

Examining the impact of ecological deficit on life expectancy in GCC countries: a nonlinear panel data investigation

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Abstract

The Gulf Cooperation Council (GCC) countries have witnessed remarkable economic growth over recent decades. Arguably, this progress of these major oil and natural gas producers has come to the detriment of the environment in terms of increased CO_2 emissions and associated ecological degradation. The effects of these high emissions and environmental challenges on human health, specifically life expectancy (LE), have not been thoroughly explored in the literature. We aim to fill this research gap by assessing the relationship between Ecological footprint deficiency and the diverse and context-specific factors affecting LE in the GCC, highlighting the critical roles of urbanization, economic indicators, and digitization in shaping health outcomes. The study employs panel data for the 2000–2020 period. It utilizes linear and non-linear panel estimation methods to analyze these variables' long-term and short-term effects. Specifically, we run unit root tests, cointegration analysis to validate our datasets, and OLS, ARDL, and panel threshold regressions to examine said relationships. Our findings reveal a significant relationship between ecological footprint and LE across the GCC countries. The results indicate that a higher ecological deficit is associated with lower LE in our sampled nations. Meanwhile, our panel threshold results highlight more nuanced impacts of our variables of interest, revealing significant threshold effects and intricate dynamics influencing LE. Our results are robust when substituting CO₂ emissions for the ecological footprint suggesting and supporting our evidence for a more complex, potentially nonlinear relationship. Our study emphasizes the urgent need for sustainable environmental policies to mitigate health risks and promote long-term well-being in the GCC region. Nuanced approaches are needed to address each GCC country's health and environmental challenges.

Keywords Ecological footprint deficit \cdot Life expectancy \cdot Carbon emissions \cdot Nonlinear ARDL

JEL Classification $\ C23 \cdot F63 \cdot P28 \cdot Q57$

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1 Introduction

The relationship between life expectancy and its determinants has been of vital interest in the healthcare and sustainability literature. Despite immense advances in medicine and technology in the past 60 years, human life expectancy statistics have substantially deteriorated. Between 2020 and 2021, for instance, life expectancy at birth in the United States declined to levels not seen since 1996 (from 77.0 to 76.1 years). This was also the second year that life expectancy figures dropped (National Center for Health Statistics, 2022). According to the U.S. Center for Disease Control and Prevention, a large proportion of this decline was driven by the fatality rates at the peak of the Coronavirus (COVID-19) pandemic. However, the drop was also propelled by an increase in such chronic ailments as heart and liver diseases, unintentional injuries, homicide, and suicide, among other determinants.

Much research has focused on lifestyle-related risk factors, which according to the National Institute for Health and Welfare, only partly influences life expectancy. Quality of life factors are also emphasized for consideration in this regard. These include factors related to the environment, such as climate, atmospheric pressure, and the proportion of sunshine hours. A research avenue attracting increased interest is the interaction between life expectancy and elements related to environmental sustainability. In this regard, environmental degradation, which can be proxied by ecological footprint, has taken its toll on ecosystems for plant, animal, and human life.

The most prominent of these facets of degradation is that posed by air pollution, specifically greenhouse gas (GHG) or carbon emissions. Earlier studies connect global climate change and the resulting climatic instability to unsustainable energy consumption habits (WMO, 2021). Such consumption has been inextricably linked to increased GHG emissions, including carbon dioxide (CO_2) and other pollutants, prompting governments and international environmental and energy agencies to explore policies that can help slow or possibly reverse global climate changes. Some initiatives include research into the use of grape extract as green fuel (Zinatloo-Ajabshir et al., 2019), mitigation of hazardous organic water pollutants (Zinatloo-Ajabshir et al., 2024), and the use of zinc vanadate in green chemistry in the production of lithium batteries that has the added benefits of low cost, low toxicity, and environmental pollution (Ghodrati et al., 2020). According to Zinatloo-Ajabshir et al. (2023) for instance, using hydrogen as an alternative energy source promises several benefits such as its renewable waste byproducts, energy content, and efficiency, despite some safety concerns in its utilization.

Weather events related to climate change and natural disasters worldwide such as floods, hurricanes, and wildfires, among other things, have led to deaths. However, a more widespread challenge is the effect of climate change on food production, trade, and overall food security. For instance, a worsening drought in East Africa over the past 4 years is causing severe food shortages, putting 22 million people at risk of starvation by the third quarter of 2022. Such events have domino effects on the economies of these developing nations, leading back to a host of other elements intertwined with life expectancy. Global climate change in the form of heat waves, too, has affected life expectancy. On 19th July 2022, for example, the UK experienced its highest temperatures ever on record (Kendon, 2022), and perhaps coincidentally, a higher total (1,775) of reported deaths in England in one day according to the county's Meteorological Office. The scope of the current study is limited to investigating more direct life expectancy.

determinants, including ecological footprint, urbanization, digitization, healthcare expenditure, unemployment, and inflation, excluding weather and other pollutants.

While life expectancy figures have begun to worry developed countries, the situation for emerging and developing countries will likely worsen. We focus on the Middle East, specifically the six resource-rich nations that comprise the GCC.¹ Vast oil and gas reserves make these countries major exporters of hydrocarbons, unavoidably causing gas flaring and other ecological pollution that is perhaps a major part of their environmental situations. The study's significance lies in its pioneering analysis of life expectancy about ecological footprint and carbon emissions in the GCC region, which has unique environmental and health challenges due to its reliance on hydrocarbon extraction. It highlights the impact of poor air quality and the increasing prevalence of medical conditions such as diabetes, exacerbated by low healthcare spending. Additionally, the research contributes to the ecological footprint literature by exploring its significant effects on life expectancy, providing critical insights for policy-making in resource-rich countries. For instance, in today's rapidly growing era of digitization, artificial intelligence (AI)-powered precision medicine can provide the healthcare sector with early intervention for chronic diseases such as diabetes through predictive analytics, even as far as tailoring such interventions for specific individuals (Subramanian et al., 2020; Venigandla, 2022).

Specifically, the contribution of our paper to the existing literature is threefold. First, to the best of our knowledge the only study that empirically investigates life expectancy is about ecological footprint and carbon emission levels in the context of emerging economies, namely, those of the GCC region. Although these well-endowed nations are striving in coalition to diversify their economies and rely less on hydrocarbon sales, they owe much of their past, ongoing, and future development to the wealth that such sales yielded. Reduced visibility due to dust particles, industrial pollutants, and the rapid construction of infrastructure and buildings all contribute to the region's concerns over air quality due to its continued dependency on oil and gas extraction (Farahat, 2022). For instance, Amoatey et al. (2020), report a disquieting lack of assessment studies for most indoor air pollutants in the GCC, except a few member states trying to track particular pollutants, though not many. Little attention is paid to the range of respiratory diseases and related phenomena in the region such as 'sick building syndrome' (Amoatey et al., 2020).

Second, we differentiate this work from prior studies by focusing exclusively on the GCC countries. Apart from the previously mentioned concerns over air quality, the region is rapidly gaining notoriety for its increasing rates of medical illness. For example, the prevalence of diabetes cases in many Middle Eastern countries has put this region among the world's most serious diabetes hotspots (al Busaidi et al., 2019). With rapid socioeconomic growth, lifestyle changes, and the increasing presence of obesity, the number of people with diabetes in the region is expected to double by 2045 (al Busaidi et al., 2019). This unique situation imposes substantial socioeconomic costs on individuals and governments in the GCC. Despite subsidizing health care/medicine for their citizens and residents, the GCC countries contribute little to the medical sector compared with European countries. We posit that some of the challenges in life expectancy figures in the region are linked to the lower priority given to healthcare facilities in some countries. For instance, according to a 2019 report by the World Bank, healthcare spending as a percentage of gross domestic product (GDP) by GCC countries was much lower than in the UK (a country that also provides universal healthcare to its citizens). Ratios for Qatar and Oman were 3.9% each,

¹ The six GCC countries comprise Qatar, Kuwait, Oman, Bahrain, Saudi Arabia, and the United Arab Emirates.

5.3% for Kuwait, 5.2% for Saudi Arabia, and 4.8% for Bahrain while the UK spent 9.6% (Al-Shboul & al Rawashdeh, 2022).

Third, we contribute to the ecological footprint literature by investigating whether (and how significantly) it impacts life expectancy. The results of this paper give us useful insights for developing policies, programs, and strategies that will address the growing life expectancy and ecological concerns for the six GCC countries, the region in general, and other resource-rich nations of the same kind. Empirically, we find evidence for a long-run, positive relationship between ecological footprint and life expectancy for countries in the GCC. Using alternative air pollution/environmental sustainability measures, the findings are robust, suggesting that more needs to be done by GCC member states to address air quality concerns and lessen the impact on longevity in the region.

The rest of this paper is organized as follows. Section 2 presents a review of the literature on determinants of life expectancy. Section 3 operationalizes the hypotheses tested in the study while Sect. 4 describes the data collection methodology and econometric approach adopted. Section 5 lists our findings which are then discussed in Sect. 6, in line with relevant literature. The paper concludes with Sect. 7, where we propose recommendations and practical applications for GCC policymakers, and their governments and offer guidance for future researchers.

2 Determinants of life expectancy

This section reviews various determinants affecting life expectancy, as the recent literature highlights. We group studies based on the nature of these determinants, whether they relate to health or unnatural causes of death, quality of life, and others. Since the current study is mainly concerned with identifying how environmental sustainability, or the lack of it, affects life expectancy, we highlight studies looking at the nexus between ecological factors as a determinant of longevity.

2.1 Health-related determinants of life expectancy

Advances in medicine and technology have increased life expectancy figures for much of the developed world. Several studies have examined the long-term increase in life expectancy over previous decades but have also acknowledged a relative decline in recent years. For instance, Mathers et al. (2015) find that the fall in tobacco use, and the lower rate of cardiovascular disease mortality are the main factors behind the observed increase in life expectancy between 1980 and 2011 for 51 countries in Europe, Latin America, and the Caribbean. Meanwhile, analyzing developed countries using cross-country data from the WHO, Ho and Hendi (2018) find that most developed countries experienced declines in life expectancy between 2014 and 2015. The authors attribute this decline to an increase in older age mortality and deaths caused by respiratory, cardiovascular, and mental diseases.

Gilligan and Skrepnek (2015) look at life expectancy in the Eastern Mediterranean region, employing panel data from 1995–2010. Using a multi-level fixed-effects linear model, the authors find that vaccination averages serve as significant positive predictors for life expectancy. In other words, were the average rates of vaccination to increase, life expectancy would also increase. The authors also find that developing countries were associated with, on average, a 14% lower life expectancy than developed countries. This result

aligns with the findings of Castro et al. (2021), who used a descriptive analysis to find a negative relationship between COVID-19 and life expectancy.

