibited by the proxies of carbon emissions and ecological footprint in the model. Our result shows that a percentage increase in carbon emission cause a rise in HDI by about 19% while ecological footprint causes HDI to rise by about 17%. This connotes that environmental degradation in the Northern region of Africa is, perhaps, a blessing to the citizens as it has significantly improved their living standards over the years. Another interesting angle to this might be due to the institutional qualities. Hence, we take a look at the coefficients of these indicators. Similar

Table 10
Climate change and quality of life in SSA using IV-Lewbel 2SLS.

DV = HDI	Model 1	Model 2	Model 3	Model 4	Model 5
EFP	−0.770*	−0.097***		−0.591**	−0.516
	(0.034)	(0.146)		(0.200)	(0.153)
CO_2	−0.562***		−0.687***	−0.120***	−0.698*
	(0.220)		(0.090)	(0.223)	(0.071)
Renewable	0.214*	0.409	0.453*	0.138*	
	(0.005)	(0.213)	(0.007)	(0.003)	
GDP per capita	0.337**	0.043*	0.424	1.253	
	(0.101)	(0.007)	(0.061)	(0.100)	
FDI	−0.551***	−0.463	−0.531	−0.976*	
	(0.101)	(0.300)	(0.013)	(0.113)	
Trade openness	0.413	0.566*	0.378*	0.879**	
	(0.290)	(0.102)	(0.150)	(0.221)	
Inflation	−0.047*	−0.150***	−1.277*	−0.034	
	(0.108)	(0.002)	(0.041)	(0.001)	
Population growth	−0.500**	−0.320*	−0.359	−0.762*	
	(0.009)	(0.012)	(0.045)	(0.055)	
Control of corruption	0.302	0.536*	0.612*		0.518
	(0.031)	(0.130)	(0.080)		(0.216)
Political stability	0.278*	0.043**	0.463		0.333*
	(0.003)	(0.009)	(0.101)		(0.011)
Regulatory quality	0.417*	0.365	0.332*		0.752***
	(0.036)	(0.102)	(0.140)		(0.013)
Rule of law	0.680	0.432*	0.409***		0.495*
	(0.005)	(0.001)	(0.055)		(0.201)
Government effectiveness	0.437**	0.264	0.573*		0.361
	(0.092)	(0.109)	(0.022)		(0.219)
Constant	27.30*	32.25	19.00***	22.685**	24.39*
	(0.578)	(0.420)	(0.157)	(0.990)	(0.201)
R^2	0.504	0.435	0.442	0.501	0.453
K–P LM-stat	34.15***	41.09***	32.11***	28.21***	33.00***
Cragg-Donald F-stat	57.13***	45.17***	49.04***	51.16***	56.02***
Hansen J-stat	2.61	4.33	4.21	5.13	4.22
Observations	513	513	513	513	513

Notes: This table presents the main regression results for the nexus between climate change and quality of life in sub-Saharan Africa. Estimation is performed by IV-Lewbel 2SLS regression, with coefficients computed using standard errors robust to heteroskedasticity. The validity of the 2SLS estimates are assessed by employing the Kleibergen-Paap (K–P) LM statistic, the Hansen J-statistic and Cragg-Donald Wald F-statistic. The probability values of the K–P LM statistic are below the threshold of conventional statistical significance while the probability value of the Hansen J-statistic is found to be greater than the customary thresholds of statistical significance. Standard errors are shown in parentheses. The outcome variable is HDI which is a proxy for quality of life. The key explanatory variables are climate change proxied with carbon emission and ecological footprint. Other explanatory variables are grouped into two: (i) economic and development (E&D) indicators and (ii) political, governance and institutional (PGI) factors. Model 1 includes all variables in the estimation. Model 2 includes all variables except carbon emission (CO_2). Model 3 includes all variables except ecological footprint (EFP). Model 4 includes all variables except PGI factors and model 5 captures all variables except E&D factors. All regressions control for country fixed effects, and year fixed effects as well as an intercept term. *, **, and *** denote significance at 10%, 5% and 1%, respectively. Definitions of variables and data sources are provided in Table 1.

Table 11
Climate change and quality of life in Northern Africa using IV-Lewbel 2SLS.

