Energy Policy 168 (2022) 113089

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Time series analysis of environmental quality in the state of Qatar

Ammar Abulibdeh

Applied Geography and GIS Program, Department of Humanities, College of Arts and Sciences, Qatar University, P.O. Box: 2713, Doha, Qatar

ARTICLE INFO

Keywords:
GHGs emissions
Environmental degradation
ARDL technique
Unit root test with structural breaks
Qatar

ABSTRACT

This study investigated the impact of economic growth, electricity consumption, energy consumption, and the crop production index on environmental quality in Qatar by considering four different types of GHGs emissions (carbon dioxide, methane, nitrous oxide, and F-GHGs) and using a time-series dataset for the period of 1990–2019. This study investigated the long- and short-term impacts between these variables using ARDL bounds testing, while the stationarity properties of the variables were tested by applying the Zivot–Andrews test. The results indicate that electricity consumption, energy consumption, and the crop production index have a positive and significant relationship with GHGs, while economic growth has a negative and significant relationship in the long term with these gases. The VECM Cranger and Toda-Yamamoto causality tests were used to understand the causal relationship between the variables, and the results suggest a different causality relationship between the variables. Several key policy implications derived from the findings of this research to sustain environmental quality in the state of Qatar are discussed in this paper.

1. Introduction

Several environmental issues have received extensive attention since the Rio de Janeiro Earth Summit held in 1992, which aimed to establish and implement suitable international and national sustainable development policies. During the last few decades, good economic development performance has contribute to environmental degradation and in a significant rise in GHG emissions. Maintaining sustainable use of the environment is critical when discussing the implementation of sustainable development strategies to boost economic growth and development. Environmental issues such as global warming, biodiversity loss, and deforestation have stimulated significant quantitative and qualitative studies that have predominantly concentrated on the theoretical examinations and explanations of the economic growth environmental degradation nexus, known as the Environmental Kuznets Curve (EKC) (Grossman and Krueger, 1995)– (Zambrano-Monserrate et al., 2018). Energy use is another cause of GHG emissions (El-Montasser and Ben-Salha, 2019), (Magazzino and Cerulli, 2019).

Recently, sustainable development has attracted growing attention by policymakers in many countries. The key pillar in achieving this goal is decidedly linked to the environment (Zmami and Ben-Salha, 2020). However, to develop active emission reduction policies, factors that contribute to the growth of carbon emissions must be identified and quantified. This study contributes to the existing literature by examining the determinants of environmental degradation in Qatar between 1990 and 2019. Therefore, the focus of this research is to answer the following questions: What are the short- and the long-term impacts of economic growth, electricity consumption, energy consumption, and crop production index on carbon dioxide, methane, Nitrous oxide, and other GHGs emissions? What are the nature of the causal relationship between these variables? What are their impact on environmental degradation in Qatar? What are the key policy implications that can be derived to sustain environmental quality in Qatar? To answer these questions, this paper utilize various econometric models to identify the short- and long-term as well the causal relationships between these variables. Although numerous time-series studies have been conducted to investigate the causes of environmental degradation, no single study has considered four types of GHG emissions to measure environmental quality. This study is a significant and unique contribution, particularly for an arid country with abundant energy sources, such as Qatar. Few studies have investigated Qatar, and these studies have considered only CO_2 as the indicator of environmental degradation in the country (Charfeddine et al., 2018)– (Salahuddin and Gow, 2019a). Other studies [see (Magazzino)– (Salahuddin and Gow, 2014)] focused on the Gulf Region, which includes Qatar, where the results are comprehensive and do not reflect a single-country result. To fill this gap in the literature, the focus of this study is to investigate the causes of environmental degradation in the state of Qatar using four different types of GHG emissions (carbon dioxide, methane, nitrous oxide, and other GHGs) and four different indicators (economic growth, energy consumption, electricity

E-mail address: aabulibdeh@qu.edu.qa.

https://doi.org/10.1016/j.enpol.2022.113089
Received 5 March 2022; Received in revised form 17 May 2022; Accepted 30 May 2022
Available online 14 June 2022

consumption, and the crop production index). The reason for considering these indicators is the comprehensive measures they provide for measuring environmental quality. Furthermore, depending only on one measure, that is, CO_2, as the indicator of environmental quality may draw conclusive and comprehensive conclusions on the causes of environmental degradation. Qatar is an interesting case because of the high rate of air pollution and its effect on the quality of life and residential health. Furthermore, the country has abundant energy wealth (oil and gas), which is its main source of economic growth. Furthermore, the electricity sector is subsidized, constituting a burden on the government budget and motivating residents to consume more, consequently increasing air pollution.

All the countries worldwide have considered protecting our planet from environmental crises as a first priority and have been involved in many international agreements concerning this issue, including the Kyoto Protocol (COP3), Kyoto Protocol (MOP 1), United Nations Framework Convention on Climate Change (UNFCCC), Paris Agreement (COP21), Doha Amendment to the Kyoto Protocol, and Bali Road Map (COP13) (Charfeddine, 2017). Intergenerational equity theory suggests that preserving the environment is a moral and ethical commitment for future generations (Clayton et al., 2016), (Hunt and Fund, 2016), and many researchers have emphasized the significance of formulating and imposing national, regional, and international laws that guarantee planetary rights and obligations for all generations (Charfeddine, 2017), (Demirel et al., 2017), (Foley et al., 2005). Nevertheless, these agreements have not achieved the goal of significantly reducing different types of pollutants, including CO_2 emissions. Several factors contribute to the increase in these pollutants and consequently to environmental

Table 1
Different studies on GHGs emission.