However, in the US, the younger population is disproportionately affected by the reduction in life expectancy, which has been shown to be mostly caused by drug overdoses, alcoholism, and suicides. Using a linear regression on US data from the National Center for Health Statistics and the US Mortality Database, Woolf and Schoomaker (2019) also come to similar conclusions. They concentrate on midlife mortality (deaths between the ages of 25 and 64), divided by gender, race, socioeconomic level, and geography. Meanwhile, using a narrative approach, Poli et al. (2019) argue that dietary habits are a significant factor in life expectancy. Specifically, the authors find that the Italian diet positively affects life expectancy. Thus, rather than restricting the consumption of harmful nutrients such as alcohol and tobacco, they insist that policymakers should encourage the consumption of beneficial nutrients. Ho and Hendi (2018) found that a variety of factors, including environmental pollution, access to basic services, and medical resources influence life expectancy at birth. The study also found that women's life expectancy was positively impacted by population coverage and inpatient care rates, and negatively impacted by heart disease. The authors concluded that improved access to healthcare resources, education, and lifestyles may increase life expectancy. Furthermore, they emphasized the need to address the social determinants of health to improve life expectancy.

2.2 Quality of life determinants of life expectancy

The literature often examines shortened life expectancy or mortality caused by vices like those above. However, other determinants of quality of life have also attracted much attention. They include (among others) factors such as access to shelter, clean water, sanitation, and overall economic, social, and environmental well-being. Braveman and Gottlieb (2014) find that income, education, housing, transportation, and access to health care can profoundly affect health and well-being, and that addressing them can have a positive impact on addressing them can positively impact health outcomes. Evans and Soliman (2019) use cross-country data from the 2012 Happy Planet Index (HPI)² project report to study the relationship between life expectancy and subjective well-being. Controlling for income, population size, and ecological footprint, the authors find that an increase of 1 unit in the well-being scale is associated on average with an increase of 4 years in life expectancy. Their results suggest that subjective well-being and life expectancy are positively related (Evans & Soliman, 2019).

Other studies have considered additional economic and socio-demographic variables and their relation to life expectancy in countries with varied development and inequalities. An earlier study by Sede and Ohemeng (2015) using VAR and VECM econometric methods finds that government health expenditure, secondary school enrollment, and per capita income have no significant relationship to life expectancy in Nigeria from 1980 to 2011. Such results contrast with those of Hassan et al. (2017), for instance, who focus on 108 developing countries on GDP, education level, water and sanitation coverage as well as healthcare expenditure. These authors find a positive relationship between these listed variables and that of life expectancy. Hassan et al. (2017) also highlight that poverty and

² HPI is a measure that combines average well-being, life expectancy, and ecological footprint to determine whether a country is able to foster sustainable well-being in its citizens or not.

unemployment have a significant negative relationship with life expectancy. Similar findings were reported by Khouri et al. (2017), Tafran et al. (2020), and Rahman et al. (2022).

Khouri et al. (2017) focus on European regions over the period 2001–2014 using various demographic and socio-economic indicators from the Eurostat database. Using regression-specific fixed and random effects models, the authors find evidence for a positive relationship between indicators of economic activity and income and life expectancy. Unexpectedly, they do not see similar evidence for GDP per capita, which puts their results at odds with the theoretical suppositions that they and a swathe of other empirical studies present (Khouri et al., 2017). In a study by Tafran et al. (2020), determinants of life expectancy at birth were investigated in 13 Malaysian states from 2002 to 2014, using a fixed effects panel regression. Their results demonstrated that poverty and unemployment have a significant but negative relationship on life expectancy while income has a significant positive relationship.

Ladoy et al. (2021) also study inequalities concerning life expectancy in Switzerland. The authors utilized an indicator of the years of potential life lost or gained (YPLLG), combined with spatial cluster detection, to focus on geographical inequalities. The results suggest significant disparities in YPLLG between different geographical clusters. Additionally, populations in low YPLLG clusters were found to have significantly lower proportions of women, Swiss individuals, and lower neighborhood median income and age figures than populations in high YPLLG clusters. In another study, Mackenbach et al. (2019) used individual-level mortality and risk factor data from 15 European countries to study determinants of the inequality in life expectancy between these countries. Their findings reveal that people with higher education had a longer life expectancy. Furthermore, the authors reported educational inequality across countries by other factors including smoking, low income, and high body weight, and discerned a strong heterogeneity between European countries (Mackenbach et al., 2019).

Research by Rahman et al. (2022) used panel data from 31 of the most polluted nations. The Preston Curve, a long-term relationship between economic growth and life expectancy, was studied using panel-corrected standard errors (PCSE) and practicable generic least squares (FGLS) estimators. The study's findings showed that economic expansion had a favorable impact on favorably impacted life expectancy (Rahman et al., 2022). The authors conclude that, while environmental deterioration in the form of carbon emissions poses a risk to life expectancy, clean water, better sanitation, and increased health spending can have a favorable countereffect. The ecological variables and their effects on life expectancy are of special interest to our investigation.

2.3 Nexus between ecology and life expectancy

Several studies in this stream of literature focus on the factors driving the ecological footprint and the relationship between different economic and/or demographic variables and life expectancy (Charfeddine & Mrabet, 2017; Knight, 2014; Mahalik et al., 2022; Sahoo & Sethi, 2022; Sharma et al., 2021). In their earlier comparative study, Dietz et al. (2007) estimated the effect of various covariates of a regression model of the ecological footprint. According to their findings, population size and GDP per capita are the main drivers. In particular, higher levels of GDP per capita are associated with increasingly higher levels of ecological footprint. Sabir and Gorus (2019) focus on 5 South Asian countries from 1975 to 2017. The authors employ various indicators, including trade openness, the KOF Globalization Index,³ built-up land, cropland, CO_2 emission, and others to investigate whether globalization affects ecological footprint. Their ARDL results show that globalization and the ecological footprint are positively related (Sabir & Gorus, 2019).

Knight (2014) examines the link between ecological footprint and life expectancy throughout 1961–2007 and provides more examples of how economic variables/determinants may impact environmental sustainability and life expectancy. In developed countries, the relationship between ecological footprint and life expectancy has weakened significantly over time, turning negative in later years, according to the findings of two-panel regression specifications: the first with year-fixed effects only, and the second with year and country-fixed effects for both developed and developing countries (Knight, 2014). However, for less developed nations, the association is positive and strengthens over time (per one specification), although with a minor downward trend (according to the second specification).

Using panel data from oil-rich nations in Africa, Oduyemi et al. (2021) investigate the possible impacts of the resource curse on health outcomes. Using a threshold regression model, the authors demonstrate a negative link at lower levels of growth and a positive relationship at higher levels of development. Their findings imply an economic growth-dependent link between health outcomes and resource availability. Sharma et al. (2021) examine the effects of various factors, such as per capita income, renewable energy use, life expectancy, and population density, on the ecological footprint in eight South and South-east Asian developing nations between 1990 and 2015. Using a CS-ARDL technique, they discover a favorable correlation between population density and ecological footprint. With a panel regression to analyze the effects of several factors on the ecological footprint in newly industrialized nations during the period 1990–2017, Sahoo and Sethi (2022) reach comparable findings. Their findings show a favorable correlation between the ecological footprint and industrialization, urbanization, population density, energy use, and life expectancy.

To study the relationship between life expectancy, on the one hand, and environmental degradation, on the other, Mahalik et al. (2022) consider panel data on 68 low and middleincome countries over the period 1990–2017. Through various panel regression methods, the authors find that environmental degradation, measured using CO_2 emissions per capita, is negatively related to life expectancy. They also find Granger causality going from environmental degradation to life expectancy. Their results coincide with those of Rahman et al. (2022) but not those of Sahoo and Sethi (2022) regarding the relationship between life expectancy and ecological footprint.

From a different perspective, Gündüz (2020) investigates whether a causal effect exists between environmental degradation measured by carbon footprint and US health expenditure. The author finds a hidden cointegration relationship between the positive components of healthcare expenditure and carbon footprint. In particular, an increase of 1% in carbon footprint is associated in the long run with a 2.04% increase in health expenditure in the US. The author also confirms that a positive component of the carbon footprint exerts a causal effect on health expenditure. Therefore, not only does ecological footprint affect health expenditure, but also subjective well-being, as supported by the findings of Zhang et al. (2021).

³ The KOF Globalization Index measures the social, economic, and political dimensions of globalization.

2.4 Life Expectancy Research in the GCC

A study of life expectancy in the GCC region shows that air pollution significantly impacts life expectancy in GCC countries. A study by Sweidan and Alwaked (2016) examines the relationship between economic growth and human well-being energy intensity in his GCC country from 1995 to 2012. Data were analyzed using a Prais-Winsten regression model with panel-corrected standard errors. The results showed that economic development significantly and positively impacted energy-intensive human well-being throughout the study period. Environmental stress showed that this increased dramatically from 1995 to 2006, and declined substantially from 2007 to 2012, returning the country to its 1995 level. The impact of this knowledge is related to sustainable management, making up for the lack of environmental progress in the GCC.

The gross domestic product (GDP) per capita, environmental indicators, and the connection between income and health in the GCC nations are all topics covered in a study by Bader and Ganguli (2019). The study examines the connections between GDP per capita and greenhouse gases (carbon dioxide, nitrous oxide, and methane) and between GDP per capita and health factors, using time-series data from 1980 to 2012 (life expectancy, infant mortality, and child mortality). Although most GCC states lack an Environmental Kuznets Curve (EKC), Bahrain and Saudi Arabia show signs of a U-shaped association between environmental contaminants and GDP per capita. Although not statistically significant, there is evidence of an EKC in the United Arab Emirates. This study explores the relationship between GDP and health in the GCC and finds that higher incomes lead to longer life expectancy, higher living standards, and better health interventions. Increased income therefore positively impacts health and compensates for the lack of ecosystem development in the GCC.

Our study differs from previous studies on life expectancy in the GCC region in several ways. While previous studies have focused on the impact of air pollution on life expectancy, our study considers other factors such as ecological footprint deficit, urbanization, unemployment, GDP deflator, and digitization. Furthermore, we conduct robustness tests by substituting ecological footprint deficit with CO_2 emissions and digitization with a Technology Achievement Index. This allows us to broaden the scope of our analysis and gain a more comprehensive understanding of the factors that impact life expectancy in the GCC region.

3 Hypotheses development

3.1 GCC as a study setting

Examining the relationship between ecological footprint and life expectancy in the GCC countries can allow researchers to contribute to understanding the complex interactions between environmental factors, human health, and the region's economy. The GCC also has unique characteristics that make investigations of this nature interesting. First, the GCC region is by default considered to have a significant ecological footprint. The key contributor is their heavy reliance on the energy-intensive fossil-fuel industries of extracting and refining oil and gas. Therefore, carbon emissions and the resulting ecological degradation are commonplace among fossil fuel producers of this sort. Second, the GCC countries have undergone rapid development and urbanization in the last three decades. This growth has

undoubtedly been accompanied by increased energy consumption, pollution, and environmental degradation. Third, however, the GCC has a unique healthcare infrastructure due to significant investment by each country's government. This has resulted in considerably higher access to quality healthcare than many other countries have, rivaling even more developed ones.