DV = HDI	Model 1	Model 2	Model 3	Model 4	Model 5
EFP	0.168***	−0.273		0.093*	0.660***
	(0.320)	(0.051)		(0.004)	(0.012)
CO_2	0.189***		0.729*	0.250**	0.721*
	(0.207)		(0.103)	(0.002)	(0.342)
Renewable	0.355	0.429*	0.450	0.044*	
	(0.110)	(0.003)	(0.102)	(0.052)	
GDP per capita	0.013**	0.346**	0.975*	0.865**	
	(1.441)	(0.230)	(0.021)	(0.014)	
FDI	0.012	0.590*	0.394*	0.448***	
	(0.370)	(0.012)	(0.210)	(0.103)	
Trade openness	0.048*	0.205**	0.042*	0.679*	
	(1.079)	(0.116)	(0.001)	(0.024)	
Inflation	−0.125	−0.338	−0.943**	−0.543	
	(0.030)	(0.032)	(0.003)	(0.022)	
Population growth	−0.011	−0.725*	−0.651	−0.504*	
	(0.034)	(0.103)	(0.023)	(0.229)	
Control of corruption	0.126	0.672**	0.506*		0.450*
	(0.204)	(0.021)	(0.024)		(0.003)
Political stability	0.376***	0.463*	0.473		0.583
	(3.008)	(0.016)	(0.012)		(0.220)
Regulatory quality	0.254*	0.923	0.519**		0.674*
	(0.101)	(0.014)	(0.331)		(0.315)
Rule of law	0.099**	0.617*	0.537		0.287**
	(0.038)	(0.034)	(0.002)		(0.011)
Government effectiveness	0.449***	0.268	0.450*		0.340***
	(0.026)	(0.011)	(0.031)		(0.103)
Constant	25.63**	20.11*	19.66***	18.35**	25.31*
	(0.220)	(0.042)	(0.302)	(0.510)	(0.204)
R^2	0.327	0.376	0.351	0.470	0.399
K–P LM-stat	22.30*	20.01**	31.91*	22.81***	15.10*
Cragg-Donald F-stat	35.22**	31.59**	44.02*	31.23**	30.41***
Hansen J-stat	4.30	2.61	4.47	3.25	3.09
Observations	76	76	76	76	76

Notes: This table presents the main regression results for the nexus between climate change and quality of life in Northern Africa. Estimation is performed by IV-Lewbel 2SLS regression, with coefficients computed using standard errors robust to heteroskedasticity. The validity of the 2SLS estimates are assessed by employing the Kleibergen-Paap (K–P) LM statistic, the Hansen J-statistic and Cragg-Donald Wald F-statistic. The probability values of the K–P LM statistic are below the threshold of conventional statistical significance while the probability value of the Hansen J-statistic is found to be greater than the customary thresholds of statistical significance. Standard errors are shown in parentheses. The outcome variable is HDI which is a proxy for quality of life. The key explanatory variables are climate change proxied with carbon emission and ecological footprint. Other explanatory variables are grouped into two: (i) economic and development (E&D) indicators and (ii) political, governance and institutional (PGI) factors. Model 1 includes all variables in the estimation. Model 2 includes all variables except carbon emission (CO_2). Model 3 includes all variables except ecological footprint (EFP). Model 4 includes all variables except PGI factors and model 5 captures all variables except E&D factors. All regressions control for country fixed effects, and year fixed effects as well as an intercept term. *, **, and *** denote significance at 10%, 5% and 1%, respectively. Definitions of variables and data sources are provided in Table 1.

finding is observed as the coefficients of regulatory quality are positive and statistically significant at 1% level. This indicates that better institutional qualities in the face of environmental degradation could improve the quality of life (see Asongu and Nwachukwu, 2017). Meanwhile, just like the preceding results, we also find negative and statistically significant coefficients for population growth and inflation, thus affirming previous stance that these variables cause a reduction in HDI.