Author(s)	Elements	Period	Methodology	Findings
Omri et al. (2014)	CO_2 emissions, economic growth and foreign direct investment (FDI)	1990 – 2011	Dynamic simultaneous-equation panel data models	Bidirectional causality between the CO_2 and both the economic growth and FDI
Zhang and Bin Da (2015)	CO_2, CO_2 intensity, industrial structure and energy sources	1996 – 2010	LMDI method, decoupling index	Strong positive correlation between CO_2 and economic growth
Arvin et al. (2015)	Urbanization, transportation intensity, CO_2 emissions, and economic growth	1961 – 2012	Panel vector auto-regressive model	The network of causal connections among the extent of urbanization, economic growth, transportation intensity, and CO_2 emissions in the short- and long-run.
Shahbaz et al. (2015)	CO_2 emissions, economic growth, and energy intensity	1980–2012	Panel cointegration, VECM Granger causality,	Positive correlation between energy use and the increase of CO_2.
Alam and Paramati (2015)	Oil consumption, economic growth, internationalization, CO_2 emissions, trade openness and financial development	1980–2012	Panel cointegration tests and a vector error correction model (VECM) framework	A significant positive relationship between oil consumption, economic growth, internationalization, CO_2 emissions, trade openness and financial development.
He et al. (2017)	CO_2 emissions, affluence, population, technology	1995-2013	Stochastic impacts by regression on population, affluence and technology (STIRPAT) model	There existed an inverted U link between CO_2 emissions and urbanization in three regions.
(Muhammad)	Economic growth, energy consumption and CO_2 emissions	2001–2017	Seemingly unrelated regression (SUR), dynamic models estimated through means of the generalized method of moments (GMM), System generalized method of moments (Sys GMM)	CO_2 emissions increase in all countries due to increase in energy consumption. The CO_2 emissions increased while the energy consumption decreased in developed and MENA countries but energy consumption increased and CO_2 emissions decreased in emerging countries due to increase in economic growth.
Saidi and Omri (2020)	Renewable energy, nuclear energy, CO_2 emissions	1990–2018	Modified OLS (FMOLS), the vector error correction model approach (VECM) estimation methods	Investments in nuclear and renewable energy reduce CO_2 emissions.
Hu et al. (2020)	CO_2 emissions, income,	1991-2016	Tapio decoupling model, Kaya-LMDI model	CO_2 emissions significantly rise due to economic growth. Energy intensity reduces CO_2 emissions to some extent. Energy exports increase CO_2 emissions to varying degrees.
Dauda et al. (2021)	Innovation, CO_2 emissions	1990-2016	Cross Sectional Augmented Dickey Fuller (CADF), Westerlund and Johansen cointegration tests, fixed effect model and generalized method of moments, ordinary least square	Inverted U-shape relationship between innovation and CO_2 emission at panel level. Renewable energy use lessens CO_2 emissions. Human capital decreases CO_2 emissions.
Ko ç ak et al. (2020)	CO_2 emissions, tourism developments	1995-2014	Continuously updated fully modified (CUP-FM), the continuously updated bias-corrected (CUP-BC) estimators	Tourism arrivals have an increasing effect on CO_2 emissions, while tourism receipts have a reducing effect on CO_2 emissions.
Danish and Zhang (2019)	Natural resources' abundance, carbon dioxide (CO_2) emissions	1990-2015	The augmented mean group (AMG) panel algorithm	Abundance of natural resources mitigates CO_2 emission.
Khan et al. (2019)	Globalization, economic factors, energy consumption, CO_2 emissions	1971-2016	Dynamic ARDL simulations model	Energy consumption, financial development, trade, foreign direct investment, economic globalization, social globalization and political globalization have positive effect on CO_2 emissions. Urbanization, economic growth and innovation have negative effect on CO_2 emissions.
Chen et al. (2018)	CO_2 emission intensity of fossil energy, energy consumption structure, energy intensity, per capita Gross Domestic Product (GDP), population distribution, population size, CO_2 emissions	2001-2015	Logarithmic Mean Divisia Index (LMDI). Tapio decoupling analysis, the LMDI decomposition formula	Energy intensity and per capita GDP are the main factors affecting CO_2 emissions. The impact of population distribution on CO_2 emissions is negligible.
Ali et al. (2019)	Urbanization, carbon dioxide emissions	1972–2014	Auto Regressive Distributed Lag (ARDL), VECM model	Urbanization was found to enhance CO_2 emissions both in the long- and short- terms.

degradation, including human activities, urbanization, energy use, and population growth (Shahbaz et al., 2013), (Sadorsky, 2014).

Various studies have explored the link between environmental degradation and other determinants, such as economic growth, internationalization, foreign direct investment (FDI), transportation intensity, population, industrial structure, and energy use and consumption at different time periods (see Table 1). These studies have found a positive correlation between CO_2 emissions and these determinants. For example, economic growth was found to be the main driver of increased CO_2 emissions in China (Zhang and Bin Da, 2015). From the perspective of industrial development, innovative global achievements in reducing CO_2 emissions are a major concern with globalization. One of the strategies adopted to control global warming is to lower the percentage of CO_2 emissions. Ma et al. (2016) investigate the relationship between economic growth and Chinese household CO_2 emissions during 1994–2012 based on a decoupling indicator. The results of their study revealed that China's household CO_2 emissions increased rapidly between 1994 and 2012, owing to an increase in energy consumption due to economic growth. Furthermore, the study demonstrated weak expansive decoupling and a decoupling state during the change in CO_2 emissions resulting from economic and population growth. Muhammad (Muhammad) investigated the unidirectional effects of energy consumption, economic growth, and CO_2 emissions for 68 countries between 2001 and 2017. The results of the study revealed a positive relationship between economic growth and energy consumption in developed and emerging countries but a negative relationship in MENA countries. The study also found that when energy consumption decreased, CO_2 emissions increased in developed and Middle East and North Africa (MENA) countries. However, the study found that energy consumption increased and CO_2 emissions decreased in emerging countries because of economic growth.