3.2 Ecological footprint and life expectancy

A better understanding of the factors of human life expectancy in developing and emerging economies is urgently needed if we recall that prosperity in their context depends on the health of their population (Rahman et al., 2022). Esmaeili et al. (2023) suggest that uncertain economic policies hurt social welfare, and the effect is more pronounced in countries with a high deficit regarding ecological footprint. The study indicates that in the long term considering the ecological footprint when making economic policy decisions can help improve social welfare. However, findings from other studies suggest a less linear relationship between ecological footprint and life expectancy. For the above reasons, we hypothesize that the ecological footprint has a nonlinear relationship with male and female life expectancy in the GCC.

3.3 Digitization and life expectancy

According to some studies, ICT has positively impacted life expectancy by improving access to health information and health services and facilitating early disease detection and treatment. For example, telemedicine has been shown to reduce mortality rates in rural areas by providing remote access to medical services (Concepcion & Forbes, 2020). Additionally, ICT has been used to improve health education and public awareness about healthy lifestyles, leading to better health outcomes and longer life expectancy (Rahman & Alam, 2022). However, other studies have found that prolonged exposure to digital screens has been linked to negative health outcomes, such as increased risk of cardiovascular disease, obesity, and reduced life expectancy. It should not be forgotten that the relationship between ICT and life expectancy is complex and depends on various factors such as the type of ICT used, how it is used, and the populations it is used with. For these reasons, we hypothesize that digitization is associated (either negatively or positively) with male and female life expectancy in the GCC.

3.4 Healthcare spending and life expectancy

The literature reviewed thus far suggests that social determinants of health, such as income and access to quality healthcare, significantly impact life expectancy (Hassan et al., 2017). The level of healthcare spending by GCC nations can affect life expectancy reducing health inequalities. We thus hypothesize that healthcare expenditure is positively associated with male and female life expectancy in the GCC.

3.5 Unemployment and life expectancy

Policies and strategies to promote social equity in health can reduce health inequalities and improve life expectancy. Money also appears to matter regarding life expectancy, with increased healthcare spending associated with longer life expectancy. For these reasons, we expect unemployment expenditure to negatively affect male and female life expectancy in the GCC.

3.6 Urbanization and life expectancy

A nation's ecological footprint can be largely affected by industrialization, urbanization, population density, and energy consumption (Sahoo & Sethi, 2022). For newly industrialized countries, such as those in the GCC, rapid urbanization and population growth experienced in the region in recent decades has led to a host of new health challenges and the emergence of lifestyle diseases such as obesity and diabetes. We therefore hypothesize that urban living is negatively associated with male and female life expectancy in the GCC.

3.7 Consumer prices and life expectancy

An inflationary economy is expected to increase consumer prices, making it difficult for people, particularly those on low incomes, to access quality goods and services. This could negatively impact their life expectancy. We, therefore, assume that GDP deflators are negatively associated with life male and female expectancy in the GCC.

We posit further relationships between the variables chosen in this paper, in the context of the GCC. We specify these variables in Sect. 4.1 in our discussion of our models and independent variables.

4 Methodology

This section presents the various tests used in the current study. Descriptive statistics, correlation analysis, and unit root tests (LLC and IPS) were performed, confirming mixed stationarity with most variables being stationary at first difference. Moreover, cointegration tests (Kao, Pedroni, and Westerlund) were used, indicating long-term relationships among the variables, and justifying the use of ARDL models. Below we detail the dependent, independent, and control variables used, as well as additional variables used for robustness. We then present the various models used for linear and nonlinear estimation. Preliminary OLS regressions are used to investigate linear relationships followed by, panel threshold regressions, and nonlinear Panel ARDL models, estimated using Pooled Mean Group (PMG) and Dynamic Fixed Effect (DFE) methods, to explore short- and long-term effects of ecological deficit and other factors on life expectancy. Results from these nonlinear analyses are then reported and discussed in relation to studies from prior literature.

Table 1 Variable	Table 1 Variable names, definitions, and sources	
Variables	Definition	Source
LE	Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life	WDI Indicators (World Bank, 2023)
LEM	Same as above but restricted to male newborn infants	Same as above
LEF	Same as above but restricted to female newborn infants	Same as above
GDPDEF	GDP Deflator is a measure of the level of prices of all the goods and services produced in an economy, relative to a base year	Same as above
URB	Urban population refers to people living in urban areas as defined by national statistical offices	Same as above
CURHEPC	Current expenditures on health per capita expressed in international dollars	Same as above
ECOLDEF	Represents the difference between Biocapacity and Ecological Footprint	Global Footprint Network (2022) and Authors' calculation
TAI	Technological Achievement Index is a composite index originally developed by Desai et al., (2002) measuring a nation's skill/ability to participate in the information age	TAI Database (Thamprasert, 2020)
CO_2	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during the consumption of solid, liquid, and gas fuels and gas flaring	WDI Indicators (World Bank, 2023)
ICTINDEX	A composite index of mobile, fixed telephone and internet subscriptions	Same as above and Author's calculations

4.1 Variables

The current study employs GCC data for 21 years, namely 2000–2020. Table 1 summarizes the variables operationalized and examined in this study. Most variables are sourced from the reputable World Bank's World Development Indicators database.

Dependent variables: we test our model using 'life expectancy at birth' (*LE*), our main dependent variable. We also run additional models to examine whether our hypotheses hold for life expectancy at birth for males (*LEM*) and females (*LEF*).

Main independent variable: ecological deficit (*ECOLDEF*) in individual member states of the GCC serves as our main independent variable.

Control variables: to improve the reliability of our models, we control for country size using urban population (*URB*) as a percentage of total population, and current health expenditure per capita (*CURHEPC*). Data on GDP deflator (*GDPDEF*) figures are used to gauge whether prices can inadvertently affect life expectancy figures in the region.

Additional variables for robustness testing: we also test our models using substitute variables for our independent variable an ECOLDEF with CO_2 by constructing a substitute for our Technological Achievement Index (TAI) variable using a composite digitization variable (ICTINDEX).

4.2 Models

4.2.1 Linear and nonlinear estimation models

To explore the nonlinear effects of ecological footprint deficit and gain a comprehensive understanding of the relationship and potential asymmetry between other independent variables of interest and their impact on life expectancy, we use a nonlinear panel autoregressive distributed lag (ARDL) model with a pooled mean group (PMG). The ARDL model distinguishes between short- and long-run coefficients and can be reliably used on relatively short sample periods:

$$LE = \alpha_1 ECOLDEF_{(t)} + \alpha_2 ECOLDEF_{(t-1)} + \alpha_3 UNEMP_{(t)} + \alpha_4 URB_{(t)} + \alpha_5 CURHEPC_{(t)} + \alpha_6 TAI_{(t)} + \alpha_7 GDPDEF_{(t)} + \beta_1 (Controls of Panel 1) + \beta_2 (Controls of Panel 2) + e_{(t)}$$
(1)

$$LEM = \alpha_1 ECOLDEF_{(t)} + \alpha_2 ECOLDEF_{(t-1)} + \alpha_3 UNEMP_{(t)} + \alpha_4 URB_{(t)} + \alpha_5 CURHEPC_{(t)} + \alpha_6 TAI_{(t)} + \alpha_7 GDPDEF_{(t)} + \beta_1 (Controls of Panel 1) + \beta_2 (Controls of Panel 2) + e_{(t)}$$
(2)

$$LEF = \alpha_1 ECOLDEF_{(t)} + \alpha_2 ECOLDEF_{(t-1)} + \alpha_3 UNEMP_{(t)} + \alpha_4 URB_{(t)} + \alpha_5 CURHEPC_{(t)} + \alpha_6 TAI_{(t)} + \alpha_7 GDPDEF_{(t)} + \beta_1 (Controls of Panel 1) + \beta_2 (Controls of Panel 2) + e_{(t)}$$
(3)

where α_1 , α_2 , α_3 , α_4 , α_5 , α_6 , and α_7 are the coefficients of the independent variables and β_1 and β_2 are the coefficients of the PMG. We also rerun the models using the Dynamic Fixed Effect (DFE) estimator to compare results.

4.2.2 Panel threshold regression models

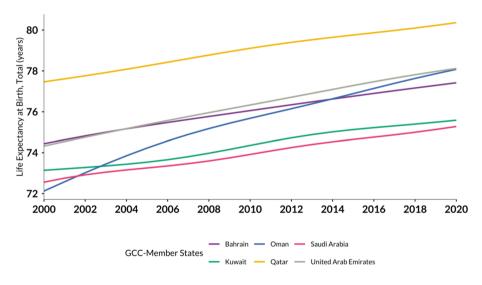
We employ a panel threshold regression model to examine the nonlinear relationship between ECOLDEF and LE while controlling for the additional factors of URB, UNEMP,

Table 2	Descriptive	statistics
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Variable	OBS	Mean	Std. Dev.	Min	Max	
LE	126	75.850	1.988	72.126	80.363	
UNEMP	126	2.547	1.787	0.100	7.450	
GDPDEF	126	4.326	12.030	-25.958	33.751	
URB	126	88.307	8.702	71.509	100.000	
CO_2	126	0.747	0.170	0.445	1.063	
CURHEPC	126	2053.566	608.532	895.602	3626.995	
ICTINDEX	126	1.157	1.302	-1.647	3.497	
ECOLDEF	126	-7.620	3.20	-14.463	-0.624	
TAI	126	0.3963	0.082	0.207	0.558	

LE, life expectancy at birth; CO₂, carbon dioxide emission; URB, urban population (as % of total); GDPDEF, gross domestic product deflator; UNEMP, unemployment; CURHEPC, current health expenditure per capita, PPP (current international \$); ICTINDEX, composite index of mobile, fixed telephone and internet subscriptions; TAI, Technological Achievement Index

Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.



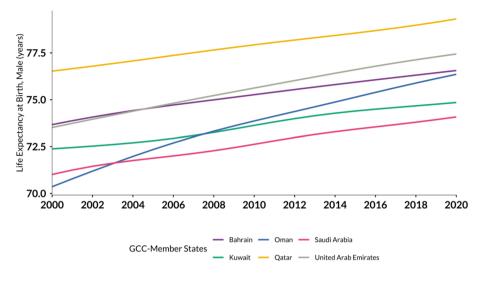
Data points obtained from World Development Indicators (World Bank)

Fig. 1 Life expectancy trends in the GCC

CURHEPC, and TAI. This is a robustness test for our (non)linear ARDL estimation models. Results from this testing can also provide valuable insights into the effect of a higher ecological footprint on LE, and the other independent variables.

$$lnLE = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \gamma_{11} D_1 \Theta_{11} + \gamma_{12} D_2 \Theta_{12} + \gamma_{13} D_3 \Theta_{13} + \gamma_{14} D_4 \Theta_{14}$$
(4)

Deringer

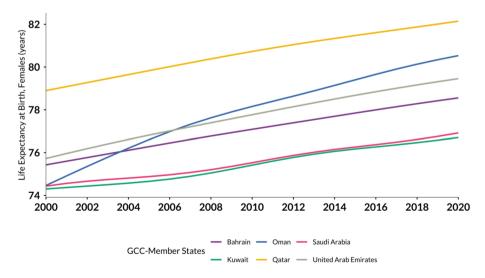


Life expectancy at birth indicates the number of years a newborn male infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.