4.6. Robustness checks: alternative estimation technique and other measures of quality of life

In order to account for possible cross-sectional dependence in the baseline models, we utilise fixed effects regression with Driscoll and Kraay (D-K) standard errors. The goal of this approach is to account for unobservable heterogeneity, which can potentially add bias into regression estimates. By employing the D-K standard error, we also effectively address the issue of bias caused by cross-sectional dependency, as well as account for heteroskedasticity and autocorrelation. Furthermore, in this analysis, we follow the climate change literature and use alternative measures of quality of life. We utilise food production index, access to power, provision of basic drinking water services, and Gini index. We employ these indicators as proxies for quality of life due to the substantial ecological ramifications that are linked to them. Studies have shown that climate change has made the issues encountered by these proxies more severe, thereby necessitating their inclusion in the United Nations Agenda for Sustainable Development Goals. Ozturk (2015) specifically highlights that the scarcity or lack of energy and water resources caused by climate change can have an impact on food security in developing countries.

The fixed effects analysis, as shown in Tables 12–14, demonstrates that after considering unobservable differences and cross-sectional interdependence, the indicators of climate change are shown to make a substantial impact on the various indicators of quality of life in the region. The findings indicate that the severity of climate change will lead to a decline in food output, availability of electricity, provision of essential drinking water services, and the Gini index. This discovery corroborates the assertions made by Nyiwul (2021a) and Daka (2023), who uncovered similar results in their investigation. Furthermore, our fixed effects result shows that when unobservable heterogeneity and cross-sectional dependence are accounted for, political, governance, and institutional (PGI) factors significantly reduce these proxies of quality of life. Moreover, our results based on regional classification are in tune with our baseline IV 2SLS regression estimates, suggesting that the severity of climate crises are more pronounced in the SSA region.

5. Conclusion

In this study, we analyse the severity of environmental degradation and how it affects quality of life of African citizens. While our results show negative impact of environmental degradation variables on quality of life, the indicators of quality of institutions and trade openness are however positive, suggesting that these indicators can foster living standards despite the negative effects of environmental degradation. Studies have shown that SSA suffers from poor governance (institutional) quality. Hence, in the face of climate catastrophe, we propose that improving the quality of governance should be incorporated as part of the mechanisms for improving quality of life in Africa, especially in SSA. Our results also show that population growth and inflation have damaging effects on HDI. Our finding is in tandem with prior studies that have argued that an increase in the cost of living and population, without a commensurate increase in disposable income, is detrimental to quality of life.

Important policy implications are derived from our findings, which might be applied by international organisations, national governments, and sub-national governments throughout Africa. In light of our findings, one of the most important implications is that the relationship between the environmental degradation and the quality of life in Africa is complex and multifaceted. As a result, policy measures aimed at alleviating the effects of climate crises ought to take into consideration the regional dynamics of the continent. We urge policymakers to focus on tailor-made sustainable climate solutions that would, on the one hand, mitigate the negative impacts of environmental degradation and, on the other hand, improve the quality of life of African residents.

Lastly, we contend that our study opens a pathway for future research. Our paper has examined the relationship between environmental degradation variables and quality of life, using human development index. A potential avenue for further studies is considering other dimensions of human development apart from the alternative measures used in this study. future research may also consider micro-level data

Table 12
Climate change and quality of life in Africa using Fixed effects regression with D-K.

