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Does environmental degradation matter for healthcare expenditure and health outcomes? Evidence from the Caucasus region and Russia (2000–2020)

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Abstract

Purpose: The study explores the complex relationship between environmental degradation, healthcare expenditure and health outcomes in the Caucasus region and Russia between 2000 and 2020. Methodology: We employ ARDL (Autoregressive Distributed Lag) and Granger causality analyses to assess the impact of greenhouse gas emissions on healthcare expenditure and quality of life indicators in Armenia, Azerbaijan, Georgia, and Russia. Findings: Our results reveal a significant and lasting impact of carbon dioxide and methane emissions on healthcare expenditures, but we did not find a clear causal link between greenhouse gas emissions and quality of life indicators. This points to an intricate correlation between environmental factors and health systems. Implications: we emphasize the need for sustainable development strategies that effectively address both environmental and health challenges. Originality: This study fills a critical gap in the existing literature on the intersection of environmental economics and public health. It offers valuable insights for policymakers grappling with the dual challenges of environmental degradation and healthcare management.

Keywords

climate change, emissions, quality of life, sustainable development, healthcare spending

Аннотация

Цель: Исследование направлено на изучение сложной взаимосвязи между деградацией окружающей среды, расходами на здравоохранение и показателями здоровья в Кавказском регионе и России в период с 2000 по 2020 годы. Методология: Авторы применяют методы ARDL (модель авторегрессии и распределенного лага) и анализ причинно-следственной связи Грейнджера для оценки влияния выбросов парниковых газов на расходы на здравоохранение и показатели качества жизни в Армении, Азербайджане, Грузии и России. Результаты: Результаты показывают значительное и длительное влияние выбросов углекислого газа и метана на расходы на здравоохранение, однако авторы не обнаружили четкой причинно-следственной связи между выбросами парниковых газов и показателями качества жизни. Это указывает на сложную корреляцию между экологическими факторами и системами здравоохранения. Вклад: На основе этих выводов авторы рассматривают влияние региональной политики и подчеркивают необходимость разработки устойчивых стратегий развития, которые эффективно решают как экологические, так и здравоохранительные проблемы. Оригинальность: Данное исследование восполняет критический пробел в существующей литературе, касающейся пересечения экологической экономики и общественного здоровья. Оно предлагает ценные идеи для политиков, сталкивающихся с двойными вызовами деградации окружающей среды и управления здравоохранением.

Ключевые слова

изменение климата; выбросы; качество жизни; устойчивое развитие; расходы на здравоохранение.

JEL: Q32, Q53.

1. Introduction

Man-made emissions and air pollutants are causing “global boiling” (United Nations, 2023a) and a range of adverse health effects, including respiratory illnesses, increased hospitalizations, higher mortality rates, and exacerbated suffering from the novel SARS-CoV-2 infections (Kurt et al., 2016; Xue et al., 2018; Hwang et al., 2018; Li et al., 2020; Marín-Palma et al., 2023). With the world’s population projected to increase from 8 billion in 2022 to 10 billion by 2050 (United Nations, 2022a), there have been urgent calls from scientists, scholars and policymakers for a global transition to low-carbon systems, reduction in emissions, and adoption of sustainable development practices. The rise in greenhouse gas emissions (GHG) has intensified social, economic, and environmental instabilities. Besides the climate emergency, both short- and long-term exposure to air pollution has significant health implications, including strokes, chronic obstructive pulmonary disease, cancers of the trachea, bronchus and lungs, aggravated asthma, and lower respiratory infections (United Nations, 2022b). Consequently, there is global pressure to reduce GHG emissions and meet the environmental goals set by the UN Sustainable Development Goals and the Paris Climate Accords. The 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015, provides a shared blueprint for achieving peace and prosperity for people and the planet, now and into the future.

The Paris Agreement is a legally binding international treaty on climate change. Its primary goal is to limit the increase in the global average temperature to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature rise to 1.5°C above pre-industrial levels. Achieving a 45% reduction in emissions by 2030 and reaching the net zero by 2050 (United Nations, 2023b) will contribute to improvements in health and wellbeing (SDG 3), clean water and sanitation (SDG 6), decent work and economic growth (SDG 8), and sustainable cities and communities (SDG 11). The health burden attributed to carbon dioxide (CO2) emissions and particulate matter (PM10) is estimated to cost the global economy over $8.1 trillion in health expenses, with the poorest populations suffering the most, while the wealthier countries experience lower levels of pollution-induced illnesses and deaths (World Bank, 2022).

A substantial body of research into the determinants of healthcare expenditure in developing and emerging countries over the past decade can be broadly categorized into two strands. The first, represented by Muhammad Malik & Azam Syed (2012), Adisa (2015), Attia-Konan et al. (2019), Ampaw et al. (2020), Eze et al. (2022), focuses on household determinants of out-of-pocket or catastrophic healthcare expenditure (CHE). These studies reveal a positive relationship between factors such as low socioeconomic status, larger household sizes, greater illness severity, and lower levels of education and CHE. The second strand examines significant macroeconomic determinants of health expenditure (e.g., Ke et al., 2011; Kumar et al., 2015; Nketiah-Amponsah, 2019; Ekpenyong, 2023), e.g. income per capita, access to healthcare professionals, the size of youth and elderly populations, and the general nature of a country's healthcare system.

An important sub-strand of the macroeconomic literature focuses on the role of greenhouse gas emissions and air pollution in determining healthcare spending. Among others, it includes Wang et al. (2019), Ullah et al. (2020); Aydin & Bozatli (2023), Ecevit et al. (2023). These studies mostly report a positive effect of emissions and pollutants on health spending, though some also find a bi-directional relationship, where increased health spending leads to higher emissions and pollution. Since most of this literature has largely overlooked the Caucasus region focusing instead on Africa, Asia, and Latin America, the present paper aims to investigate the effects of various GHG emissions on healthcare expenditure in the Caucasus region, which includes Armenia, Azerbaijan, Georgia, the Russian Federation, between 2000 and 2020[1]. It also assesses the impact of emissions on health outcome indicators such as infant mortality, death rates, and life expectancy at birth. As a result, the paper provides

1 Although only part of the Russian Federation is situated in the North Caucasus, this research uses data on Russia as a whole since the data on the North Caucasus part of Russia was not available on the databases employed in this paper. We hope that it is clear from the title that refers to 'the Caucasus region and Russia'.

a comprehensive view of how emissions influence taxpayer-funded, government-provided healthcare systems and development outcomes in the Caucasus and Russia. Our joint focus on healthcare spending and outcomes differs from much of the existing literature, which tends to examine these determinants separately.