Data points obtained from World Development Indicators (World Bank)

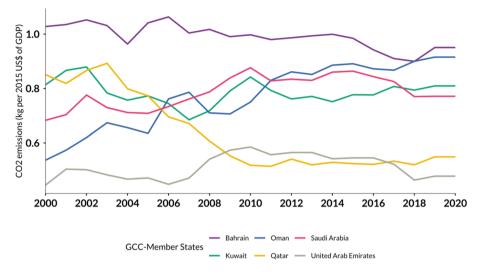
Fig. 2 Male life expectancy trends in the GCC

Life expectancy at birth indicates the number of years a newborn female infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.



Data points obtained from World Development Indicators (World Bank)

Fig. 3 Female life expectancy trends in the GCC



CO2 emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring.

Data points obtained from World Development Indicators (World Bank)

Fig. 4 Carbon dioxide emission trends in the GCC

$$lnLEM = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \gamma_{11} D_1 \Theta_{11} + \gamma_{12} D_2 \Theta_{12} + \gamma_{13} D_3 \Theta_{13} + \gamma_{14} D_4 \Theta_{14}$$
(5)
$$lnLEF = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \gamma_{11} D_1 \Theta_{11} + \gamma_{12} D_2 \Theta_{12} + \gamma_{13} D_3 \Theta_{13} + \gamma_{14} D_4 \Theta_{14}$$
(6)

where: lnLE = general life expectancy, lnLEF = female life expectancy, lnLEM = male life expectancy, X_1 = lnURB, X_2 = lnUNEMP, X_3 = lnCURHEPC, X_4 = lnICTINDEX, X5 = lnGDPDEF, D_1 = ECOLDEF, Θ_{11} = Threshold value of ECOLDEF. Θ_{12} = Difference in coefficient between D_1 = 0 and D_1 = 1.

5 Results

5.1 Descriptive analysis⁴

This section presents descriptive statistics for the variables used in our study (Table 2 comprises statistics used in our econometric analysis).

To illustrate trends in our data, we show select variables as graphs using R and derive the following comments. Although all the GCC countries experienced improvements in the figures for total life expectancy at birth, Qatar had the highest of them throughout the sample period (77.467 years in 2000 to 80.363 years in 2020). This trend also held good for both male and female life expectancy figures. The largest improvement however was

⁴ See Appendices section for graphical illustrations (Figs. 1, 2, 3, 4, 5, 6) of data points for the variables used in the study.

	LE	URB	UNEMP	CO_2	ICTINDEX	CURHEPC	GDPDEF	ECOLDEF	TAI
LE	1								
URB	0.3934	1							
UNEMP	-0.6023	-0.6835	1						
CO_2	-0.2287	0.0502	-0.0038	1					
ICTINDEX	0.5596	0.279	-0.1763	-0.0821	1				
CURHEPC	0.4604	0.4369	-0.187	-0.3655	0.5127	1			
GDPDEF	-0.2267	-0.1216	0.0505	-0.0019	-0.3528	-0.2378	1		
ECOLDEF	-0.6269	-0.5814	0.7173	0.2892	-0.3282	-0.5328	0.0418	1	
TAI	0.6413	0.3849	-0.3409	-0.1599	0.9652	0.5844	-0.3252	0.4871	1

Table 3 Pairwise correlation

LE, life expectancy; CO_2 , carbon dioxide emission; URB, urban population (as % of total); CURHEPC, public expenditure on health from domestic sources per capita; GDPDEF, consumer price index; TAI, Technology Achievement Index; ECOLDEF ecological footprint deficit; ICT, composite index of mobile, fixed telephone and internet subscriptions; UNEMP, unemployment. The variables ICTINDEX and CO_2 serve as robustness variables

found in Oman, where the level jumped approximately 8 years, from 72.126 years in 2000 to 78.078 in 2020. Figures 1, 2, and 3 in the Appendices illustrate the life expectancy at birth data.

Correlation results in Table 3 show that the unemployment rate has a negative correlation with the urbanization rate (-0.6835) and a positive correlation with the ecological deficit (0.7173). ICTINDEX has a weak negative correlation with the unemployment rate (-0.1763) and a positive correlation with current health expenditure per capita (0.5127). There is a weak negative correlation between current health expenditure per capita and the unemployment rate (-0.1870), and a weak positive correlation between the urbanization rate and current health expenditure per capita (0.4369). The GDP deflator has a weak positive correlation with the unemployment rate (0.0505) and a weak negative correlation with ICTINDEX (-0.3528) and ecological deficit (-0.5328). The results suggest that there may be multicollinearity between the variables, since some correlations are significant but weak, despite having neither positive nor negative correlation over 0.8000 between variables. We also take the added measure of analyzing variance inflation factors (VIF) to evaluate the presence of multicollinearity further, if any. According to the data, CO2 emissions levels in the GCC remained relatively stable throughout the 20-year sample period. Nevertheless, Oman witnessed the greatest growth from 0.55 kg per US\$ of GDP in 2000, and from second last place to first place at 1.01 kg per US\$ in 2020. Meanwhile, Qatar witnessed a spike in 2005 and then a decline until 2011 when it plateaued to follow other GCC member states. Figure 4 illustrates the data on CO₂ emissions for each GCC member state.

5.2 Unit root tests

To consider the potential presence of cross-sectional dependence and heterogeneity, which can lead to incorrect inferences and low power, we used second-generation Im-Pesaran-Shin (IPS) and Levin-Lin-Chu (LLC) unit root tests. This also allowed us to ensure that our results were reliable and robust, especially when analyzing panel data (Table 4).

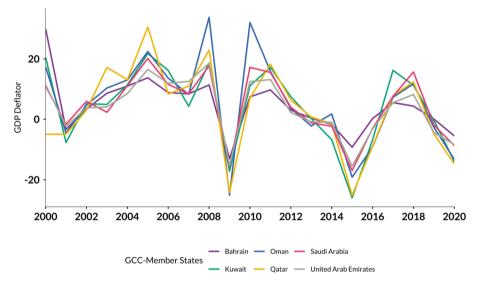
For most variables, the LLC test statistics indicate non-stationarity at level, but stationarity at first difference. This suggests that these variables follow a random walk

Variables	LLC test		IPS test	
	Level	First Difference	Level	First Difference
LE	-1.3496 ^c	-10.0113 ^a	-3.8118 ^a	-0.0128
LEF	-2.2405 ^b	-5.7512 ª	-2.7925 ^a	2.9677
LEM	1.0476	-6.9995 ^a	-2.5701 ^a	1.2426
URB	0.7661	-3.0181 ^a	0.3125	-0.8656
UNEMP	-1.5716 °	-0.0430	2.2354	-1.9858 ^b
ECOLDEF	-2.4089 ^a	-3.4158 ^a	-1.4912 ^c	-5.3977 ^a
ICTINDEX	-2.9911 ^a	-1.1199	-0.5761	0.0179 ^b
CURHEPC	-0.005	-4.4351 ^a	-0.4047	-5.6977 ^a
GDPDEF	-2.3197 ^b	-5.8771 ^a	-4.947 ^a	-7.0259 ^a
TAI	-2.6301 ^a	-2.1004 ^b	-0.2667	-3.9939 ^a
CO_2	-2.2056 ^b	-6.8966 ^a	-0.973	-4.8035 ^a

Table 4	LLC and IPS tests	
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^{a,b}, and ^c indicate significance levels at 1%, 5%, and 10%, respectively. LE, general life expectancy at birth; ECOLDEF ecological footprint deficit; URB, urban population (as % of total); GDPDEF, gross domestic product deflator; UNEMP, unemployment; CURHEPC, current health expenditure per capita, PPP (current international \$); TAI, Technology Achievement Index; CO₂, carbon dioxide emissions; ICTINDEX composite index of mobile, fixed telephone and internet subscriptions

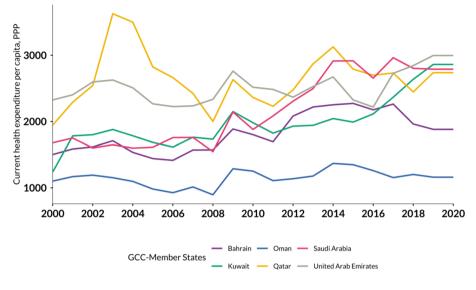
Reflects the rate of price change in the economy as a whole.



Data points obtained from World Development Indicators (World Bank)

Fig. 5 Inflation trends in the GCC

process with drift, and taking the first difference removes the random walk component and makes the series stationary. In contrast, the IPS test statistics indicate stationarity for most variables at the level, but non-stationarity at first difference. This suggests



Current expenditures on health per capita expressed in international dollars at purchasing power parity.

Data points obtained from World Development Indicators (World Bank)

Fig. 6 Healthcare expenditure trends in the GCC

that these variables have a unit root at the level, and taking first differences removes the unit root and makes the series stationary. The signs and magnitudes of the test statistics differ between the two tests, indicating that the power of the tests is different. To illustrate, for the LE variable, the LLC test indicates non-stationarity at level, but the IPS test does not, whereas the IPS test indicates non-stationarity at first difference, but the LLC test does not. Moreover, for some variables, such as UNEMP, the test results are mixed, with one test indicating stationarity at the level and the other indicating non-stationarity at the level. Mixed stationarity therefore can be concluded.

5.3 Tests of cointegration

Determining the presence of cointegration allows us to better understand the dynamics between the variables of interest, such as the existence of a stable long-run relationship between variables that may have a spurious correlation in the short run. Results from cointegration testing allow us to develop more accurate models for forecasting and policy analysis. The Kao (1999), Pedroni (2001, 2004), and Westerlund (2008) tests are popular econometric tests used in such scenarios.

The Kao test for cointegration is used to test the null hypothesis of no cointegration among panels, against the alternative hypothesis that all panels are cointegrated. The test result shows that the p values for the Modified Dickey-Fuller, Dickey-Fuller, and Augmented Dickey-Fuller tests are less than the 0.05 significance level. This suggests that there

Cointegrating vector: Panel specific		Kernel:	Bartlett	
Panel means:	Included	Lags:	1.00 (Newey-West)	
Time trend:	Not included	Augmented lags:	1	
AR parameter:	Same	Number of panels:	6	
		Number of periods:	19	
		Statistic	<i>p</i> value	
Modified Dickey-Fuller t		-1.9534	0.0254	
Dickey-Fuller t		-1.0899	0.1379	
Augmented Dickey-Fuller	t	-1.6291	0.0516	
Unadjusted modified Dick	ey-Fuller t	-0.2650	0.3955	
Unadjusted Dickey-Fuller	t	-0.3567	0.3607	

Table 5 Kao test for cointegration

Table 6 Pedroni test for cointegration

Cointegrating vector:	Panel specific	Kernel:	Bartlett
Panel means:	Included	Lags:	1.00 (Newey-West)
Time trend:	Not included	Augmented lags:	1
AR parameter:	Panel specific		
		Statistic	p value
Modified Phillips-Perron t		3.9265	0.0000
Phillips-Perron t		3.0523	0.0011
Augmented Dickey-Fuller t		2.5288	0.0057

is evidence to reject the null hypothesis of no cointegration, indicating that all the panels are cointegrated (Table 5).