Qatar is considered one of the highest per capita carbon dioxide (CO_2) emitters worldwide (Salahuddin and Gow, 2019b). CO_2 emissions are one of the primary causes of climate change that has severely affected Qatar's economy, such as the supply of desalinated water, public health, and food security (Zhang et al., 2017), (Al-Maamary et al., 2017). Over the past 50 years, Qatar has experienced one of the fastest growth rates in energy consumption worldwide due to population and economic growth, and recently, because of the preparation for the 2022 FIFA World Cup and the objectives of the Qatar National Vision 2030 (Abulibdeh, 2021a). However, the country depends exclusively on hydrocarbons for its energy supply (Al-Awadhi et al., 2022)– (Ghofrani et al., 2021). Qatar is ranked third in terms of having the largest natural gas (LNG) reserves in the world (Salahuddin and Gow, 2019a); hence, the economy of the country heavily depends on natural sources that contribute significantly to government revenues (Abulibdeh et al., 2019).

Over the past three decades, the world has witnessed an increasing concentration of GHGs, particularly CO_2, emitted to the atmosphere. GHG emissions are considered the main contributors to global climate change (Pachauri et al., 2014), (Wu et al., 2020). Countries worldwide must collaborate to face this common challenge by reducing CO_2 emissions. Therefore, Qatar has increased its commitment nationally and internationally toward reducing climate-changing carbon emissions. Qatar has ratified several international agreements, implemented stronger policies and initiatives, and developed strong clean projects. For instance, Qatar was among the first countries to accede to the United Nations Framework Convention on Climate Change in 1996, to ratify the Kyoto Protocol in 2005, and the recent Paris Agreement in 2016 (Charfeddine et al., 2018). Moreover, policymakers are developing compressed natural gas (CNG) as an alternative fuel in Qatar's public transport sector. The second project is the Jetty Boil-Off Gas (JBOG) Recovery Facility, designed to reduce CO_2 emissions by approximately 2.5 million tonnes per year. Other initiatives include the gigantic target of manufacturing the first Qatari electric cars by 2023, aiming to commercialize approximately 500,000 electric cars by 2024. Qatar also plans for 10% of the transport energy mix to be produced from renewable energy, and 2% and 20% of electricity generation to be from renewable power by 2020 and 2030, respectively (Charfeddine et al., 2018).

The structure of the paper is organized as follows: section 2 gives insight into the GHG emissions profile in the State of Qatar and dives in details into the different types of GHGs emissions, their sources, and their annual growth. Section 3 describes the data and variables used in the study. Section 4 details the empirical methodology used and its implementation in the study. Section 5 presents the detailed empirical findings and discussion. Finally, section 6 provides the conclusion, policy implications and recommendations.

2. GHG emissions profile in the state of Qatar

2.1. GHGs emission in Qatar

Population and economic growth was accelerated in the State of Qatar from 1970s due to the massive reserves and trade of the natural resources oil and gas (Abulibdeh, 2021a). During the past two decades, Qatar witnessed a rapid and massive urban development driven lately by winning the right to host the 2022 FIFA World Cup (Zaidan and Abulibdeh, 2018). The country witnessed as well a rise in government expenditure and large-scale investment projects resulting in increased population and economic growth rate. For example, the population and economic growth rates in the country between 2004 and 2016 were 10% and 15%, respectively (Abulibdeh, 2021a). The main financial source and the keystones for this development was the revenues from the hydrocarbon resources (Zaidan and Abulibdeh, 2020), (Abulibdeh, 2021b). The production and usage of oil and gas are main contributors to the deterioration of the environment. This gradually increased the atmospheric GHGs emissions concentrations in the country (Charfeddine, 2017). The GHGs emissions plays a major role in increasing land and air surface temperature contributing in the global warming phenomenon. This section presents GHG emissions profile in Qatar.

Figure (1a) shows the total GHG emissions, including the land use changes. The figure indicates that GHG emissions in Qatar have increased rapidly during the past three decades. Figure (1b) illustrates how much GHGs the average person emits, calculated as the total emissions owing to human activities in the country divided by the total population. The figure shows an increase in the per capita GHG emissions, reaching a peak in 2005, and decreasing thereafter. This might be due to the global economic recession and the increase in population after 2010, when the country began preparing for the 2022 FIFA World Cup. The electricity and heat sector has the highest GHG emissions, followed by the manufacturing, construction, and transport sectors, as illustrated in Figure (1c). The emissions increased in all sectors during the last two decades owing to the development that took place in the country. However, agricultural and fugitive emissions from the energy production sectors produced the highest GHG emissions between 2000 and 2010, as shown in Figure (1d).

Methane (CH_4) is a key GHG emitted in Qatar in different sectors. These strong GHGs are measured in tonnes of carbon dioxide equivalents (CO_2e) based on a 100-year global warming potential value. Figure (2a) shows that this type of GHG has been increasing in the country over time; however, the per capita CH_4 emissions have started to decrease over the last two decades, as indicated in Figure (2b). The main sources of CH_4 in Qatar are fugitive emissions (leakages from oil and gas production) and other fuel combustion, as shown in Figure (2c).

Nitrous oxide (N_2O) is another GHG that has increased substantially in Qatar over the last two decades, as demonstrated in Figure (3a). N_2O emissions are measured in tonnes of carbon dioxide equivalents (CO_2e) based on a 100-year global warming potential value. Figure (3b) shows that the per capita N_2O emissions fluctuated during the last two decades. Agriculture (e.g., from the use of synthetic and organic fertilizers) and other fuel combustion are the major sectors that contribute to the