Variables	Dependent variables							
	(Model 1)	(Model 2)	(Model 1)	(Model 2)	(Model 1)	(Model 2)	(Model 1)	(Model 2)
	Food_Security	Food_Security	Access_Elec	Access_Elec	Basic_Water	Basic_Water	Gini_index	Gini_index
EFP	−0.2398***		0.0272		−0.0225**		−0.0342*	
	(0.0664)		(0.0173)		(0.0093)		(0.0201)	
CO_2		−0.0357***		−0.0172**		0.0079**		0.0220***
		(0.0059)		(0.0080)		(0.0040)		(0.0072)
Renewable	−0.0102	0.0111**	−0.0148***	−0.0145***	−0.0125***	−0.0125***	0.0112***	0.0114***
	(0.0029)	(0.0005)	(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0004)	(0.0005)
GDP per capita	0.5058***	0.2852***	0.3401***	0.2903***	0.1609***	0.1621***	0.0289	0.0111
	(0.0646)	(0.0268)	(0.0323)	(0.0323)	(0.0157)	(0.0169)	(0.0294)	(0.0302)
FDI	0.0124	0.0175***	0.0100	0.0101	−0.0107	−0.0108	−0.0115	−0.0118
	(0.0014)	(0.0014)	(0.0012)	(0.0012)	(0.0006)	(0.0006)	(0.0018)	(0.0017)
Trade openness	0.0117**	−0.0110***	−0.0208**	−0.0206	−0.0202	−0.0102	0.0216	0.0118**
	(0.0008)	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0004)	(0.0003)
Inflation	−0.0105*	−0.0109***	−0.0203**	−0.0203***	−0.0102***	−0.0103***	0.0204***	0.0123**
	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Population growth	0.0208	−0.0398***	−0.0579***	−0.0500***	−0.0484***	−0.0485***	0.0063	0.0126
	(0.0378)	(0.0145)	(0.0133)	(0.0122)	(0.0079)	(0.0075)	(0.0126)	(0.0130)
Control of corruption	−0.0510	0.0138	−0.1484***	−0.1558***	−0.0010	0.0073	0.0557**	0.0561**
	(0.0589)	(0.0369)	(0.0316)	(0.0303)	(0.0192)	(0.0183)	(0.0261)	(0.0254)
Political stability	−0.0677*	−0.0064	−0.0491***	−0.0520***	0.0038	0.0028	0.0388***	0.0317***
	(0.0344)	(0.0172)	(0.0097)	(0.0098)	(0.0080)	(0.0082)	(0.0109)	(0.0100)
Regulatory quality	−0.0109	0.0094	−0.0488***	−0.0546***	−0.0532***	−0.0538***	0.0329	0.0335
	(0.0338)	(0.0246)	(0.0165)	(0.0163)	(0.0113)	(0.0116)	(0.0203)	(0.0206)
Rule of law	0.1120*	0.0441	0.1539***	0.1689***	0.1205***	0.1209***	−0.0964***	−0.0744***
	(0.0655)	(0.0418)	(0.0328)	(0.0328)	(0.0205)	(0.0206)	(0.0286)	(0.0278)
Government effectiveness	0.0351	−0.0463	−0.0080	−0.0251	−0.1075***	−0.1059***	0.0532	0.0426
	(0.0699)	(0.0415)	(0.0466)	(0.0452)	(0.0263)	(0.0261)	(0.0382)	(0.0392)
Constant	−1.1801***	0.1135	−0.1213	−0.0848	0.4005***	0.4239***	0.2016*	0.2482**
	(0.3008)	(0.0953)	(0.1126)	(0.1042)	(0.0565)	(0.0565)	(0.1113)	(0.1090)
Within R^2	0.455	0.235	0.774	0.776	0.752	0.752	0.498	0.548
F-stats	44.36***	41.60***	56.11**	37.53***	30.13**	44.06***	44.22*	60.15***
Observations	589	589	589	589	589	589	589	589

Notes: This table presents the robustness of Models 1 and 2 in the baseline regression results for the nexus between climate change and quality of life in Africa. The estimation is performed using fixed effects regression, with coefficients computed using D-K standard errors robust to heteroskedasticity, serial correlation and cross-sectional dependence. Standard errors are shown in parentheses. The outcome variables are food security, access to electricity, people using basic water services, and the Gini index, alternative proxies for quality of life. The key explanatory variables are carbon emissions and ecological footprints. Other explanatory variables are grouped into two: (i) economic and development (E&D) indicators and (ii) political, governance and institutional (PGI) factors. Model 1 includes all variables except carbon emission (CO_2). Model 2 includes all variables except ecological footprint (EFP). All regressions control for country fixed effects, and year fixed effects as well as an intercept term. *, **, and *** denote significance at 10%, 5% and 1%, respectively. Definitions of variables and data sources are provided in Table 1.

such as greenhouse gas emission and nitrogen oxide. Furthermore, subsequent studies can examine the differential consequences of environmental degradation on men versus women using Gender Development Index (GDI).