In the case of Pedroni, evidence for cointegration exists at the 1% level of significance, as all the test statistics (Modified Phillips-Perron t, Phillips-Perron t, and Augmented Dickey-Fuller t) have p values less than 0.01 (Table 6).

Based on the results of the three cointegration tests, we can conclude that there is evidence of cointegration among the variables in the dataset. The Kao test and the Pedroni test both provide evidence of cointegration, while the Westerlund test suggests that some panels may be cointegrated (Table 7). These findings suggest that ARDL (Autoregressive Distributed Lag) could be a suitable econometric model for analyzing the data since it allows for the inclusion of lagged variables and provides a framework for estimating longrun relationships between the variables. The Pedroni test provides further support for using the ARDL model because it confirms the presence of cointegration among the panels. The panel-specific cointegrating vector implies that the cointegration relationship may vary across panels. The inclusion of a panel-specific AR parameter in the ARDL model can help capture these differences in the cointegrating relationship across panels.

Cointegrating vector:	Panel specific	Number of panels:	6
Panel means:	Included	Number of periods:	19
Time trend:	Not included		
AR parameter:	Panel specific		
		Statistic	p value
Variance ratio		2.3513	0.0094

Table 7 Westerlund test for cointegration

Table 8	ARDL-DFE (General
LE)	

D.LE	Coef.	Std. Err.	Z	P > z
LONG RUN				
UNEMP	0.1473	2.0967	0.07	0.944
CURHEPC	0.0025	0.0030	0.83	0.404
GDPDEF	-0.0047	0.0797	-0.06	0.953
ECOLDEF	-0.5723	0.5401	-1.06	0.289
TAI	-38.4827	36.6518	-1.05	0.294
SHORTRUN				
EC	-0.0045	0.0026	-1.72	0.086 ^c
URB	-0.0859	0.0162	-5.31	0.000^{a}
UNEMP	-0.0018	0.0109	-0.17	0.866
CURHEPC	0.0000	0.0000	-1.26	0.208
GDPDEF	-0.0002	0.0002	-0.93	0.350
ECOLDEF	0.0035	0.0034	1.03	0.302
TAI	0.2880	0.2137	1.35	0.178
_cons	0.6156	0.2263	2.72	0.007

^{a,b}, and ^c indicate significance levels at 1%, 5%, and 10%, respectively. LE, general life expectancy at birth; ECOLDEF ecological footprint deficit; URB, urban population (as % of total); GDPDEF, gross domestic product deflator; UNEMP, unemployment; CURHEPC, current health expenditure per capita, PPP (current international \$); TAI, Technology Achievement Index

5.4 Linear ARDL results

The results of our ARDL-DFE analysis in Table 8 reveal a negative and significant effect of urbanization in the short run. It is the only significant variable for the GCC in this regard. Substituting ECOLDEF with CO_2 emissions yields the same results. Equilibrium correction (EC) for the models, however, reveals more significant results for cointegration among the variables of interest. To further decompose the short- and long-term effects of our variables on LE for the GCC, we ran a full panel analysis. This allowed us to gain more insights on a country-by-country basis.

As shown in Table 9, urbanization has a significant positive effect in the short run for Qatar, Saudi Arabia, and the UAE, whereas it has a negative and significant effect for Bahrain. UNEMP has a significant and negative effect for Kuwait and Oman whereas it has a

Table 9Panel ARDL-PMG(General LE)		D.LE	Coef.	Std. Err.	Z	P>z
	GCC	UNEMP	-7.0681	2.7834	-2.54	0.0110 ^b
		CURHEPC	-0.0083	0.0040	-2.05	0.0410 ^b
		GDPDEF	0.0143	0.0333	0.43	0.6690
		ECOLDEF	-2.5654	1.2096	-2.12	0.0340 ^b
		TAI	88.9262	36.5143	2.44	0.0150 ^b
	Bahrain	$_EC$	0.0022	0.0011	2.04	0.0420 ^b
		ΔURB	-0.4393	0.0499	-8.80	0.0000 ^a
		Δ UNEMP	-0.0108	0.0090	-1.20	0.2320
		Δ CURHEPC	0.0000	0.0000	-1.83	0.0670 c
		$\Delta GDPDEF$	-0.0001	0.0001	-0.76	0.4500
		Δ ECOLDEF	-0.0028	0.0008	-3.44	0.0010 ^a
		ΔTAI	0.1734	0.0670	2.59	0.0100 ^a
		_cons	0.0572	0.0905	0.63	0.5270
	Kuwait	$_EC$	-0.0096	0.0051	-1.88	0.0600 ^c
		ΔURB	0.0209	0.0293	0.71	0.4760
		Δ UNEMP	0.0668	0.0227	2.94	0.0030 ^a
		Δ CURHEPC	-0.0001	0.0000	-1.83	0.0680 ^c
		$\Delta GDPDEF$	-0.0013	0.0003	-4.13	0.0000 ^a
		Δ ECOLDEF	0.0107	0.0082	1.30	0.1950
		ΔTAI	1.0148	0.2953	3.44	0.0010
		_cons	0.8189	0.4757	1.72	0.0850
	Oman	EC	0.0083	0.0052	1.61	0.1080
		ΔURB	-0.0170	0.0207	-0.82	0.4100
		Δ UNEMP	-0.0481	0.0182	-2.64	0.0080 ^a
		Δ CURHEPC	-0.0001	0.0000	-1.76	0.0780 ^c
		$\Delta GDPDEF$	-0.0002	0.0003	-0.94	0.3460
		Δ ECOLDEF	-0.0144	0.0066	-2.17	0.0300 ^b
		ΔTAI	-1.7191	0.6282	-2.74	0.0060 ^a
		_cons	-0.2718	0.4015	-0.68	0.4980
	Qatar	_EC	-0.0008	0.0005	-1.55	0.1210
		ΔURB	0.3385	0.0395	8.58	0.0000 ^a
		Δ UNEMP	0.0303	0.0206	1.48	0.1400
		$\Delta CURHEPC$	0.0000	0.0000	2.40	0.0170^{b}
		$\Delta GDPDEF$	0.0000	0.0001	0.35	0.7230
		$\Delta ECOLDEF$	0.0028	0.0023	1.22	0.2220
		ΔTAI	0.0250	0.1786	0.14	0.8880
	Saudi Arabia	_cons	0.1422	0.0394	3.61	0.0000^{a}
	Sauui Arabla	EC	-0.0075 6.5084	0.0030 2.5634	-2.49 2.54	0.0130 ^b 0.0110 ^b
		ΔURB				
		Δ UNEMP Δ CURHEPC	0.0644	0.0124	5.19	0.0000^{a}
		$\Delta CURHEPC$	0.0000	0.0000	0.05	0.9560 0.0540°
		$\Delta GDPDEF$	-0.0007 0.0116	0.0004	-1.93	0.0540 ^c
		$\Delta ECOLDEF$		0.0129	0.90	0.3700
		ΔTAI	0.5573	0.4294	1.30	0.1940
		_cons	-0.5906	0.6462	-0.91	0.3610

	D.LE	Coef.	Std. Err.	z	P > z
UAE	EC	-0.0015	0.0007	-2.16	0.0310 ^b
	ΔURB	0.2862	0.0346	8.27	0.0000^{a}
	Δ UNEMP	0.0025	0.0042	0.61	0.5440
	Δ CURHEPC	0.0000	0.0000	0.42	0.6740
	$\Delta GDPDEF$	0.0000	0.0001	-0.24	0.8090
	Δ ECOLDEF	0.0020	0.0018	1.11	0.2690
	ΔTAI	-0.0194	0.0952	-0.20	0.8390
	_cons	0.1751	0.0605	2.90	0.0040

^{a,b}, and ^c indicate significance levels at 1%, 5%, and 10%, respectively. LE, general life expectancy at birth; ECOLDEF ecological footprint deficit; URB, urban population (as % of total); GDPDEF, gross domestic product deflator; UNEMP, unemployment; CURHEPC, current health expenditure per capita, PPP (current international \$); TAI, Technology Achievement Index

positive effect for Saudi Arabia. ECOLDEF is shown to have a negative and significant effect in the short run for Bahrain and Oman but an insignificant or unclear effect for other GCC member states. Surprisingly, CURHEPC has negative and significant effects in three countries, namely, Bahrain, Kuwait, and Oman. Only for Qatar does CURHEPC have a positive and significant effect on life expectancy. As hypothesized, the GDP deflator has a negative and significant effect for Kuwait and Saudi Arabia but unclear effects for Bahrain, Oman, Qatar, and the UAE. As regards our robustness variable for digitization, TAI, we find a positive and significant effect in the short run for Bahrain and Kuwait alone. Oman in contrast exhibits a negative and significant effect. Unclear effects are found for TAI on LE for Oatar. Saudi Arabia, and the UAE.

We also conduct robustness testing in Appendices Table 13. In this instance, we replace our ECOLDEF variable with that of CO₂ emissions. However, CO₂ emissions are found to be significant for Bahrain only, and, for that matter, have a positive effect on LE. Furthermore, all other variables become insignificant in the long run despite maintaining their respective signs. These results suggest a more complicated relationship and prompt us to further investigate in terms of nonlinear effects.

5.5 Non-linear ARDL results

Table 10 presents the long- and short-run non-linear effects of our variables of interest on life expectancy.

Results for the long-term component of the model of Table 10 suggest that there is no significant relationship between life expectancy and UNEMP, GDPDEF, or CURHEPC. Yet URB, ECOLDEFincrease, and TAI are all positively associated with life expectancy in the long term, although the significance of the ecological deficit increase term is only marginal at the 10% level. As for the short term, only URB was found to be statistically significant with a negative impact on life expectancy.