Closing the knowledge gap, the paper considers the geopolitical and global economic importance of the Caucasus region known for its energy abundance, which drives economic activity but also generates high emissions that contribute to climate change, health risks, and increased healthcare expenditures. This work also adds to critical discussions of the issues related to healthcare expenditure and its outcomes, which may be of critical importance, given the region's poverty and inequality exacerbated by emissions. Finally, the research results can have significant implications for energy transition and the development trajectories of poorer countries.

The paper is structured as follows: this Introduction is followed by Literature review; the third section describes the data and explains the methodology used by the authors. In the fourth section we present and discuss the results of our research, and the final section offers a summary and conclusion.

2. Literature review

In pursuit of rapid economic growth and development, the degradation of environmental quality and its effects on public healthcare expenditure and health outcomes are often overlooked. Economic growth typically dominates developmental policy considerations. However, understanding the linkage between ecological quality, public healthcare expenditure, and health outcomes is crucial. Emissions can adversely affect individual health by reducing the quality of life and leading to increased healthcare spending (Ahmad et al., 2020; Alimi et al., 2020). Economists have traditionally used the Environmental Kuznets Curve (EKC) hypothesis to explain the relationship between economic growth, environmental degradation, and public health outcomes (Bilgili et al., 2021; Moosa, 2019; Sarac & Yaglikara, 2017). The EKC hypothesis posits that environmental degradation increases during the early stages of economic growth but, once a certain level of per capita income is reached, the environment begins to improve (Bilgili et al., 2021; Stern, 2004; Sarac & Yaglikara, 2017).

Researchers have used a substantial body of empirical evidence, as well as diverse estimation techniques and sample periods to explore the nexus between environmental degradation, public healthcare expenditure, and health outcomes across various countries. These studies can be categorized into two main strands. The first strand examines the relationship between environmental degradation and public healthcare expenditures; the second focuses on the health effects of environmental degradation.

In the former category, the research findings concerning the impact of environmental degradation on healthcare expenditures are rather mixed. Several studies document a positive effect of environmental degradation on healthcare spending. For instance, Akbar et al. (2020), Akeel (2022), Atuahene et al. (2020), Ezeruigbo & Ezeoha (2023), Fan et al. (2023), Hamid & Wibowo (2022), Ibukun & Osinubi (2020), Pervaiz et al. (2021), Raihan et al. (2023), Ramos-Meza et al. (2023), Saleem et al. (2022), Xiu et al. (2022) and Zeeshan et al. (2021) have all reported that rising environmental degradation correlates with increased healthcare expenditure. For example, Apergis et al. (2020) used the Generalized Method of Moments (GMM) to analyze the impact of environmental pollution on healthcare expenditure across four income groups, finding that higher CO2 emissions are associated with increased healthcare costs. Saleem et al. (2022) applied the GMM approach to 38 OECD countries and also found a positive relationship between CO2 levels and healthcare costs. Similarly, Akbar et al. (2020) used Structural Equation Modeling (SEM) for eight Southeast Asian countries and found that CO2 emissions positively impact healthcare expenditure. An & Hestmati (2019) employed the Pooled Mean Group (PMG) approach and found that air pollutants positively influence healthcare expenditure in South Korea.

Yet, some studies document a negative impact of environmental degradation on healthcare expenditure, suggesting that increased environmental degradation reduces healthcare spending. For example, Dritsaki and Dritsaki (2023) analyzed healthcare expenditure, CO2 levels, and economic growth in G7 countries using the Augmented Mean Group (AMG) approach, and found that rising CO2 levels are associated with decreased healthcare expenditure. Li et al. (2022) used the Fourier Autoregressive Distributed Lag (ARDL) model and found that higher healthcare costs are associated with lower CO2 emissions in BRICS countries. Similarly, Karaaslan and Camkaya (2022) applied the ARDL model and showed that increasing health expenditure is linked to decreasing CO2 emissions in Turkey. Other studies reporting negative impacts, or a combination of both effects include Alimi et al. (2020), Ampon-Wireko et al. (2022), Boztosun & Adli (2022), Moosa (2019), Mujtaba & Ashfaq (2022), and Ozyilmaz et al. (2023).

In the other category, we have literature on the health effects of environmental degradation. For instance, Bazyar et al. (2019) provided a comprehensive review of studies on the health effects of environmental degradation. Most evidence suggests that indicators of environmental degradation negatively impact health outcomes. Polcyn et al. (2023) used ARDL and AMG models to analyze the effects of health expenditure, energy consumption, and environmental pollutants on life expectancy across 46 Asian countries, finding that increased CO2 levels reduce life expectancy. Bouchoucha (2021) used FMOLS and DOLS models across 17 Middle Eastern and North African (MENA) countries and found that environmental degradation negatively affected health status in the long term. Similarly, studies by Alimi and Ajide (2021) and Dhrifi (2019), using the GMM approach across 45 African countries, proved that carbon emissions and ecological footprints reduced life expectancy of their residents. Aladejare (2023) applied the ARDL model to 29 African countries and showed that improved life expectancy is associated with reduced environmental degradation. Other relevant studies include those by Azam et al. (2023), Das and Debanth (2023), Nwani et al. (2018), Rahman & Alam (2021), and Yang et al. (2022).

Overall, there is a wealth of research on the impact of environmental degradation on healthcare expenditure; the results vary considerably depending on the country, period, and methodology used. Concerning the health effects, publications generally support the notion that environmental degradation negatively impacts health outcomes. Since no existing studies have specifically focused on the Caucasus region, our study aims to address this gap and expand the existing literature.