CRediT authorship contribution statement

Rilwan Sakariyahu: Writing – original draft, Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Temitope Fagbemi:** Writing – review & editing, Writing – original draft, Resources, Investigation, Formal analysis, Conceptualization. **Rasheed Adigun:** Writing – review & editing, Writing – original draft, Validation, Project administration, Investigation, Formal analysis. **Rodiat Lawal:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Oluwagbenga Seyingbo:** Writing – review & editing, Writing – original draft, Conceptualization. **Olayinka Oyekola:** Writing – original draft, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

APPENDIX

CORRELATION MATRIX OF VARIABLES

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. human_dev	1.00													
2. ecological_footprint	0.60*	1.00												

(*continued on next page*)

Table 13
Climate change and quality of life in SSA using Fixed effects regression with D-K.

Variables	Dependent variables							
	(Model 1)	(Model 2)	(Model 1)	(Model 2)	(Model 1)	(Model 2)	(Model 1)	(Model 2)
	Food_Security	Food_Security	Access_Elec	Access_Elec	Basic_Water	Basic_Water	Gini_index	Gini_index
EFP	0.2050***		−0.0019		0.0107		−0.0700**	
	(0.0593)		(0.0170)		(0.0094)		(0.0292)	
CO_2		−0.0457***		0.0279***		−0.0029		0.0550*
		(0.0059)		(0.0058)		(0.0040)		(0.0308)
Renewable	−0.1026	−0.1011	−0.0220***	−0.0114**	−0.1022***	−0.0122***	−0.0101	0.0103
	(0.0036)	(0.0007)	(0.0007)	(0.0007)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
GDP per capita	0.5061***	0.2564***	0.3849***	0.3383***	0.1804***	0.1821***	0.0110	−0.0061
	(0.0702)	(0.0274)	(0.0252)	(0.0226)	(0.0131)	(0.0138)	(0.0248)	(0.0238)
FDI	0.0223	0.0180***	−0.0102	−0.0212	−0.0110	−0.0310	−0.0207	−0.0312
	(0.0015)	(0.0015)	(0.0010)	(0.0010)	(0.0006)	(0.0006)	(0.0018)	(0.0017)
Trade openness	0.0218**	−0.0211**	−0.0308**	−0.0207*	−0.0102	−0.0130	0.0240	0.0109**
	(0.0009)	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Inflation	−0.0204	−0.0330***	−0.0212	−0.0232**	−0.0152***	−0.0302***	0.0250**	0.0242
	(0.0003)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Population growth	0.0143	−0.0634***	−0.0371***	−0.0248***	−0.0576***	−0.0582***	−0.0120	−0.0051
	(0.0345)	(0.0145)	(0.0108)	(0.0092)	(0.0076)	(0.0071)	(0.0103)	(0.0116)
Control of corruption	−0.0456	−0.0442	−0.0725***	−0.0614**	0.0163	0.0197	−0.0130	0.0522
	(0.0641)	(0.0402)	(0.0265)	(0.0258)	(0.0181)	(0.0188)	(0.0253)	(0.0239)
Political stability	−0.0808**	−0.0128	−0.0305***	−0.0337***	0.0460	0.0256	0.0288***	0.0251**
	(0.0361)	(0.0178)	(0.0097)	(0.0097)	(0.0085)	(0.0086)	(0.0107)	(0.0101)
Regulatory quality	0.0107	0.0275	−0.0255	−0.0353**	−0.0413***	−0.0411***	0.0260	0.0256
	(0.0356)	(0.0262)	(0.0165)	(0.0157)	(0.0117)	(0.0118)	(0.0190)	(0.0198)
Rule of law	0.1712**	0.0728	0.1077***	0.1160***	0.1216***	0.1215***	−0.0653**	−0.0549**
	(0.0693)	(0.0458)	(0.0294)	(0.0291)	(0.0205)	(0.0206)	(0.0255)	(0.0245)
Government effectiveness	−0.0133	−0.0646	−0.0553*	−0.0670**	−0.1357***	−0.1345***	0.0828***	0.0767***
	(0.0703)	(0.0466)	(0.0290)	(0.0288)	(0.0212)	(0.0213)	(0.0265)	(0.0257)
Constant	−0.8875**	0.4022***	−0.5473***	−0.5184***	0.3583***	0.3695***	0.4159***	0.4178***
	(0.3458)	(0.1041)	(0.1031)	(0.0843)	(0.0600)	(0.0552)	(0.1042)	(0.1059)
Within R^2	0.448	0.275	0.662	0.680	0.702	0.702	0.592	0.628
F-stats	64.24***	58.77**	41.32**	52.28**	42.92*	51.06**	43.20**	65.27**
Observations	513	513	513	513	513	513	513	513