Table 9	(continued)
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Table 10Nonlinear panelARDL-DFE (General LE)

	Coef.	Std. Err.	Z	P > z
LONG RUN				
UNEMP	-0.0138	0.1624	-0.09	0.932
URB	0.0713	0.0483	1.48	0.139
ECOLDEFdecrease	0.0676	0.0691	0.98	0.327
ECOLDEFincrease	0.1397	0.0736	1.90	0.058 ^c
GDPDEF	0.0006	0.0062	0.09	0.929
CURHEPC	0.0001	0.0002	0.34	0.732
TAI	7.2715	1.6065	4.53	0.000^{a}
SHORT RUN				
EC	-0.0502	0.0087	-5.77	0.000^{a}
Δ UNEMP	0.0028	0.0101	0.28	0.780
Δ URB	-0.0848	0.0142	-5.96	0.000^{a}
Δ ECOLDEFdecrease	-0.0049	0.0081	-0.61	0.545
Δ ECOLDEFincrease	-0.0070	0.0082	-0.85	0.396
Δ GDPDEF	-0.0003	0.0002	-1.20	0.231
Δ CURHEPC	0.0000	0.0000	-1.51	0.130
Δ TAI	-0.0911	0.1981	-0.46	0.646

^{a,b}, and ^c indicate significance levels at 1%, 5%, and 10%, respectively. LE, general life expectancy at birth; ECOLDEFincrease, increase in ecological footprint deficit; ECOLDEFdecrease, decrease in ecological footprint deficit; URB, urban population (as % of total); GDPDEF, gross domestic product deflator; UNEMP, unemployment; CUR-HEPC, current health expenditure per capita, PPP (current international \$); TAI, Technology Achievement Index

According to Table 11, nonlinear panel data analysis of the variable reveals noteworthy observations. First, UNEMP is found to have a significant but negative effect at the 1% level, as is the case for CURHEPC. ECOLDEFdecrease, ECOLDEFincrease, and TAI are found to have a positive and significant effect at the 1% level on LE. As with linear ARDL, further analysis is warranted in an attempt to understand what appears to be contradictory results for the long term in the GCC. Upon closer inspection at the panel-by-panel level, we find the following. For UAE, Saudi Arabia, and QATAR, nonlinear ARDL-PMG results reveal a positive and significant effect of URB on life expectancy. This is unlike Bahrain, where a negative and significant relationship is observed. The variable reveals an insignificant relationship for Kuwait and Oman.

Strangely, UNEMP reveals a strong and positive effect in the cases of Kuwait and Saudi Arabia while a strong negative effect is observed for Oman. As for ECOLDEF decrease and increase, strong and positive effects are observed for both variables in the cases of Bahrain and Oman while a strong negative effect can be observed in Qatar and Saudi Arabia. The only country where CURHEPC reveals a positive and significant effect in the short run is Qatar, while insignificant effects are observed for all other countries in the GCC.

GDPDEF, in contrast, also reveals insignificant effects on LE for all GCC states apart from Saudi Arabia, where a negative and significant effect is observed. As for TAI, shortterm nonlinear ARDL-PMG yields positive and significant results for Bahrain, Kuwait, and Saudi Arabia. Meanwhile, TAI is found to have negative and significant results in the case of Oman, while being insignificant for Qatar and the UAE.

	D.LE	Coefficient	Std. Err.	Z	P > z
GCC	UNEMP	-5.9644	1.5486	-3.85	0.000 ^a
	ECOLDEF decrease	3.8851	1.3372	2.91	0.004 ^a
	ECOLDEFincrease	3.7733	1.3740	2.75	0.006 ^a
	CURHEPC	-0.0071	0.0025	-2.79	0.005^{a}
	GDPDEF	0.0234	0.0249	0.94	0.347
	TAI	73.4452	19.5254	3.76	0.000^{a}
Bahrain	EC	0.0025	0.0010	2.56	0.011 ^b
	Δ URB	-0.4232	0.0501	-8.44	0.000^{a}
	Δ UNEMP	-0.0103	0.0095	-1.08	0.280
	Δ ECOLDEFdecrease	0.0053	0.0025	2.13	0.033 ^b
	Δ ECOLDEFincrease	0.0053	0.0028	1.91	0.056
	Δ CURHEPC	0.0000	0.0000	-1.28	0.202
	Δ GDPDEF	0.0000	0.0001	-0.24	0.813
	Δ TAI	0.1566	0.0733	2.14	0.033 ^b
Kuwait	EC	-0.0111	0.0046	-2.42	0.016 ^b
	Δ URB	0.0279	0.0284	0.98	0.325
	Δ UNEMP	0.0667	0.0228	2.92	0.003 ^a
	Δ ECOLDEFdecrease	-0.0134	0.0159	-0.84	0.400
	Δ ECOLDEFincrease	-0.0123	0.0159	-0.77	0.438
	Δ CURHEPC	-0.0001	0.0000	-2.11	0.035 ^b
	Δ GDPDEF	-0.0014	0.0003	-4.26	0.000 ^a
	Δ TAI	1.2202	0.2968	4.11	0.000 ^a
Oman	EC	0.0115	0.0054	2.14	0.032 ^b
	Δ URB	-0.0137	0.0198	-0.69	0.490
	Δ UNEMP	-0.0590	0.0191	-3.09	0.002 ^a
	Δ ECOLDEFdecrease	0.0595	0.0196	3.04	0.002 ^a
	Δ ECOLDEFincrease	0.0651	0.0214	3.04	0.002 ^a
	Δ CURHEPC	-0.0001	0.0000	-1.55	0.121
	Δ GDPDEF	-0.0002	0.0002	-1.03	0.303
	Δ TAI	-1.1731	0.6454	-1.82	0.069 ^c
Qatar	EC	-0.0009	0.0006	-1.50	0.134
	Δ URB	0.3253	0.0386	8.43	0.000 ^a
	Δ UNEMP	0.0168	0.0230	0.73	0.466
	Δ ECOLDEFdecrease	-0.0115	0.0055	-2.09	0.036 ^b
	Δ ECOLDEFincrease	-0.0121	0.0059	-2.05	0.040 ^b
	Δ CURHEPC	0.0000	0.0000	1.93	0.053 ^c
	Δ GDPDEF	0.0000	0.0001	0.09	0.925
	Δ TAI	-0.0584	0.1816	-0.32	0.748

 Table 11
 Nonlinear panel ARDL-DFE (General LE)

	D.LE	Coefficient	Std. Err.	Z	P > z
Saudi Arabia	EC	-0.0101	0.0027	-3.81	0.000 ^a
	Δ URB	6.6400	1.9769	3.36	0.001 ^a
	Δ UNEMP	0.0732	0.0093	7.84	0.000^{a}
	Δ ECOLDEF decrease	-0.0867	0.0232	-3.74	0.000 ^a
	Δ ECOLDEFincrease	-0.0954	0.0245	-3.89	0.000 ^a
	Δ CURHEPC	0.0000	0.0000	-1.35	0.179
	Δ GDPDEF	-0.0016	0.0003	-4.78	0.000 ^a
	Δ TAI	0.8598	0.3253	2.64	0.008^{a}
UAE	EC	-0.0017	0.0006	-2.71	0.007^{a}
	Δ URB	0.2751	0.0309	8.89	0.000^{a}
	Δ UNEMP	0.0016	0.0046	0.34	0.736
	Δ ECOLDEFdecrease	-0.0028	0.0049	-0.57	0.566
	Δ ECOLDEFincrease	-0.0027	0.0051	-0.53	0.597
	Δ CURHEPC	0.0000	0.0000	0.48	0.633
	Δ GDPDEF	0.0000	0.0001	-0.17	0.865
	Δ TAI	-0.0031	0.0970	-0.03	0.975

^{a,b}, and ^c indicate significance levels at 1%, 5%, and 10%, respectively. LE, general life expectancy at birth; ECOLDEFincrease, increase in ecological footprint deficit; ECOLDEFdecrease, decrease in ecological footprint deficit; URB, urban population (as % of total); GDPDEF, gross domestic product deflator; UNEMP, unemployment; CURHEPC, current health expenditure per capita, PPP (current international \$); TAI, Technology Achievement Index

5.6 Panel threshold results

Threshold regression is a type of regression analysis that looks at the probability of an event happening above or below a certain threshold. In this type of regression, the threshold is used to classify results into two categories: those above the threshold and those below (Table 12).

The results of the threshold regression indicate that InURB and InICTINDEX have a significant positive effect on LE, InUNEMP has a non-significant negative effect, InCUR-HEPC has a significant positive effect and InGDPDEF has a non-significant positive effect. Furthermore, there is a significant difference between the two categories of the ecological footprint, with the category with a higher ecological footprint having a higher effect on LE. Overall, the results suggest that a higher ecological footprint is associated with higher levels of LE in the long run, while other independent variables such as unemployment, urbanization, household consumption per capita, and the ICTINDEX also have a significant positive effect on LE.

Model	Threshold	Lower	Upper
Model Thresholds			
Th-1	5.417	5.258	5.435
Threshold	RSS	MSE	Fstat
Threshold Effect Test (Boots	strap = 100)		
Single	0.004	0	27.740
Crit10	Crit5	Crit1	Prob
18.208	22.966	29.021	0.020
Variable	Coefficient	T (Std. Err.)	P>t
Regression Coefficients			
lnURB	0.296	14.570	0.000^{a}
		(0.020)	
InUNEMP	-0.002	-1.050	0.295
		(0.002)	
InCURHEPC	0.013	3.460	0.001 ^a
		(0.004)	
InICTINDEX	0.004	5.230	0.000^{a}
		(0.001)	
lnGDPDEF	0.000	0.470	0.640
		(0.000)	
_cat#c.footprint			
0	0.005	5.880	0.000 ^a
		(0.001)	
1	0.003	4.430	0.000^{a}
		(0.001)	
_cons	2.881	31.680	0.000
		(0.091)	

Table 12 Panel threshold testing

^{a,b}, and ^c indicate significance levels at 1%, 5%, and 10%, respectively. Standard error in parenthesis. LE, general life expectancy at birth; ECOLDEFincrease, increase in ecological footprint deficit; ECOLDEF-decrease, decrease in ecological footprint deficit; URB, urban population (as % of total); GDPDEF, gross domestic product deflator; UNEMP, unemployment; CURHEPC, current health expenditure per capita, PPP (current international \$); ICTINDEX, composite index of mobile, fixed telephone and internet subscriptions

6 Discussion

In comparing the ARDL-DFE and panel ARDL-PMG models, our analysis reveals nuanced differences and similarities in the factors influencing LE in the GCC.⁵ Both models underscore the complex relationship between URB and LE. In the short term, the ARDL-DFE model shows that rapid urbanization negatively impacts LE, potentially due to immediate health challenges arising from urban sprawl. This finding aligns with the results of Rahman

⁵ We present a summarized literature review table of papers examining LE, with their methodologies, sample periods and sample countries/regions and findings in Table 14 in the appendices.

and Vu (2021) and corroborates their argument that URB has a detrimental effect on LE in developing countries.

Interestingly, our analysis also supports the robust impact of URB on LE, as highlighted by Ahmad et al. (2023). Even when substituting the ECOLDEF variable with CO_2 emissions, the negative effect of URB on LE remains significant, indicating a persistent health challenge associated with rapid urbanization. The panel ARDL-PMG model, on the other hand, provides a more nuanced view by revealing heterogeneous effects of sociodemographic variables across individual GCC countries, echoing the findings of Wirayuda et al. (2023). For instance, URB positively impacts LE in Qatar, Saudi Arabia, and the UAE, consistent with their results, while exhibiting a negative effect in Bahrain, reinforcing the idea that the impact of URB on LE varies depending on contextual factors within each country, similar to the heterogeneity found in Moutinho et al. (2020) across different OPEC countries.