3. Data and methodology

3.1. Data

In this paper, we analysed the effect of GHG emissions on healthcare expenditure and health outcomes in the Caucasus countries (namely Armenia, Azerbaijan, Georgia), and the Russian Federation using a balanced panel data over the period from 2000 to 2020. The variables used as proxies for GHG emissions are the carbon dioxide emissions, methane oxide emissions, and nitrous oxide emissions. The health expenditure variable is the domestic government health expenditure. The health outcomes are proxied by infant mortality rate, death rate and life expectancy. In addition to these key variables, the gross domestic product per capita and population growth rate are included as control variables. Table 1 gives a description of these variables.

Table 1. Data description

Symbol	Variable	Unit of measurement
HEP	Domestic general government health expenditure	Current US$
CO2	Carbon dioxide emissions	Metric tons per capita
ME	Methane oxide emissions	Kilotons (Kt) of CO2 equivalent
NOE	Nitrous oxide emissions	Thousand metric tons of CO2 equivalent
Y	Gross domestic product per capita	Current US$
PG	Population growth rate	Annual % change
IMR	Mortality rate, infant	Per 1000 live births
LE	Life expectancy at birth, total	Years
DR	Death rate, crude	Per 1000 people

The use of these variables was motivated by the previous studies such as Akbar et al. (2021), Alimi and Ajide (2021), Azam et al. (2023), Das and Debanth (2023), Ibukun and Osinubi (2020), Rahman and Alam (2021), and Polcyn et al (2023). The data for all the variables were sourced from the World Bank Development Indicators database

(World Bank, 2023). Where necessary, the data is transformed into natural logarithm form for easier interpretation[2].

3.2. Methodology

To attain our objectives, we employed two groups of models where the first model deals with the impact of GHG emissions on public healthcare expenditure while the second model tackles the effect of GHG emissions on public health outcomes (infant mortality rate, death rate and life expectancy). These two models are presented below as:

Health expenditure

$$HEP_{it} = \alpha_0 + \beta_1 CO_{2it} + \beta_2 ME_{it} + \beta_3 NOE_{it} + \beta_4 Y_{it} + \beta_5 IMR_{it} + \beta_6 PG_{it} + \epsilon_{it} \quad (1)$$

Health outcomes

$$IMR_{it} = \alpha_0 + \beta_1 CO_{2it} + \beta_2 ME_{it} + \beta_3 NOE_{it} + \beta_4 Y_{it} + \beta_5 HEP_t + \beta_6 PG_{it} + \epsilon_{it} \quad (2)$$

$$DR_{it} = \alpha_0 + \beta_1 CO_{2it} + \beta_2 ME_{it} + \beta_3 NOE_{it} + \beta_4 Y_{it} + \beta_5 HEP_t + \beta_6 PG_{it} + \epsilon_{it} \quad (3)$$

$$LE_{it} = \alpha_0 + \beta_1 CO_{2it} + \beta_2 ME_{it} + \beta_3 NOE_{it} + \beta_4 Y_{it} + \beta_5 HEP_t + \beta_6 PG_{it} + \epsilon_{it} \quad (4)$$

Where α_0 denotes the constant, and β_1, β_2, ... β_6 are slope coefficients to be estimated. The subscript i = 1, 2, 3, and 4, which denotes the individual country in the panel while t = 1, 2, ... T, representing the time in years. Regarding equation (1), we followed Zaidi and Saidi, (2018) and Ibukun and Osinubi (2020) in which the public health expenditure (HEP) is dependent on various emission variables (carbon dioxide emission [CO2], methane oxide emission [ME] and nitrous oxide emission [NOE]) and control variables (income/GDP per capita [Y], population growth rate [PG], and the infant mortality rate [IMR]). A priori, we expected that an increase in income per capita would lead to an increase in the total health expenditure. This expectation is consistent with the research conducted by Ke, Saksena & Holly (2011), Kumar et al. (2015), Nketiah-Amponsah (2019), and Ekpenyong (2023), who emphasize the significant impact of macroeconomic factors, specifically income per capita, on healthcare expenditure. These studies indicate a direct relationship between a nation's income level and its healthcare expenditure. More precisely, countries with higher average income tend to dedicate greater amounts of resources to healthcare, indicating their ability to invest in more extensive health services and infrastructure. In contrast, nations with lower income levels frequently encounter limitations in healthcare expenditure, which can affect the overall calibre and availability of health services. The observed pattern aligns with our initial anticipation that higher income per person would result in increased overall healthcare

[2] The data underpinning the analysis reported in this paper are deposited at Zenodo data repository, available at https://zenodo.org/records/13358481

spending, highlighting the substantial influence of economic well-being on healthcare funding and administration. In terms of greenhouse emissions (CO2, ME, NOE), we hypothesized higher public healthcare expenditure due to a negative externality imposed by pollution. We also expected the population growth and infant mortality rates to have a positive relationship with healthcare expenditure.

Regarding the impact of greenhouse gas (GHG) emissions on health outcomes, we follow the approach of Alimi and Ajide (2021), modelling the infant mortality rate (IMR), death rate (DR), and life expectancy (LE) as functions of GHG emissions (CO2, methane emissions [ME], and nitrous oxide emissions [NOE]) and control variables (income [Y], population growth [PG], and healthcare expenditure per capita [HEP]). These relationships are represented in equations (2), (3), and (4). Consequently, we hypothesized that an increase in GHG emissions would result in higher infant mortality and death rates, but lower life expectancy.

To estimate the parameters in equations (1)–(4), we applied the panel autoregressive distributed lag (Panel-ARDL) model, also known as the Pooled Mean Group (PMG). The application of this model is motivated by the previous studies by Alimi & Ajide (2021), Azam et al. (2023), Li et al. (2022) and Rahman & Alam (2021). The ARDL model is flexible as it is applicable when variables are either integrated in level (I (0)), first difference (I(1)) or their combination. Moreover, the model provides information on the short-run and long-run impact of variables, unlike other similar panel approaches such as panel least squares (PLS), fixed effect (FE), random effect (RE), fully modified ordinary least squares (FMOLS), and dynamic ordinary least squares (DOLS).