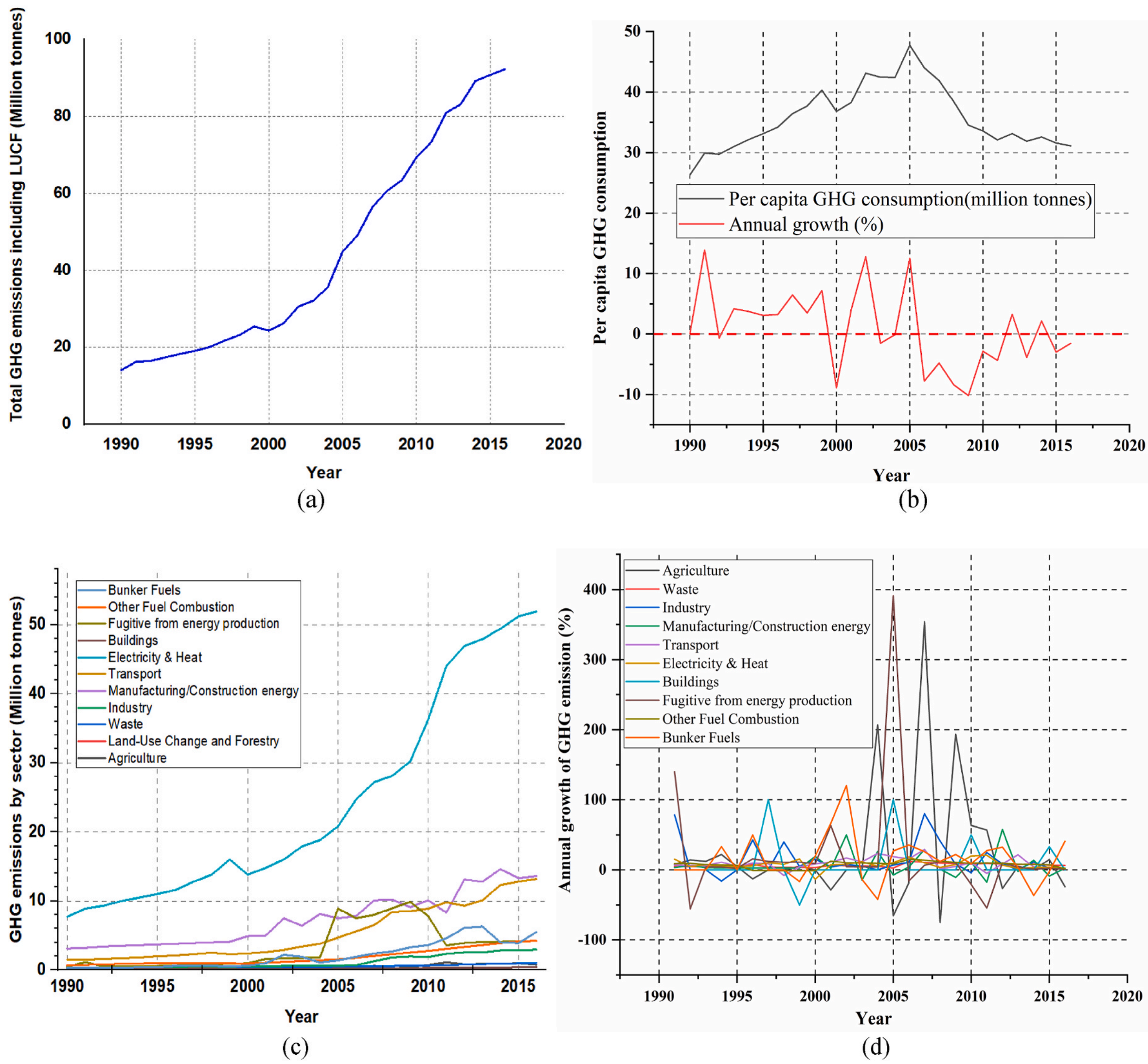

Fig. 1. GHGs emission in Qatar.

emissions of this gas, as shown in Figure (3c).

Production-based emissions represent the CO_2 emitted within the boundaries of Qatar. However, this fails to capture the emissions from traded goods (e.g., the CO_2 emitted in the production of goods elsewhere and imported to the country or the emissions from exported goods). Consumption-based CO_2 emissions are domestic emissions corrected for trade. The production and consumption of CO_2 emissions are presented in Figure (4a). The footprint of the average person (per capita emissions) in Qatar is provided in Figure (4b). The yearly growth in annual CO_2 emissions is shown in Figure (4c), where positive values indicate that CO_2 emissions in a given year were higher than in the previous year, while a negative value indicates that emissions were lower than in the previous year. The country's share of CO_2 emissions is measured by the country's CO_2 emissions, international aviation and shipping, plus the 'statistical differences' in the carbon accounts in a given year divided by the sum of the global emissions in the given year. Figure (4e) presents the annual emissions as a percentage of the global total for a given year. Figure (4f) shows the share of CO_2 emissions embedded in trade, measured as the emissions exported or imported, as the percentage of domestic production emissions. The figure shows negative values of the share of CO_2 emissions, which indicates net exporters of CO_2 (i.e. "30%" would mean Qatar exports emissions equivalent to 30% of its domestic emissions). CO_2 emissions in Qatar are from different sources and are dominated by the industrial production of materials such as cement and burning fossil fuels for energy production, as indicated in Figure (4 g). The figure shows that gas was the predominant source of CO_2 emissions in the country, followed by oil. Qatar has the third largest reserves of gas in the world and is ranked first in exporting liquefied gas. The CO_2 emissions are strongly associated with the energy mix available in the country. However, CO_2 emissions from these sources have decreased over the past two decades, as demonstrated in Figure (4h). Fig. 5 illustrates the relationship between the per capita consumption CO_2 and GDP, indicating an inverse relationship between the two.

2.2. Energy consumption and CO_2 emissions

The rapid economic growth that Qatar witnessed and in fact continues to witness poses a number of challenges including increasing energy demand (Abulibdeh, 2019; Al-Marri et al., 2018; Zaidan et al., 2022). Several studies examined the correlation between energy consumption and GHGs emissions (Muhammad), (Wu et al., 2020), (Saidi and Omri, 2020), (Salahuddin et al., 2018). Understanding this correlation enable governments to develop energy saving strategies as well emission reduction policies for mitigating the impacts on climate and slow down climate change. This section give more insight on the energy consumption effect on CO_2 emissions in Qatar.