Moreover, our findings regarding UNEMP align with the results of Laditka and Laditka (2016) and Tafran et al., (2020), showcasing its negative impacts on LE in the literature and in our case for Kuwait and Oman, but a positive impact in Saudi Arabia. This variation reflects the diverse economic structures and labor market conditions across the GCC nations. The significant negative effect of ECOLDEF on LE in Bahrain and Oman, as found in our analysis, supports the argument made by Iqbal et al. (2023) regarding the adverse health effects of environmental degradation. Conversely, our mixed results for CURHEPC resonate with the findings of AlSaied and AlAli (2021), indicating disparities in healthcare spending efficiency and quality across different GCC countries.

In line with Balouza (2019), who argues that economic freedom is critical for shaping a relationship between the development of ICT and health outcomes, our findings on the impact of digitization on life expectancy in the GCC are consistent. In this context, it has a critical role in facilitating the widespread adoption and dissemination of information and communication technologies. In the case of healthcare expenditure, we have established a positive relationship, in our panel threshold as well as OLS results, (not reported, owing to space constraints), to life expectancy. However, we have not detected similar evidence for our long-term analysis with ARDL. Expenditure on healthcare can also contribute to environmental footprint and emissions, in accordance with Yang et al. (2021), due to the rebound effect of strong investment in healthcare assets, transport, and around-the-clock services. The mixed results for the CURPEC variable we have studied could therefore be a result of this.

Our non-linear ARDL analysis adds depth to the discussion by revealing positive longterm associations between LE and URB, increases in ecological deficit, and the TAI, aligning with the findings of Arif et al. (2023). However, the marginal significance of the ecological deficit increase suggests a need for further exploration of its impact on LE. Furthermore, the identification of significant threshold effects for URB in our threshold regression analysis echoes the findings of Zhang et al. (2023) who find that urbanization's impact on public health could be mediated through living standards. This further highlights the context-dependent nature of URB's impact on LE in the case of the GCC.

In conclusion, our study's results corroborate and expand upon existing literature, emphasizing the complex interplay of factors shaping LE in the GCC and the need for tailored policy interventions addressing country-specific health and environmental challenges.

7 Conclusion and recommendations

In conclusion, our study emphasizes the intricate connection among emissions, ecological footprint, and life expectancy in the GCC countries. It highlights the urgent need for action to decrease emissions, enhance ecological sustainability, and prioritize public health and well-being.

The results confirm several hypotheses concerning the relationships outlined in Sect. 3 of the paper. This article attempts to fill the gap in the sustainability/healthcare empirical literature investigating the short- and long-term, linear, and non-linear relationships between ecological footprint and life expectancy for the GCC. Specifically, we focused our analysis on six GCC countries for the 2000–2020 period in a multivariate framework by including digitization, urbanization, GDP deflator, and current healthcare expenditure independent/control variables.

Given the mixed results between long- and short-run estimates from our ARDL model as well as panel threshold analysis and OLS models, we can surmise a nuanced relationship between the variables studied and life expectancy. Our results have significant implications for the GCC region as well as other resource-rich nations with similar economic characteristics. Taking into consideration our results for the GCC, we provide several policy recommendations for the region that can also be applied to other oil/gas exporting countries to improve life expectancy by focusing on its determinants. In comparing DFE with PMG results, specifically for the long-term effects on life expectancy, the latter specification reveals more significant relationships. Analysis on a panel-by-panel basis produces richer information regarding the individual effects of the independent variables on LE. Policy implications can therefore be dialed down or up depending specifically on which variables have more of an impact in which countries in the GCC. To surmise, we highlight the main findings of our study below.

- *Short-term impact of urbanization*: Rapid urbanization negatively affects life expectancy in the short term.
- *Robustness of CO₂ emissions*: Replacing ecological deficit with CO₂ emissions confirms the significant impact of urbanization.
- Variable impact across GCC countries: Urbanization positively impacts life expectancy in Qatar, Saudi Arabia, and UAE, but negatively in Bahrain. Unemployment negatively impacts life expectancy in Kuwait and Oman, but positively in Saudi Arabia.
- *Negative ecological footprint:* Ecological footprint deficit significantly negatively affects life expectancy in Bahrain and Oman.
- *Mixed health expenditure effects:* Health expenditure per capita positively impacts Qatar but negatively affects Bahrain, Kuwait, and Oman.
- *Non-linear relationship:* Long-term positive associations between life expectancy, urbanization, and the Technology Achievement Index; threshold effects indicate variable impacts of urbanization on life expectancy.
- *Policy implications:* Findings suggest nuanced policy approaches are needed, addressing specific health and environmental challenges in each GCC country. Further investigation into non-linear and threshold effects is warranted.

For that matter, the following policy recommendations and practical applications are suggested to improve mortality and life expectancy in the GCC region.

- Focus on healthcare quality; Despite the positive relationship between healthcare resources and life expectancy, there is evidence that the quality of the healthcare provided in the region may require closer scrutiny. Policymakers are recommended to focus on the quality of medical care, for example by increasing the number of medical specialists and reducing medical ailments such as obesity, hypertension, and diabetes through public health initiatives. This may include further investment in and use of artificial intelligence in the public health sphere of the GCC such as the incorporation of predictive analytics and decision support systems for the (early) diagnosis of patients.
- 2. Pollution reduction measures: The GCC region's heavy dependence on natural resource extraction and its climate and geographical opportunities for renewable energy sources make it crucial for policymakers and regulators to support existing carbon neutrality initiatives and encourage the development of greener infrastructure and alternative energy sources. This will help reduce carbon emissions and improve air quality in the region, positively impacting life expectancy. Fulfillment of individual GCC country 2030–2050 visions such as the transformation of all public transportation such as bus fleets to electric vehicles is one of the more practical steps governments in the country can take.
- 3. *Investment in ICT*: The rapid digitization and increased use of ICT have the potential to positively impact access to credit, information processing, and data analysis. Policymakers are encouraged to pay close attention to the role of ICT in the region via investment in blockchain solutions is also another avenue that countries can take to manage resources more efficiently to both improve healthcare quality and better allocate resources to the areas that need it most (Charfeddine et al., 2024).
- 4. *Political will:* The diversification away from heavy dependency on fossil fuels requires a realignment of political will and a focus on alternative, sustainable sources of energy. This includes regional and bilateral relations between GCC countries in areas of energy production, water and electricity consumption, healthcare, and general environmental conservation.

Our study is not without its limitations. The data used for the study may not cover the full range of factors that can influence life expectancy, such as housing quality, and access to education. While we have made efforts to include relevant variables, it is possible that other unaccounted factors could play a role in shaping life expectancy outcomes. Furthermore, as our study spans a 21-year period, it may not fully capture short-term fluctuations in life expectancy due to external events and influences. Factors such as pandemics, economic crises, or natural disasters can have significant impacts on population health and life expectancy, but their effects might not be fully reflected in our long-term analysis. To further enhance our understanding of the relationship between ecological footprint or CO₂ emissions and life expectancy in the GCC countries, future studies could delve into exploring the individual country-level dynamics. This approach could shed light on potential variations and disparities in the region, allowing for more targeted interventions and policy recommendations. Utilizing a larger dataset would immensely contribute to making the non-linear ARDL results more robust. With a broader range of observations, we could obtain more reliable findings, ensuring a stronger foundation for decision-making and informing public health strategies in the GCC region.

Appendix

Abbreviations

CURHEPCCurrent Health Expenditure per capitaCO2Carbon dioxideCDCCenters for Disease Control and PreventionCS-ARDLCointegrating Structural Autoregressive Distributed LagECOLDEFEcological Footprint DeficitFGLSFeasible General Least SquareGCCGulf Cooperation CouncilGDPDEFGross Domestic Product DeflatorGHGGreenhouse gasGDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	ARDL	Autoregressive Distributed Lag
CDCCenters for Disease Control and PreventionCS-ARDLCointegrating Structural Autoregressive Distributed LagECOLDEFEcological Footprint DeficitFGLSFeasible General Least SquareGCCGulf Cooperation CouncilGDPDEFGross Domestic Product DeflatorGHGGreenhouse gasGDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	CURHEPC	Current Health Expenditure per capita
CS-ARDLCointegrating Structural Autoregressive Distributed LagECOLDEFEcological Footprint DeficitFGLSFeasible General Least SquareGCCGulf Cooperation CouncilGDPDEFGross Domestic Product DeflatorGHGGreenhouse gasGDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	CO_2	Carbon dioxide
ECOLDEFEcological Footprint DeficitFGLSFeasible General Least SquareGCCGulf Cooperation CouncilGDPDEFGross Domestic Product DeflatorGHGGreenhouse gasGDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	CDC	Centers for Disease Control and Prevention
FGLSFeasible General Least SquareGCCGulf Cooperation CouncilGDPDEFGross Domestic Product DeflatorGHGGreenhouse gasGDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	CS-ARDL	Cointegrating Structural Autoregressive Distributed Lag
GCCGulf Cooperation CouncilGDPDEFGross Domestic Product DeflatorGHGGreenhouse gasGDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	ECOLDEF	Ecological Footprint Deficit
GDPDEFGross Domestic Product DeflatorGHGGreenhouse gasGDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	FGLS	Feasible General Least Square
GHGGreenhouse gasGDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	GCC	Gulf Cooperation Council
GDPGross Domestic ProductHPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMWorld Meteorological Organization	GDPDEF	Gross Domestic Product Deflator
HPIHappy Planet IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	GHG	Greenhouse gas
ICTInfermation Communication Technology IndexICTInformation Communication Technology IndexKOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	GDP	Gross Domestic Product
KOFKOF Globalization IndexLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	HPI	Happy Planet Index
IterIterLELife ExpectancyNCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	ICT	Information Communication Technology Index
NCHSNational Center for Health StatisticsNIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	KOF	KOF Globalization Index
NIHWNational Institute for Health and WelfarePCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	LE	Life Expectancy
PCSEPanel Corrected Standard ErrorsPM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	NCHS	National Center for Health Statistics
PM10Particulate Matter 10 (airborne particulate matter)URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	NIHW	National Institute for Health and Welfare
URBUrbanizationUNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	PCSE	Panel Corrected Standard Errors
UNEMPUnemploymentVARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	PM10	Particulate Matter 10 (airborne particulate matter)
VARVector AutoregressionVECMVector Error Correction ModelWMOWorld Meteorological Organization	URB	Urbanization
VECMVector Error Correction ModelWMOWorld Meteorological Organization	UNEMP	Unemployment
WMO World Meteorological Organization	VAR	Vector Autoregression
	VECM	Vector Error Correction Model
	WMO	World Meteorological Organization
WHO World Health Organization	WHO	World Health Organization