Following Pesaran et al (2001), we modified equations (1)–(4) into the panel ARDL model as:

$$\begin{aligned}\Delta HEP_{it} = \alpha_0 &+ \sum_{i=1}^{p}\phi_1 \Delta HEP_{it} + \sum_{i=1}^{p}\phi_2 \Delta CO_{2it} + \sum_{i=1}^{p}\phi_3 \Delta ME_{it} + \sum_{i=1}^{p}\phi_4 \Delta NOE_{it} + \\ &+ \sum_{i=1}^{p}\phi_5 \Delta Y_{it} + \sum_{i=1}^{p}\phi_6 \Delta IMR_{it} + \sum_{i=1}^{p}\phi_7 \Delta PG_{it} + \beta_1 CO_{2it} + \beta_2 ME_{it} + \beta_3 NOE_{it} + \\ &\beta_4 Y_{it} + \beta_5 IMR_{it} + \beta_6 PG_{it} + \varepsilon_{it}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta IMR_{it} = \alpha_0 &+ \sum_{i=1}^{p}\phi_1 \Delta IMR_{it} + \sum_{i=1}^{p}\phi_2 \Delta CO_{2it} + \sum_{i=1}^{p}\phi_3 \Delta ME_{it} + \sum_{i=1}^{p}\phi_4 \Delta NOE_{it} + \\ &+ \sum_{i=1}^{p}\phi_5 \Delta Y_{it} + \sum_{i=1}^{p}\phi_6 \Delta HEP_{it} + \sum_{i=1}^{p}\phi_7 \Delta PG_{it} + \beta_1 CO_{2it} + \beta_2 ME_{it} + \beta_3 NOE_{it} + \\ &\beta_4 Y_{it} + \beta_5 HEP_{it} + \beta_6 PG_{it} + \varepsilon_{it}\end{aligned} \tag{6}$$

$$\begin{aligned}\Delta DR_{it} = \alpha_0 &+ \sum_{i=1}^{p}\phi_1 \Delta DR_{it} + \sum_{i=1}^{p}\phi_2 \Delta CO_{2it} + \sum_{i=1}^{p}\phi_3 \Delta ME_{it} + \sum_{i=1}^{p}\phi_4 \Delta NOE_{it} + \\ &+ \sum_{i=1}^{p}\phi_5 \Delta Y_{it} + \sum_{i=1}^{p}\phi_6 \Delta HEP_{it} + \sum_{i=1}^{p}\phi_7 \Delta PG_{it} + \beta_1 CO_{2it} + \beta_2 ME_{it} + \beta_3 NOE_{it} + \\ &\beta_4 Y_{it} + \beta_5 HEP_{it} + \beta_6 PG_{it} + \varepsilon_{it}\end{aligned} \tag{7}$$

$$\Delta LE_{it} = \alpha_0 + \sum_{i=1}^{p}\phi_1 \Delta LE_{it} + \sum_{i=1}^{p}\phi_2 \Delta CO_{2it} + \sum_{i=1}^{p}\phi_3 \Delta ME_{it} + \sum_{i=1}^{p}\phi_4 \Delta NOE_{it} + $$
$$+ \sum_{i=1}^{p}\phi_5 \Delta Y_{it} + \sum_{i=1}^{p}\phi_6 \Delta HEP_{it} + \sum_{i=1}^{p}\phi_7 \Delta PG_{it} + \beta_1 CO_{2it} + \beta_2 ME_{it} + \beta_3 NOE_{it} +$$
$$\beta_4 Y_{it} + \beta_5 HEP_{it} + \beta_6 PG_{it} + \varepsilon_{it} \tag{8}$$

Equations (5)–(8) are the ARDL model which combines the short-run and long-run information about the variables under consideration. Specifically, the parameters ϕ_1, ϕ_2, ... ϕ_7 are the short-run coefficients while β_1, β_2, ... β_6 are the long-run coefficients. The constant is given by α_0 and Δ represents the first difference operator. The evidence of cointegration is determined by testing the null hypothesis that there is no cointegration when $\beta_1 = 0$, $\beta_2 = 0$, ..., $\beta_6 = 0$ against the alternative that there is cointegration, when $\beta_1 \neq 0$, $\beta_2 \neq 0$, ... ,$\beta_6 \neq 0$. However, the application of this hypothesis testing in a panel approach is difficult to achieve. Consequently, studies have used other cointegration approaches such as Pedroni, Kao and/or Westerlund cointegration tests (Aladejera, 2023; Ampon-Wireko, 2022; Rahman & Alam, 2021). To this end, we applied the Pedroni (2004) cointegration test to ascertain the evidence of cointegration.

Once co-integration is established, the next step is to estimate the short run impact by transforming equations (5)–(8) into their error correction model (ECM) forms. However, it is important to note that such transformations can only take place if there is evidence of cointegration. The ECM for equations (5)–(8) is expressed as:

$$\Delta HEP_{it} = \alpha_0 + \sum_{i=1}^{p}\phi_1 \Delta HEP_{it} + \sum_{i=1}^{p}\phi_2 \Delta CO_{2it} + \sum_{i=1}^{p}\phi_3 \Delta ME_{it} + \sum_{i=1}^{p}\phi_4 \Delta NOE_{it} +$$
$$+ \sum_{i=1}^{p}\phi_5 \Delta Y_{it} + \sum_{i=1}^{p}\phi_6 \Delta IMR_{it} + \sum_{i=1}^{p}\phi_7 \Delta PG_{it} + \pi ECT_{it} + \varepsilon_{it} \tag{9}$$