Fig. 6a indicates that energy is a key contributor of the CO_2 emissions in the country. Qatar is characterized by excessively high rates of energy

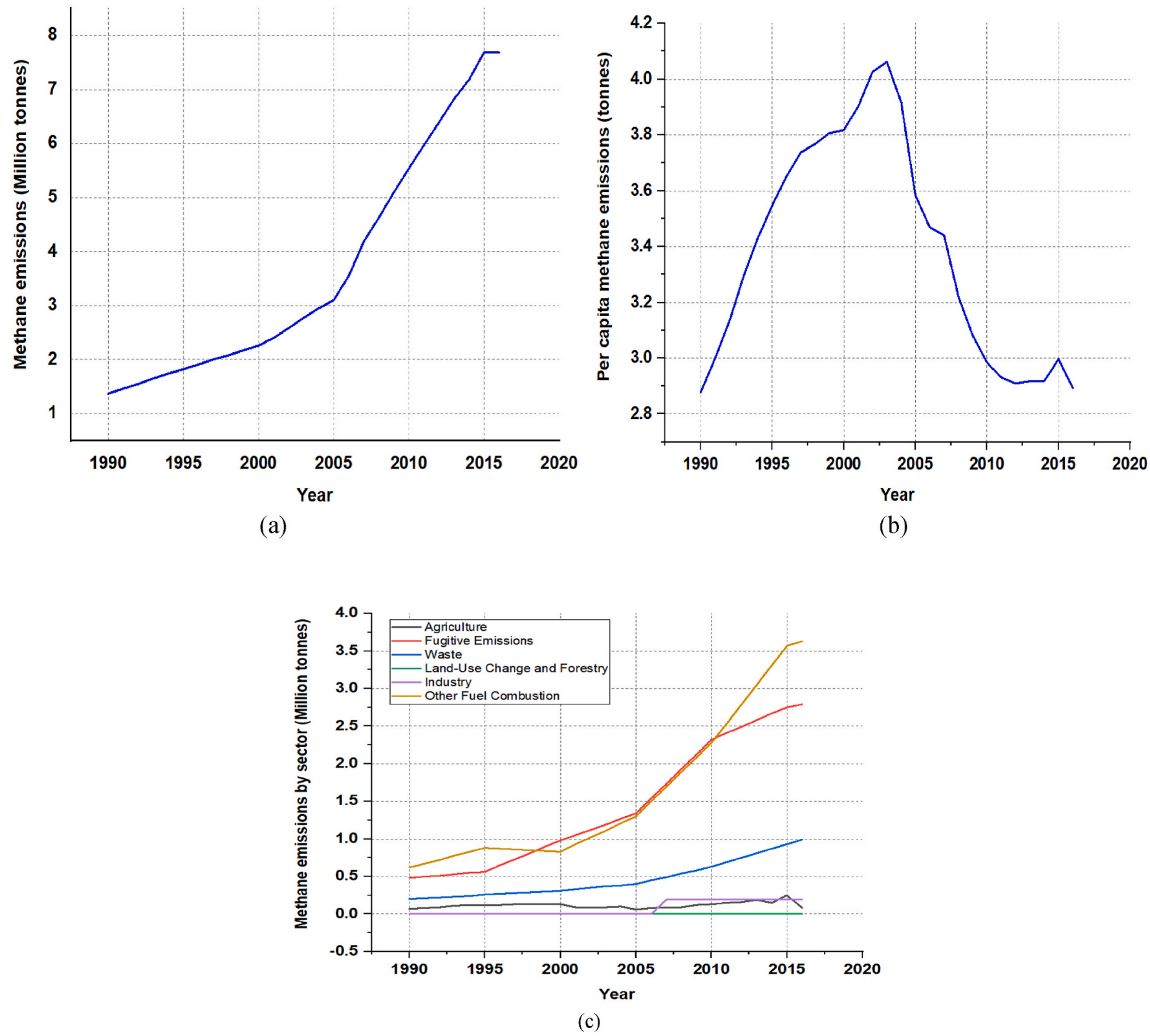

Fig. 2. Methane emissions in Qatar.

use due to the population and economic growth. Furthermore, Qatar is located in arid region with a high level of water scarcity (Abulibdeh, 2021c). The country depends on non-renewable water sources to meet the needs of the population and economic activities. Therefore, seawater desalination has been adopted as a solution to produce fresh water and overcome this water scarcity (Abulibdeh, 2019). Seawater desalination is energy-intensive process that adds to the country's energy demand and subsequently high emissions. Therefore, reducing energy consumption can help to reduce emissions. Energy intensity is a useful metric to monitor, calculated as the amount of primary energy consumption per unit of gross domestic product in kilowatt-hours per 2011$ (PPP). Energy intensity can be used to effectively measure how efficiently Qatar uses energy to produce a given amount of economic output. A lower energy intensity means that the country needs less energy per unit of GDP. The carbon intensity of energy production (i.e., the amount of CO_2 emitted per unit of energy) is another valuable metric to monitor whether countries are making progress in reducing emissions. It is measured as the quantity of carbon dioxide emitted per unit of energy production in kilograms of CO_2 per kilowatt-hour. Using lower-carbon energy and transitioning the energy mix toward lower-carbon sources helps to reduce carbon emissions emitted per unit energy. Fig. (6b) presents the annual CO_2 emissions per unit energy in the State of Qatar. The figure clearly demonstrates that the annual CO_2 emissions per unit energy was reduced during the last two decades.

3. Data and variables description

In this study, per capita GHG emissions, per capita methane emissions, per capita nitrous oxide emissions, and per capita CO_2 emissions were used as proxies for the environmental degradation in the State of Qatar. The GHG data emissions were obtained from different resources, including the World Bank, Worldometer, Climate Analysis Indicators Tool, and Our World in Data. These GHG emissions are summed and measured in tonnes of carbon dioxide equivalents (CO_2e) based on the 100-year global warming potential factors for non-CO_2 gases, meaning that gases have the same warming effect as CO_2 over a period of 100 years. Therefore, the emissions of each gas were multiplied by its 'global warming potential' (GWP) value. The GWP measures the amount of warming that one-ton of that gas would create relative to one-ton of CO_2. The estimates of CO_2 emissions include fossil fuel combustion from different activities and functionalities (e.g., industry, transport, natural gas flaring, heating and cooling, and fossil industry use), production of cement, production of chemicals and fertilizers, and CO_2 uptake during the cement carbonation process. Furthermore, the estimation of CO_2 emissions relied primarily on the energy consumption data. The explanatory variables used to assess environmental degradation include economic growth, represented by GDP, electricity consumption, energy consumption, and CPI. The dependent and independent variables are expressed as per capita or GDP. Annual data for 1990–2019 were used in