Notes: This table presents the robustness of Models 1 and 2 in the baseline regression results for the nexus between climate change and quality of life in SSA. The estimation is performed using fixed effects regression, with coefficients computed using D-K standard errors robust to heteroskedasticity, serial correlation and cross-sectional dependence. Standard errors are shown in parentheses. The outcome variables are food security, access to electricity, people using basic water services, and the Gini index, alternative proxies for quality of life. The key explanatory variables are carbon emissions and ecological footprints. Other explanatory variables are grouped into two: (i) economic and development (E&D) indicators and (ii) political, governance and institutional (PGI) factors. Model 1 includes all variables except carbon emission (CO_2). Model 2 includes all variables except ecological footprint (EFP). All regressions control for country fixed effects, and year fixed effects as well as an intercept term. *, **, and *** denote significance at 10%, 5% and 1%, respectively. Definitions of variables and data sources are provided in Table 1.

(*continued*)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
3. carbon_emmission	0.64*	0.60*	1.00											
4. Renew	−0.12*	−0.10*	−0.14*	1.00										
5. Gdpcapi	−0.01	0.00	−0.04	0.58*	1.00									
6. fdi	−0.04	−0.13*	−0.10*	0.08	0.06	1.00								
7. Trade_open	0.32*	0.10*	0.14*	0.00	0.02	0.38*	1.00							
8. Inflation	−0.05	−0.11*	−0.06	−0.09*	−0.10*	0.05	0.03	1.00						
9. Popu_growth	−0.55*	−0.52*	−0.52*	0.22*	0.03	0.12*	−0.13*	0.08*	1.00					
10. Political	0.11*	0.32*	0.20*	0.00	0.02	0.10*	0.29*	−0.16*	−0.11*	1.00				
11. Government	0.45*	0.68*	0.53*	−0.03	0.07	−0.07	0.11*	−0.13*	−0.51*	0.55*	1.00			
12. Regulatory	0.25*	0.54*	0.38*	0.09*	0.15*	−0.03	0.04	−0.16*	−0.24*	0.53*	0.60*	1.00		
13. Rule	0.28*	0.54*	0.36*	0.01	0.07	−0.02	0.09*	−0.16*	−0.29*	0.68*	0.57*	0.61*	1.00	
14. corruption	0.29*	0.60*	0.40*	0.00	0.08	−0.01	0.16*	−0.12*	−0.39*	0.63*	0.62*	0.48*	0.63*	1.00

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Variance inflation factor

	VIF	1/VIF
government	8.369	0.119
rule	8.228	0.122
corruption	6.186	0.162
ecological footprint	4.28	0.234
carbon emmission	4.273	0.234
regulatory	3.546	0.282
gdpcap	3.495	0.286
renewable	2.958	0.338

(*continued on next page*)

Table 14
Climate change and quality of life in Northern African using Fixed effects regression with D-K.