$$\Delta IMR_{it} = \alpha_0 + \sum_{i=1}^{p}\phi_1 \Delta IMR_{it} + \sum_{i=1}^{p}\phi_2 \Delta CO_{2it} + \sum_{i=1}^{p}\phi_3 \Delta ME_{it} + \sum_{i=1}^{p}\phi_4 \Delta NOE_{it} +$$
$$+ \sum_{i=1}^{p}\phi_5 \Delta Y_{it} + \sum_{i=1}^{p}\phi_6 \Delta HEP_{it} + \sum_{i=1}^{p}\phi_7 \Delta PG_{it} + \pi ECT_{it} + \varepsilon_{it} \tag{10}$$

$$\Delta DR_{it} = \alpha_0 + \sum_{i=1}^{p}\phi_1 \Delta DR_{it} + \sum_{i=1}^{p}\phi_2 \Delta CO_{2it} + \sum_{i=1}^{p}\phi_3 \Delta ME_{it} + \sum_{i=1}^{p}\phi_4 \Delta NOE_{it} +$$
$$+ \sum_{i=1}^{p}\phi_5 \Delta Y_{it} + \sum_{i=1}^{p}\phi_6 \Delta HEP_{it} + \sum_{i=1}^{p}\phi_7 \Delta PG_{it} + \pi ECT_{it} + \varepsilon_{it} \tag{11}$$

$$\Delta LE_{it} = \alpha_0 + \sum_{i=1}^{p}\phi_1 \Delta LE_{it} + \sum_{i=1}^{p}\phi_2 \Delta CO_{2it} + \sum_{i=1}^{p}\phi_3 \Delta ME_{it} + \sum_{i=1}^{p}\phi_4 \Delta NOE_{it} +$$
$$+ \sum_{i=1}^{p}\phi_5 \Delta Y_{it} + \sum_{i=1}^{p}\phi_6 \Delta HEP_{it} + \sum_{i=1}^{p}\phi_7 \Delta PG_{it} + \pi ECT_{it} + \varepsilon_{it} \tag{12}$$

In equations (9)–(12), apart from the error correction term (ECT), the models represent short term effects as previously indicated. Importantly, the ECT indicates the speed of adjustment to equilibrium relationship. In other words, it shows how long it takes the system to return to equilibrium after a given shock. The coefficient (π)

of the error correction term is expected to be negative based on economic theory. Lastly, to analyze the causal relationship between the greenhouse emissions, public healthcare expenditure and health outcomes, we applied the panel Granger causality test. For simplicity, the panel causality is compactly represented as:

$$\Delta X_{it} = \alpha_0 + \sum_{i=1}^{p} \delta_1 \Delta GHG_{it-1} + \sum_{i=1}^{p} \tau_1 \Delta C_{it-1} + \varepsilon_{it} \quad (13)$$

$$\Delta GHG_{it} = \alpha_0 + \sum_{i=1}^{p} \varrho_1 \Delta X_{it-1} + \sum_{i=1}^{p} \tau_1 \Delta C_{it-1} + \varepsilon_{it} \quad (14)$$

Where X_{it} represents a vector for variables (HEP, IMR, DR or LE), the greenhouse gas emission (GHG) is a vector for the variables (CO2, ME, and NOE), and C is a vector of control variables (Y and PG). The coefficient vector δ indicates whether a given greenhouse variable has a causal effect on either the public health expenditure or any of the health outcomes. Similarly, the coefficient vector ϱ indicates whether the public health expenditure or any of the health outcomes has a cause effect on any of the greenhouse emission variables. Therefore, the significance of both δ and ϱ implies bidirectional causality whereas unidirectional causality exists when either coefficient is significant. The significance of coefficient is tested through the F-statistic.

4. Data Analysis and Result Discussion

This section presents and discusses the results from the models used to analyze the effects of GHG emissions on healthcare expenditure and health outcomes. The section is divided into two parts: the first deals with the preliminary results (namely the descriptive statistical analysis of the data, correlation analysis and unit root test) and the second part describes empirical results relating to cointegration test, panel ARDL model and panel Granger causality.

4.1. Preliminary results

This section presents descriptive statistics, correlation matrix and unit root tests for healthcare expenditure, carbon dioxide emissions, methane oxide, nitrous oxide emissions, GDP per capita, population growth rate, infant mortality rate, death rates, and life expectancy for the entire sample. Starting with descriptive statistic, the report in Table 2 shows that all the variables are positively skewed, except death rates and life expectancy which are negatively skewed. On average, the Caucasus region spends approximately US$708 on healthcare, with the Russian Federation spending the highest amount at US$2,278, and Azerbaijan the lowest at US$98 during the assessed period. The major pollutant over the period was carbon dioxide emissions which recorded an average of 415 215kt, with Russia hitting a maximum of 1 703 588Kt and Georgia having the lowest record of 2958kt. The region's average life expectancy over the period is at 70years with Armenia reaching the greatest longevity of 75 years in 2019. The crude death rate continues to be low, reaching 10 per 1,000 people, on average.

Table 2. Descriptive Statistics

	HEP	ME	NOE	CO2	PG	IMR	Y	LE	DR
Mean	708.172	144713.7	16513.74	415215.4	-0.037	19.224	4743.025	70.715	10.458
Median	600.386	7792.249	2283.835	17430.75	-0.266	15.450	4019.492	71.335	11.299
Maximum	2278.232	620983.2	69231.05	1703589.	2.100	61.100	15974.62	75.439	16.400
Minimum	98.106	1800.413	528.673	2958.400	-1.945	4.400	603.298	64.891	5.600
Std. Dev.	457.233	240296.1	25236.82	699989.3	0.787	12.607	3642.679	2.701	3.248
Skewness	0.864	1.174	1.172	1.157	0.583	1.410	1.279	-0.619	-0.100
Kurtosis	3.484	2.411	2.419	2.346	3.048	4.653	4.173	2.526	1.860
Jarque-Bera	11.277	20.511	20.419	20.252	4.763	37.419	27.715	6.158	4.691
Probability	0.003	0.000	0.000	0.000	0.092	0.000	0.000	0.046	0.096
Observations	84	84	84	84	84	84	84	84	84

Note: HEP denotes the public health expenditure, ME is the methane oxide emission, NOE is the nitrous oxide emission, CO2 is the carbon dioxide emission, PG is the population growth rate, Y is the income per capita, IMR is the infant mortality rate, DR is the death rate and LE is the life expectancy.