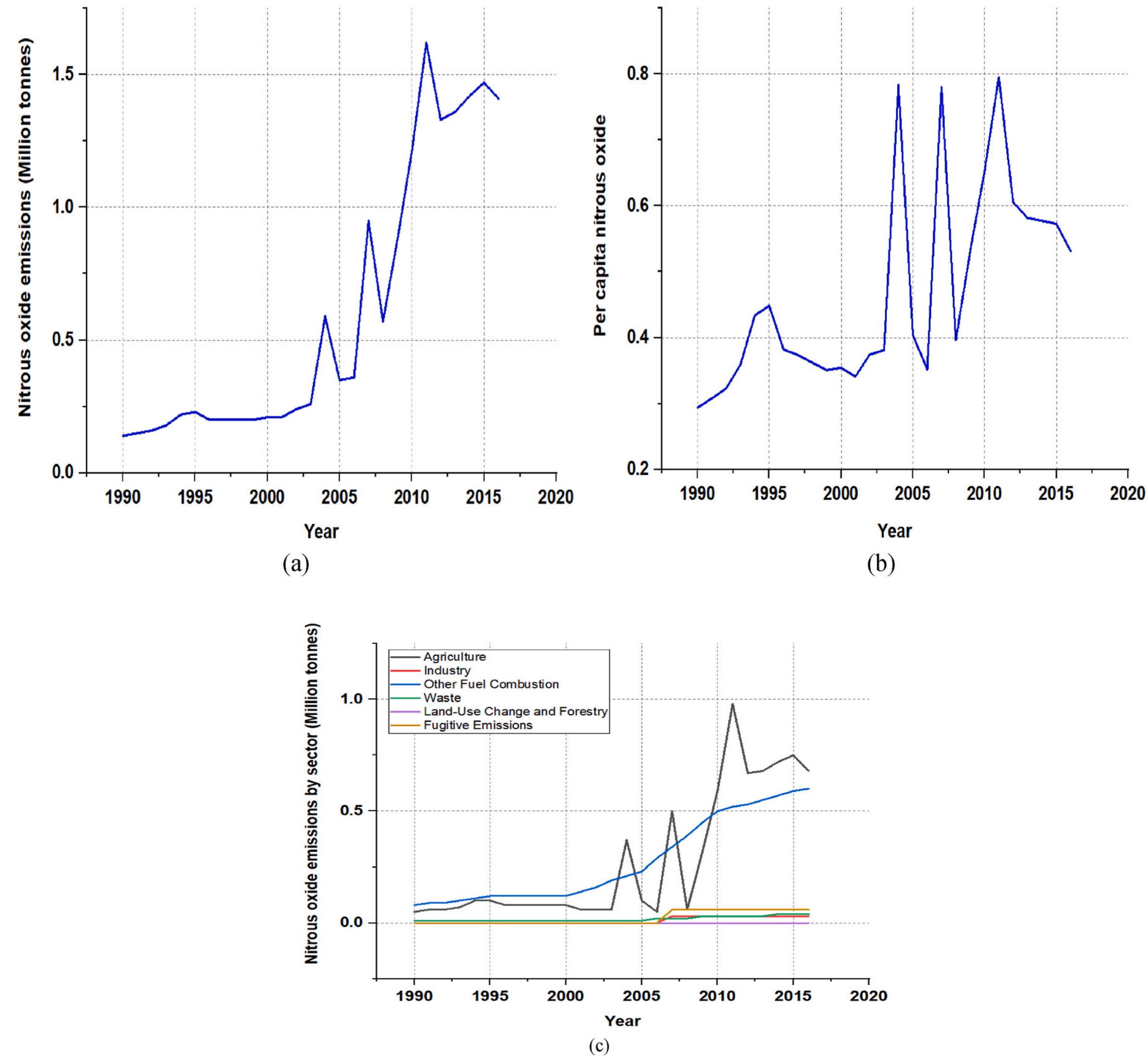

Fig. 3. Nitrous oxide emissions in Qatar.

this study for the State of Qatar. Table 2 lists the dependent variables used in this study.

4. Methodology

This study examined the long-term and short-term relationships between four indicators of environmental quality (per capita GHG emissions, per capita methane emissions (ME), per capita nitrous oxide (NO) emissions, and per capita CO_2 emissions) as dependent variables to develop four models to measure the environmental quality in Qatar. Four determinants (independent variables) were used to examine their effects on environmental quality, including economic growth (GDP), energy consumption (ENER), electricity consumption (ELEC), and the crop production index (CPI), from 1990 to 2019 in the state of Qatar. Accordingly, four models were constructed to examine the impact of the independent variables on environmental quality. The first model investigated the impacts of these independent variables on environmental quality using the per capita CO_2 emissions as the dependent variable ($GHGCO_2$), while models 2 (GHGF), 3 (GHGME), and 4 (GHGNO) were constructed using the F-GHGs, per capita ME, and per capita NO emissions as the dependent variables. A linear form was constructed to examine the long-term, short-term, and causality relationships between the dependent and independent variables, as specified in Equation (1).

$$GHG_n = \beta_0 + \beta_1 GDP_t + \beta_2 ELEC_t + \beta_3 ENER_t + \beta_4 CPI_t + \varepsilon_t \quad (1)$$

where *GHGn* is $GHGCO_2$, GHGF, GHGME, and GHGNO; β_0 is a constant form; β_1–β_4 are coefficients of the model; and ε_t is an error term. To ensure the mobilization of stationarity in the variance–covariance matrix, all the variables used in this study were transformed into natural logarithms (ln) (Chang et al., 2001). The log-linear model specification avoids heteroscedasticity problems and generates more efficient and symmetric results (Lau et al., 2014). The proposed methodology to assess the environmental degradation in the State of Qatar is shown in Fig. 7.