Robustness testing

Kobustness substituting ECOLDEF with CO_2 $_ec$ UNEMP -43.1273 102.7200 -0.42 0.673 CURHEPC -0.0065 0.0147 -0.44 0.665 GDPDEF -0.0222 0.0671 -0.33 0.741 CO2 11.3597 27.4567 0.41 0.667 TAI 42.0222 101.799 0.41 0.668 URB -0.7056 0.1498 -4.71 0.000 UNEMP -0.2155 0.0571 -3.77 0.000 CURHEPC 0.0000 0.0000 -4.22 0.000 GDPDEF -0.0002 0.0001 -2.32 0.020 CURHEPC 0.0002 0.0005 0.29 0.775 URB -0.0652 0.0510 -1.28 0.201 Kuwait ecc 0.0001 0.0001 -1.28 0.201 UNEMP -0.0194 0.0244 -0.83 0.000 GDPDEF -0.0001 0.0001 -1.48 0.135 <th>Table 13 ARDL-PMG</th> <th></th> <th>D.LE</th> <th>Coef.</th> <th>Std. Err.</th> <th>z</th> <th>P>z</th>	Table 13 ARDL-PMG		D.LE	Coef.	Std. Err.	z	P>z
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	e		D.LE	C0e1.	Std. E11.		F > Z
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	<i>ECOLDEF</i> with CO_2		ec				
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			UNEMP	-43.1273	102.7200	-0.42	0.6750
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			CURHEPC	-0.0065	0.0147	-0.44	0.6620
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			GDPDEF	-0.0222	0.0671	-0.33	0.7410
$\begin{array}{llllllllllllllllllllllllllllllllllll$			CO_2	11.3597	27.4567	0.41	0.6790
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			TAI	42.0222	101.7999	0.41	0.6800
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		Bahrain	ec	0.0053	0.0117	0.45	0.6490
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			URB	-0.7056	0.1498	-4.71	0.0000
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			UNEMP	-0.2155	0.0571	-3.77	0.0000
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			CURHEPC	0.0000	0.0000	-4.22	0.0000
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			GDPDEF	-0.0002	0.0001	-2.32	0.0200
Kuwait $_ec$ 0.00020.00050.290.775 URB -0.0652 0.0510 -1.28 0.201 $UNEMP$ -0.0194 0.0244 -0.8 0.422 $CURHEPC$ -0.0001 0.0001 -1.95 0.551 $GDPDEF$ -0.0100 0.0005 -1.88 0.060 CO_2 0.15840.19480.810.416 TAI 1.68850.48193.50.000Oman $_ec$ 0.00130.00340.380.707 URB -0.1173 0.0242 -4.85 0.000 URB -0.1173 0.0222 -1.87 0.062 CO_2 0.07400.15800.470.639 CO_2 0.07400.15800.470.539 CO_2 0.07400.06674.290.000 $UNEMP$ 0.02250.02440.920.358 $CURHEPC$ 0.00000.00001.220.221 $GDPDEF$ 0.00000.00001.220.221 $GDPDEF$ 0.00000.00020.667.429 CO_2			CO_2	0.0572	0.0246	2.33	0.0200
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			TAI	0.1967	0.0626	3.14	0.0020
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		Kuwait	ec	0.0002	0.0005	0.29	0.7750
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			URB	-0.0652	0.0510	-1.28	0.2010
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			UNEMP	-0.0194	0.0244	-0.8	0.4270
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			CURHEPC	-0.0001	0.0001	-1.95	0.0510
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			GDPDEF	-0.0010	0.0005	-1.88	0.0600
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			CO_2	0.1584	0.1948	0.81	0.4160
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			TAI	1.6885	0.4819	3.5	0.0000
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		Oman	ec	0.0013	0.0034	0.38	0.7070
$\begin{array}{cccccc} CURHEPC & -0.0001 & 0.0001 & -1.49 & 0.135 \\ GDPDEF & -0.0005 & 0.0004 & -1.48 & 0.135 \\ CO_2 & 0.0740 & 0.1580 & 0.47 & 0.639 \\ TAI & -2.2688 & 0.8167 & -2.78 & 0.005 \\ Qatar & _ec & -0.0003 & 0.0009 & -0.37 & 0.711 \\ URB & 0.2866 & 0.0667 & 4.29 & 0.000 \\ UNEMP & 0.0225 & 0.0244 & 0.92 & 0.358 \\ CURHEPC & 0.0000 & 0.0000 & 1.22 & 0.221 \\ GDPDEF & 0.0000 & 0.0002 & 0.26 & 0.793 \\ CO_2 & -0.0601 & 0.0899 & -0.67 & 0.503 \\ TAI & 0.0387 & 0.1908 & 0.2 & 0.839 \\ Saudi Arabia & _ec & -0.0012 & 0.0028 & -0.43 & 0.667 \\ \end{array}$			URB	-0.1173	0.0242	-4.85	0.0000
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			UNEMP	-0.0434	0.0232	-1.87	0.0620
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			CURHEPC	-0.0001	0.0001	-1.49	0.1370
TAI -2.26880.8167-2.780.005Qatar $_ec$ -0.00030.0009-0.370.711 URB 0.28660.06674.290.000 $UNEMP$ 0.02250.02440.920.358 $CURHEPC$ 0.00000.00001.220.221 $GDPDEF$ 0.00000.00020.260.793 CO_2 -0.66010.0899-0.670.503 TAI 0.03870.19080.20.839Saudi Arabia $_ec$ -0.00120.0028-0.430.667			GDPDEF	-0.0005	0.0004	-1.48	0.1390
Qatar $_ec$ -0.0003 0.0009 -0.37 0.711 URB 0.2866 0.0667 4.29 0.000 UNEMP 0.0225 0.0244 0.92 0.358 CURHEPC 0.0000 0.0000 1.22 0.221 GDPDEF 0.0000 0.0002 0.26 0.793 CO2 -0.6601 0.0899 -0.67 0.503 TAI 0.0387 0.1908 0.2 0.839 Saudi Arabia $_ec$ -0.0012 0.0028 -0.43 0.667			CO_2	0.0740	0.1580	0.47	0.6390
URB 0.28660.06674.290.000 $UNEMP$ 0.02250.02440.920.358 $CURHEPC$ 0.00000.00001.220.221 $GDPDEF$ 0.00000.00020.260.793 CO_2 -0.6601 0.0899 -0.67 0.503 TAI 0.03870.19080.20.839Saudi Arabia $_ec$ -0.0012 0.0028 -0.43 0.667			TAI	-2.2688	0.8167	-2.78	0.0050
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		Qatar	ec	-0.0003	0.0009	-0.37	0.7110
CURHEPC 0.0000 0.0000 1.22 0.221 GDPDEF 0.0000 0.0002 0.26 0.793 CO_2 -0.0601 0.0899 -0.67 0.503 TAI 0.0387 0.1908 0.2 0.839 Saudi Arabia $_ec$ -0.0012 0.0028 -0.43 0.667			URB	0.2866	0.0667	4.29	0.0000
GDPDEF0.00000.00020.260.793 CO_2 -0.0601 0.0899 -0.67 0.503 TAI 0.0387 0.1908 0.2 0.839 Saudi Arabia $_ec$ -0.0012 0.0028 -0.43 0.667			UNEMP	0.0225	0.0244	0.92	0.3580
CO_2 -0.0601 0.0899 -0.67 0.503 TAI 0.0387 0.1908 0.2 0.839 Saudi Arabia $_ec$ -0.0012 0.0028 -0.43 0.667			CURHEPC	0.0000	0.0000	1.22	0.2210
TAI 0.0387 0.1908 0.2 0.839 Saudi Arabia _ec -0.0012 0.0028 -0.43 0.667			GDPDEF	0.0000	0.0002	0.26	0.7930
Saudi Arabiaec -0.0012 0.0028 -0.43 0.667			CO_2	-0.0601	0.0899	-0.67	0.5030
—			TAI	0.0387	0.1908	0.2	0.8390
URB -3.2844 1.5066 -2.18 0.029		Saudi Arabia	ec	-0.0012	0.0028	-0.43	0.6670
			URB	-3.2844	1.5066	-2.18	0.0290
UNEMP 0.0544 0.0109 4.97 0.000			UNEMP	0.0544	0.0109	4.97	0.0000
CURHEPC 0.0000 0.0000 -1.09 0.277			CURHEPC	0.0000	0.0000	-1.09	0.2770
<i>GDPDEF</i> -0.0007 0.0003 -1.94 0.052			GDPDEF	-0.0007	0.0003	-1.94	0.0520
CO_2 -0.0729 0.1185 -0.62 0.538			CO_2	-0.0729	0.1185	-0.62	0.5380
				0.5093	0.3962	1.29	0.1990

	D.LE	Coef.	Std. Err.	z	P > z
UAE	ec	-0.0005	0.0012	-0.42	0.6730
	URB	0.4029	0.0507	7.94	0.0000
	UNEMP	0.0094	0.0021	4.5	0.0000
	CURHEPC	0.0000	0.0000	-0.46	0.6450
	GDPDEF	0.0000	0.0000	-0.1	0.9190
	CO_2	-0.0654	0.0180	-3.62	0.0000
	TAI	-0.0354	0.0428	-0.83	0.4080

^{a,b}, and ^c indicate significance level at 1%, 5%, and 10%, respectively. LE, general life expectancy at birth; ECOLDEF ecological footprint deficit; URB, urban population (as % of total); GDPDEF, gross domestic product deflator; UNEMP, unemployment; CURHEPC, current health expenditure per capita, PPP (current international \$); TAI, Technology Achievement Index; CO₂, carbon dioxide emissions

Table 13 (continued)

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Article	Sample period	Sample period Sample country/region	Econometric Method	Findings
Dietz et al. (2007)	I	1	Regression model	Population size and GDP per capita (\uparrow EF)
Sabir and Gorus (2019)	1975-2017	South Asian countries (5 countries)	ARDL	Globalization (↑ EF)
Knight (2014)	1961–2007	Developed and developing countries	Panel regression with fixed effects	Panel regression with fixed effects Developed: EF (\downarrow LE); Developing: EF (\uparrow LE)
Oduyemi et al. (2021)	I	Oil-rich nations in Africa	Threshold regression model	Low growth: Resource availability (↓ health outcomes); High growth: Resource availability (↑ health outcomes)
Sharma et al. (2021)	1990–2015	South and Southeast Asian countries	CS-ARDL	Population density (\uparrow EF)
Sahoo and Sethi (2022)	1990–2017	Newly industrialized nations	Panel regression	Industrialization, URB, population density, energy use, LE (\uparrow EF)
Mahalik et al. (2022)	1990–2017	Low and middle income countries (68 countries)	Various panel regression methods	CO ₂ per capita (↓ LE); Granger causality: Environmental degradation (↓ LE)
Gündüz (2020)	I	United States	Hidden cointegration analysis	Carbon footprint (\uparrow healthcare expenditure); 1% \uparrow carbon footprint = 2.04% \uparrow health expenditure (long run)
Sweidan and Alwaked (2016) 1995	1995–2012	GCC countries	Prais-Winsten regression with panel-corrected standard errors	Economic development († energy-intensive well-being); Environmental stress († 1995–2006, J 2007–2012)
Bader and Ganguli (2019)	1980–2012	GCC countries	Time-series analysis	Higher incomes († LE, living standards, health interventions); U-shaped: Environ- mental contaminants and GDP per capita in Bahrain, Saudi Arabi

 Table 14
 Summarized literature review table

Literature summary

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Data availability The dataset used in this research can be made available with a reasonable request from the corresponding author.

Declarations

Conflict of interest The authors declared no conflicts of interest in the publication of this article.

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