The correlation matrix of the variable in Table 3 shows that healthcare expenditure is positively correlated with all the variables of interest, except CO2, income per capita and population growth, which is negative, against economic theory. All independent variables show a neutral (weak) correlation, meaning that the variables are free from multicollinearity, which makes it difficult to determine the individual effect of each independent variable on the dependent variable. Although the death rates and life expectancy have a strong negative collinearity (-0.8) they will not be used in the same regression model.

Table 3. Correlation Matrix

	HEP	CO2	ME	NOE	Y	PG	IMR	LE	DR
HEP	1.000								
CO2	-0.209	1.000							
ME	0.197	0.046	1.000						
NOE	0.104	-0.041	0.161	1.000					
Y	-0.198	0.057	-0.057	-0.070	1.000				
PG	-0.106	-0.047	0.367	0.057	0.297	1.000			
IMR	0.156	-0.111	0.379	0.079	-0.624	0.461	1.000		
LE	0.007	0.060	0.126	-0.052	-0.024	0.037	0.145	1.000	
DR	0.052	-0.042	-0.082	0.051	-0.093	-0.113	-0.063	-0.817	1.000

Note: HEP denotes the public healthcare expenditure, ME is methane oxide emission, NOE is the nitrous oxide emission, CO2 is the carbon dioxide emission, PG is the population growth rate, Y is the income per capita, IMR is the infant mortality rate, DR is the death rate and LE is the life expectancy.

Before embarking on econometric modelling, it is essential to recognize that assessing the stationarity of the datasets is a fundamental prerequisite, especially when working with time series and panel macroeconomic or financial data prior to testing for co-integration. Since co-integration (the long-term relationship between variables) is a necessary condition for the model, it is crucial to determine the order of integration, which can only be achieved with stationary data.

This analysis is necessary to avoid the potential pitfalls of spurious regressions that may arise if the variables are non-stationary. The literature suggests that macroeconomic variables generally exhibit a unit root, while other variables may not. A variable is considered to have a unit root if it is non-stationary at its levels, as noted by Sankaran and Samantaraya (2015) and Pantula et al. (1994). The results of the unit root tests are presented below.

Table 4. Summary of panel unit root tests

Variable	Levin, Lin & Chu t*		Lm, Pesaran and Shin /ADF-Fisher Chi-square stat		Stationary	Test Equation
	Level	*1st Difference*	*Level*	*1st Difference*		
HEP	-3.85(0.00)***	-5.54(0.00)***	-0.93(0.18)	-4.11(0.00)***	I(1)	Intercept
CO2	-0.84(0.20)	-5.69(0.00)***	-0.47(0.32)	-5.30(0.00)***	I(1)	Intercept
ME	-2.10(0.02)**	-3.01(0.00)***	-0.03(0.49)	-3.35(0.00)***	I(1)	Intercept
NOE	0.17(0.57)	-3.26(0.00)***	1.73(0.96)	-4.46(0.00)***	I(1)	Intercept
Y	-3.85(0.00)***	-2.92(0.00)***	-1.80(0.04)**	-1.36(0.08)*	I(0)	Intercept
PG	-2.61(0.00)***	-2.75(0.00)***	-1.35(0.08)*	-2.67(0.00)***	I(0)	Intercept
IMR	-4.92(0.00)***	-0.53 (0.30)	1.82(0.03)**	-0.72(0.23)	I(0)	Intercept
LE	-2.18 (0.98)	-2.11 (0.01)***	1.76 (0.98)	-11.62 (0.1)*	I(1)	None
DR	2.27 (0.98)	-2.25 (0.01)***	1.67 (0.98)	12.87 (0.11)*	I(1)	None

Note: *, **, *** indicate significance at 10%, 5%, 1% level. HEP denotes the public healthcare expenditure, ME is the methane oxide emission, NOE is the nitrous oxide emission, CO2 is the carbon dioxide emission, PG is the population growth rate, Y is the income per capita, IMR is the infant mortality rate, DR is the death rate and LE is the life expectancy.

Table 4 reveals that some of the variables (carbon dioxide, nitrous oxide, life expectancy and death rate) are not stationary at levels, meaning that they possess a unit root which is the rationale for differencing to make them stationary (Sankaran & Samantaraya, 2015). These variables are not stationary because the results of the unit root tests are not statistically significant at levels. However, the unit root tests for public healthcare expenditure and methane oxide produce mixed results. While both variables are stationary in level under the Levin, Lin, and Chu (LLC) test, they are nonstationary in level under the Im, Pesaran and Shin (IPS) test. The other variables (income per capita, population growth and infant mortality rate) are stationary at levels and do not need to be differenced. Overall, the unit root test results show that all the variables are either 1(0) or I(1), which is consistent with the application of the ARDL mode. Next, we applied the Pedroni cointegration tests to assess the long run relationship between the variables.

4.2. Empirical results

This section presents and analyses the results of the Pedroni cointegration test, the panel ARDL results, and the panel Granger causality test. The findings are discussed in the subsequent paragraphs. Table 5 displays the Pedroni cointegration results among GHG emissions, healthcare expenditure, and health outcomes. Specifically, Table 5 presents the cointegration results between GHG emissions and healthcare expenditure in Panel A, and between GHG emissions and health outcomes in Panel B. The Pedroni cointegration test produces two sets of statistics to assess the presence of long-term relationships among variables: within-dimension statistics and between-dimension statistics.