4.1. Unit root test

Different methodological steps were considered to examine the long- and short-term relationships between the dependent variables and their determinants. Stationary tests were conducted to determine the unit root of the time-series data. To detect the stationarity at I (0), I (1), or I (d), the augmented Dickey-Fuller test statistic using generalized least squares (DF-GLS), Phillips–Perron (P–P), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) were employed (Bekhet et al., 2017). However, unlike the other tests, the KPSS unit root test considers the series in

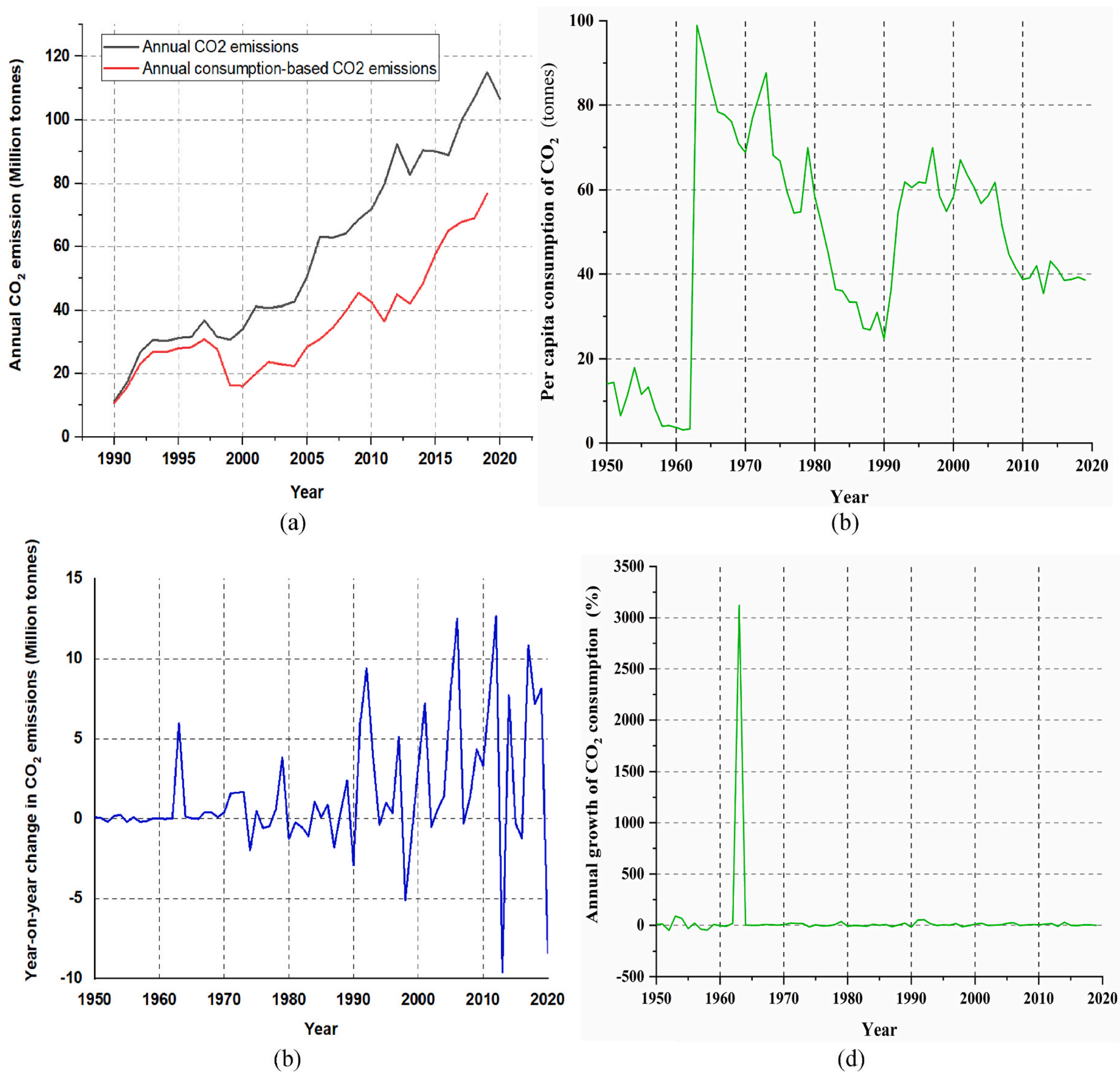

Fig. 4. CO_2 emissions in Qatar.

the null hypothesis to be level-stationary. A stationarity test is necessary before conducting the regression analysis, because if the time series is non-stationary, the regression results will become spurious. Furthermore, a regression analysis would not be true if the time-series data were not stationary. In this case, it is a spurious regression (Bekhet et al., 2017). It is necessary to ensure that the variables are not at the I (2) stationary level prior to processing a bounds-testing approach to avoid spurious results (Pesaran et al., 2001). Furthermore, bounds testing is based on the assumption that the variables are stationary at I (0), I (1), or both. Therefore, the F-statistics are not valid if the variables are stationary at I (2). To ensure that none of the variables are stationary at the I (2) level, the implementation of a bounds test procedure may still be necessary.

4.2. Unit root test assuming a single break point in data

The Zivot–Andrews (Zivot and Andrews, 2012) unit root test was employed to identify the presence of a single structural break point in the data. Structural tests can take the following form, considering the series as X (Salahuddin and Gow, 2019b):

$$\Delta X_t = \Phi + \Phi X_{t-1} + ct + dD_t + dDT_t \sum_{j=1}^{k} d_j \Delta X_{t-j} + \varepsilon_t \quad (2)$$

$$\Delta X_t = \propto + \propto X_{t-1} + bT + cD_t + \sum_{j=1}^{k} d_j \Delta X_{t-j} + \varepsilon_t \quad (3)$$

$$\Delta X_t = ¥ + ¥X_{t-1} + ct + bDT_t + \sum_{j=1}^{k} d_j \Delta X_{t-j} + \varepsilon_t \quad (4)$$

$$\Delta X_t = \gamma + \gamma X_{t-1} + ct + dDT_t + \sum_{j=1}^{k} d_j \Delta X_{t-j} + \varepsilon_t \quad (5)$$

where:

D: is a dummy variable shows the mean shift at each point.