Variables	(Model 1) Food_Security	(Model 2) Food_Security	(Model 1) Access_Elec	(Model 2) Access_Elec	(Model 1) Basic_Water	(Model 2) Basic_Water	(Model 1) Gini_index	(Model 2) Gini_index
EFP	−0.3836***		0.1384		−0.2018		−0.1292	
	(0.1059)		(0.0905)		(0.0498)		(0.0163)	
CO_2		−0.0061		0.0608		−0.1226***		0.0660
		(0.0521)		(0.0180)		(0.0197)		(0.0051)
Renewable	0.0263***	0.0389***	−0.0118***	−0.0207	−0.0333***	−0.0215*	−0.0108**	0.0203
	(0.0013)	(0.0015)	(0.0007)	(0.0008)	(0.0010)	(0.0008)	(0.0003)	(0.0002)
GDP per capita	0.4062***	0.7181***	−0.1022**	−0.0144	−0.2688***	−0.1579***	−0.0347	0.0409***
	(0.1192)	(0.1136)	(0.0435)	(0.0826)	(0.0731)	(0.0509)	(0.0215)	(0.0137)
FDI	−0.0313	−0.0238	0.0401	0.0201	0.0313	0.0217	−0.0220	−0.0306
	(0.0042)	(0.0052)	(0.0017)	(0.0014)	(0.0026)	(0.0022)	(0.0010)	(0.0008)
Trade openness	−0.0130*	−0.0200	0.0112**	0.0311	0.0213*	0.0305	0.0410**	0.0220
	(0.0017)	(0.0019)	(0.0006)	(0.0008)	(0.0007)	(0.0006)	(0.0003)	(0.0002)
Inflation	0.0345	0.0148	0.0220	0.0201	0.0413*	0.0234*	0.0511**	0.0200*
	(0.0027)	(0.0031)	(0.0023)	(0.0022)	(0.0023)	(0.0019)	(0.0005)	(0.0004)
Population growth	0.0646	0.2382***	0.0300	0.0513	0.0846**	0.0900**	−0.0102	0.0215
	(0.0814)	(0.0732)	(0.0528)	(0.0658)	(0.0408)	(0.0362)	(0.0128)	(0.0096)
Control of corruption	0.1338	0.1844*	−0.0647	−0.0260	−0.0589	0.0083	0.0120	0.0506***
	(0.0894)	(0.1099)	(0.0406)	(0.0394)	(0.0465)	(0.0461)	(0.0148)	(0.0140)
Political stability	0.0958*	0.0535	−0.0414***	−0.0299***	−0.0815***	−0.0493*	−0.0298***	−0.0148*
	(0.0568)	(0.0650)	(0.0067)	(0.0058)	(0.0256)	(0.0296)	(0.0083)	(0.0077)
Regulatory quality	0.0473	−0.0526	0.0396	0.0382	0.0280	0.0453	0.0152	0.0188*
	(0.0452)	(0.0456)	(0.0395)	(0.0297)	(0.0287)	(0.0287)	(0.0073)	(0.0046)
Rule of law	0.2854***	0.2115**	−0.0058	0.0220	0.0528	0.1263***	−0.0390***	−0.0035
	(0.0676)	(0.0928)	(0.0351)	(0.0272)	(0.0381)	(0.0357)	(0.0117)	(0.0106)
Government effectiveness	−0.3576**	−0.1510	0.0682*	0.0533**	0.1180*	0.0454	0.0251	−0.0024
	(0.1392)	(0.1512)	(0.0413)	(0.0254)	(0.0623)	(0.0720)	(0.0190)	(0.0176)
Constant	−1.0924***	−1.9301***	0.9028***	0.7160	1.1943***	1.0033***	0.4955***	0.3517***
	(0.3804)	(0.3744)	(0.2906)	(0.4415)	(0.2479)	(0.2103)	(0.0686)	(0.0563)
Within R^2	0.690	0.619	0.482	0.476	0.696	0.745	0.511	0.530
F-stats	27.08***	39.13**	54.81**	24.03***	22.22**	31.06**	25.20**	30.65**
Observations	76	76	76	76	76	76	76	76

Notes: This table presents the robustness of Models 1 and 2 in the baseline regression results for the nexus between climate change and quality of life in Northern African. The estimation is performed using fixed effects regression, with coefficients computed using D-K standard errors robust to heteroskedasticity, serial correlation and cross-sectional dependence. Standard errors are shown in parentheses. The outcome variables are food security, access to electricity, people using basic water services, and the Gini index, alternative proxies for quality of life. The key explanatory variables are carbon emissions and ecological footprints. Other explanatory variables are grouped into two: (i) economic and development (E&D) indicators and (ii) political, governance and institutional (PGI) factors. Model 1 includes all variables except carbon emission (CO_2). Model 2 includes all variables except ecological footprint (EFP). All regressions control for country fixed effects, and year fixed effects as well as an intercept term. *, **, and *** denote significance at 10%, 5% and 1%, respectively. Definitions of variables and data sources are provided in Table 1.

(*continued*)

	VIF	1/VIF
political	2.46	0.407
popu growth	2.097	0.477
trade open	1.636	0.611
fdi	1.248	0.801
inflation	1.059	0.944
Mean VIF	3.834	

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