Table 5. Pedroni cointegration test

Test	Within-dimension		Between-dimension	
	statistic	Probability	statistic	Probability
Panel A: Health expenditure (HEP = CO2 ME NOE Y PG IMR)				
Panel v-Statistic	-1.869	0.985	--	--
Panel rho-Statistic	0.430	0.663	1.563	0.942
Panel PP-Statistic	-8.637***	0.000	-15.419***	0.000
Panel ADF-Statistic	-5.259***	0.000	-6.824***	0.000
Panel B: Health outcomes				
i. IMR = CO2 ME NOE Y PG HEP				
Panel v-Statistic	-2.275	1.000	--	--
Panel rho-Statistic	2.940	1.000	3.596	1.000
Panel PP-Statistic	3.406	1.000	3.828	1.000
Panel ADF-Statistic	4.730	1.000	5.766	1.000
ii. DR = CO2 ME NOE Y PG HEP				
Panel v-Statistic	1.460*	0.072	--	--
Panel rho-Statistic	1.725	0.957	1.750	0.960
Panel PP-Statistic	2.673	0.996	2.200	0.986
Panel ADF-Statistic	4.721	1.000	5.150	1.000
iii. LE = CO2 ME NOE Y PG HEP				
Panel v-Statistic	5.510***	0.000	--	--
Panel rho-Statistic	0.624	0.734	1.263	0.897
Panel PP-Statistic	1.384	0.917	1.734	0.957
Panel ADF-Statistic	0.723	0.765	2.780	0.997

Note: *, **, *** indicate significance at 10%, 5%, 1% level. HEP denotes the public healthcare expenditure, ME is the methane oxide emission, NOE is the nitrous oxide emission, CO2 is the carbon dioxide emission, PG is the population growth rate, Y is the income per capita, IMR is the infant mortality rate, DR is the death rate and LE is the life expectancy.

Panel A of Table 5 gives evidence of cointegrating relationship between GHG emissions and healthcare expenditure. The within-dimension results indicate that two out of four test statistics (Panel PP-Statistic and Panel ADF-Statistic) are statistically significant while between-dimension results indicate that two out of three test statistics (Group PP-statistic and Group ADF-statistic) are statistically significant. Thus, we establish that there is evidence of cointegrating relationship between GHG emission and public healthcare expenditure. This finding indicates that, although there could be some deviations between these variables in the short term due to disturbances, the relationship tends to converge to their long-term trend over time, suggesting that the GHG emission and healthcare expenditure move together in the long run. This finding is consistent with the previous studies by Ampon-Wireko et al (2022), An and Heshmati (2019), Karaaslan and Camkaya (2022) and Mujtaba and Ashfaq (2022).

In contrast, the second half of Table 5 (Panel B), which examines the impact of GHG emissions on health outcomes—specifically, infant mortality, death rate, and life expectancy—reveals no evidence of a cointegrating relationship, as the null hypothesis of no cointegration cannot be rejected. This finding suggests that GHG emissions do not have a long-term relationship with infant mortality rate, death rate, or life expectancy in the Caucasus region. Given the absence of a long-term relationship, further analysis of the health outcomes in relation to GHG emissions will focus on the short-run causal relationship.

Given the evidence of cointegration between GHG emission and healthcare expenditure as depicted in Table 5, we proceed to estimate the panel ARDL model for equation (5). However, it is important to note that the ARDL cannon be estimated for equations (6) – (8) due to the absence of cointegration. Consequently, we report only the panel ARDL model result for the GHG emission and healthcare expenditure in Table 6 below. Specifically, the table presents the short and long run ARDL results. In the short run, we observe that carbon dioxide emission is statistically significant at 5%, indicating that the variable has a negative relationship with health expenditure in the short run. That is, a 1% increase in carbon dioxide emission leads to a 0.64% decline in health spending. However, none of the other GHG emission variables are statistically significant. Also, we observe that the error correction term (ECT) is negative and statistically significant, which supports the evidence of cointegrating relationship between GHG emissions and public healthcare expenditure. In addition, ECT shows that approximately 100% of deviation is corrected within one year.

The long-run estimates in Table 6 show that carbon dioxide (CO2) and methane emissions are positively correlated with healthcare expenditure in the panel countries, with statistical significance at the 10% and 1% levels, respectively. Conversely, nitrous oxide emissions are statistically insignificant. Our findings suggest that a 1% increase in CO2 emissions leads to approximately a 0.21% increase in healthcare spending, while a 1% increase in methane emissions results in a 0.54% increase in healthcare spending. The positive long-run effect of these emissions underscores the various long-term health impacts associated with air pollution, such as chronic asthma, pulmonary insufficiency, cardiovascular diseases, and cardiovascular mortality (Manisalidis et al., 2020). Moreover, prolonged exposure to air pollution has been associated with an increased risk of diabetes (Eze et al., 2014), further contributing to higher healthcare expenditures.

Table 6. Panel ARDL model result

Variable	Coefficient	Standard error	t-Statistic	Probability
		Short run		
ΔCO2	-0.641**	0.267	-2.405	0.021
ΔME	0.216	0.282	0.766	0.448
ΔNOE	0.268	0.204	1.314	0.196
ΔY	-0.085	0.117	-0.725	0.473
ΔPG	-0.053	0.273	-0.195	0.847
ΔIMR	2.392	3.831	0.624	0.536
C	-1.421***	0334	-4.255	0.000
ECT	-1.050***	0.269	-3.902	0.000
		Long run		
CO2	0.206*	0.120	1.716	0.093
ME	0.535***	0.192	2.792	0.008
NOE	0.037	0.188	0.199	0.843
Y	0.089***	0.023	3.855	0.000
PG	0.053*	0.031	1.733	0.090
IMR	0.303***	0.050	6.068	0.000

Note: *, **, *** indicate significance at 10%, 5%, 1% level. HEP denotes the public healthcare expenditure, ME is the methane oxide emission, NOE is the nitrous oxide emission, CO2 is the carbon dioxide emission, PG is the population growth rate, Y is the income per capita, IMR is the infant mortality rate, DR is the death rate and LE is the life expectancy. Model selection is based on the Schwarz information criterion (SIC) and ARDL (1,1,1,1,1,1,1).

All three control variables—income (Y), population growth (PG), and infant mortality rate (IMR)—align with our a priori expectations and economic theory, showing a positive and statistically significant effect on health spending. These findings are consistent with the results of Khoshnevis Yazdi and Khanalizadeh (2017), which demonstrate that income and CO2 emissions have statistically significant positive effects on health expenditure in the Middle East and North Africa (MENA) region. Similarly, our findings are in line with those of Ibukun and Osinubi (2020), which provide evidence of a significant positive effect of economic growth on healthcare expenditure and a positive relationship between CO2 and methane oxide emissions and health spending.

To analyze the effects of GHG emissions on public healthcare expenditure and health outcomes, we applied panel Granger causality tests, with the results presented in Table 7. Panel A reports the causality test results between GHG emissions and public healthcare expenditures. The results in Panel A indicate that among the GHG emissions, only methane has a unidirectional causal effect on public healthcare expenditure. Unidirectional causality is observed from income per capita and population growth rate to public healthcare expenditure.

Regarding the relationship between GHG emissions and health outcomes, Panels B and D show no evidence of causality between infant mortality rate, life expectancy, and any of the GHG emissions. However, Panel C reveals that nitrous oxide emissions Granger-cause the death rate, indicating unidirectional causality. Our findings align with the studies by Azam et al. (2023) and Yang et al. (2022), which also found no causality between GHG emissions and life expectancy.

Table 7. Granger causality test results

Null hypothesis	F-statistic	Probability
Panel A: HEP = CO2M, ME, NOE, Y, PG, IMR		
CO2M does not Granger Cause HEP	2.272	0.111
HEP does not Granger Cause CO2M	0.798	0.455
ME does not Granger Cause HEP	2.386*	0.100
HEP does not Granger Cause ME	0.130	0.878
NOE does not Granger Cause HEP	0.376	0.688
HEP does not Granger Cause NOE	0.171	0.843
MR does not Granger Cause HEP	1.731	0.185
HEP does not Granger Cause MR	0.096	0.909
Y does not Granger Cause HEP	13.441***	0.000
HEP does not Granger Cause Y	1.190	0.311
PG does not Granger Cause HEP	4.627**	0.013
HEP does not Granger Cause PG	1.056	0.354
Panel B: IMR = CO2M, ME, NOE, HEP, LY, PG		
CO2M does not Granger Cause MR	0.967	0.386
MR does not Granger Cause CO2M	0.918	0.404
ME does not Granger Cause MR	0.584	0.560
MR does not Granger Cause ME	1.635	0.203
NOE does not Granger Cause MR	1.863	0.163
MR does not Granger Cause NOE	0.777	0.464
HEP does not Granger Cause MR	0.096	0.909
MR does not Granger Cause HEP	1.731	0.185
Y does not Granger Cause MR	0.420	0.659
MR does not Granger Cause Y	0.256	0.775
PG does not Granger Cause MR	0.407	0.667
MR does not Granger Cause PG	2.40336*	0.098

Panel C: DR = CO2M, ME, NOE, HEP, LY, PG		
CO2M does not Granger Cause DR	0.097	0.908
DR does not Granger Cause CO2M	1.856	0.165
ME does not Granger Cause DR	1.410	0.252
DR does not Granger Cause ME	1.944	0.152
NOE does not Granger Cause DR	3.470**	0.037
DR does not Granger Cause NOE	0.288	0.751
HEP does not Granger Cause DR	0.127	0.881
DR does not Granger Cause HEP	0.010	0.990
Y does not Granger Cause DR	0.062	0.940
DR does not Granger Cause Y	1.430	0.247
PG does not Granger Cause DR	0.486	0.617
DR does not Granger Cause PG	0.269	0.765
Panel D: DR = CO2M, ME, NOE, HEP, LY, PG		
CO2M does not Granger Cause LE	0.655	0.523
LE does not Granger Cause CO2M	0.931	0.399
ME does not Granger Cause LE	0.095	0.910
LE does not Granger Cause ME	1.658	0.198
NOE does not Granger Cause LE	0.158	0.854
LE does not Granger Cause NOE	0.287	0.751
HEP does not Granger Cause LE	0.780	0.462
LE does not Granger Cause HEP	0.277	0.757
Y does not Granger Cause LE	0.303	0.740
LE does not Granger Cause Y	3.070*	0.053
PG does not Granger Cause LE	0.271	0.763
LE does not Granger Cause PG	1.085	0.344

Note: ***, **, * indicates significance at 1%, 5% and 10% respectively. HEP denotes the public healthcare expenditure, ME is the methane oxide emission, NOE is the nitrous oxide emission, CO2 is the carbon dioxide emission, PG is the population growth rate, Y is the income per capita, IMR is the infant mortality rate, DR is the death rate and LE is the life expectancy.

Conclusion and implications

In conclusion, this study emphasizes the substantial and lasting effect of environmental degradation on healthcare spending in the Caucasus region. This is supported by the positive correlation observed between carbon dioxide, methane oxide emissions and healthcare spending. For individual countries within the Caucasus region, our findings suggest the existence of long-term effects of environmental degradation on healthcare spending. In other words, individual countries of the region will require increased healthcare spending to address the long-term effects of environmental degradation.

Although no direct causation is found between environmental factors and quality of life, the results underscore the complex relationship between these factors and health outcomes. These findings highlight the necessity for robust environmental policies aimed at reducing greenhouse gas emissions. Such policies should not only address climate change but also prioritize lowering healthcare costs by investing in renewable energy, improving public transportation, and adopting sustainable agricultural practices.

It is now crucial to strengthen healthcare systems by increasing financial resources, enhancing physical infrastructure, and improving capacity to address environment-related health issues, ensuring a just transition. The study underscores the importance of regional collaboration in environmental governance, aligning with global efforts on climate change and health. It also sets the stage for future research to explore the causal relationships between environmental degradation and various aspects of health and well-being, particularly in diverse regional and healthcare contexts.

The present paper is limited to the Caucasus region with annual panel data over the period of 2000-2020. Our findings, therefore, cannot be applied to countries outside this region and to different observation periods; the future research, however, may extend the area of study to other regions and use time series data as well as high frequency data, such as quarterly observations. Moreover, given that panel ARDL model used in this paper assumes linear relationship, the future studies can utilize the non-linear models that facilitate the revealing of more intricate relationships, in which modifications to one variable may not necessarily induce proportional changes in another. Non-linear models may offer a more profound understanding of the existing relationships.

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