DTt: is a trend shift variable.

In the Zivot–Andrews test, the null hypothesis (C = 0) states that the presence of a unit root in the data is without a structural break, against the alternative that the series trend is stationary with an unknown time break. Therefore, the Zivot–Andrews unit root test selects the time break

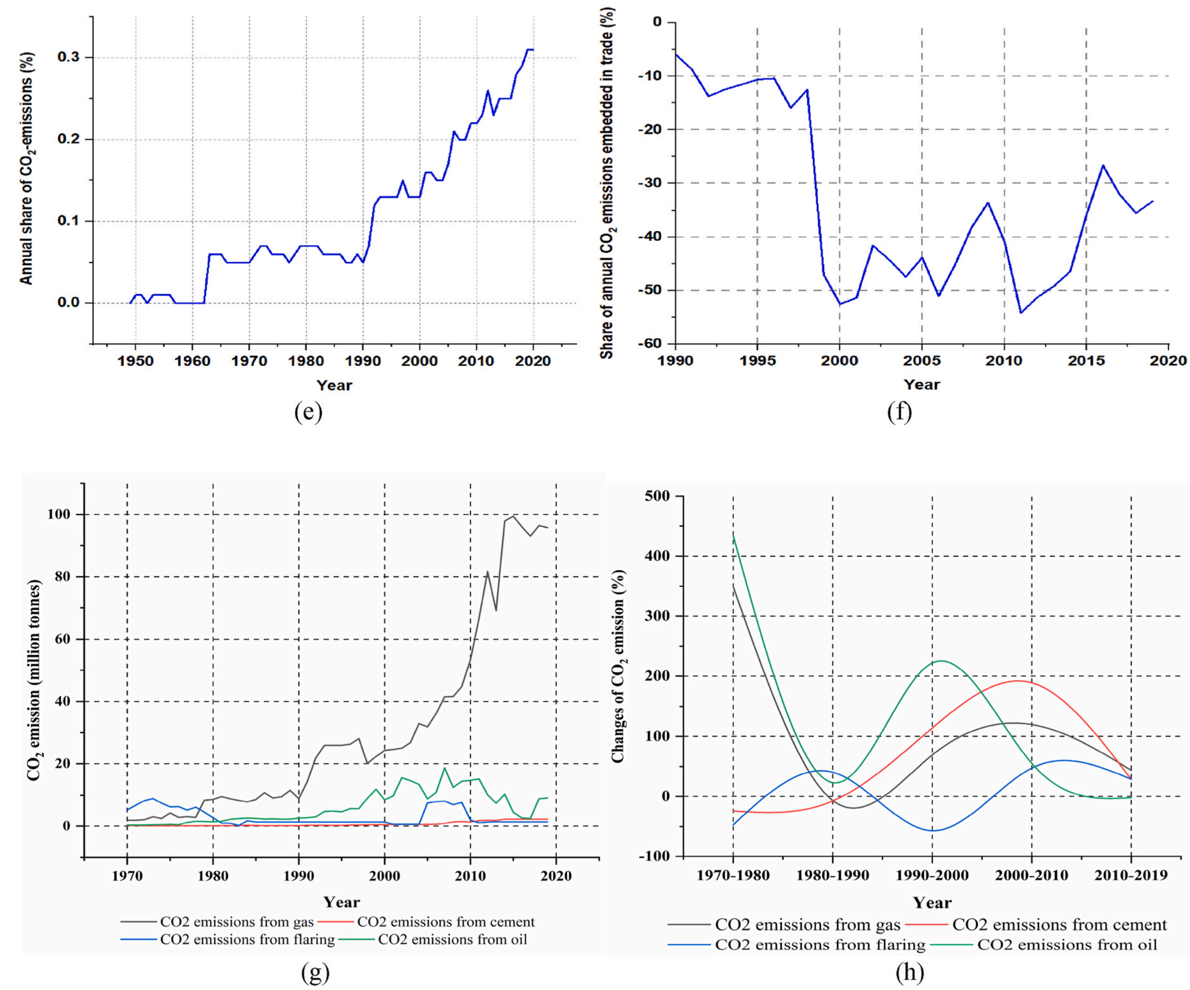

Fig. 4. (*continued*).

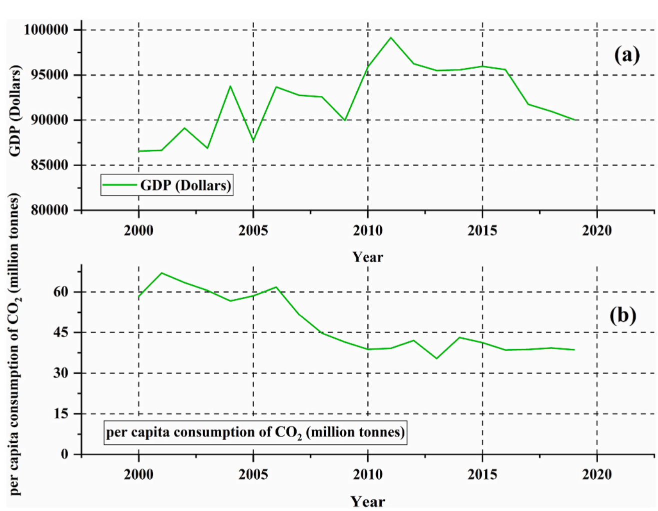

Fig. 5. Relationship between per capita consumption CO_2 and GDP.

that reduces the one-sided t-statistics to test c (= c−1) = 1 (Salahuddin et al., 2018).

4.3. ARDL bounds testing approach to cointegration

Conventional cointegration techniques do not provide reliable results when data are plagued with structural breaks (Uddin et al., 2013). Therefore, autoregressive distributed lag (ARDL) bounds testing, proposed by (Shahbaz et al., 2012), was used in this study to estimate the cointegrating or long-term and short-term relationships between the variables. The ARDL technique has been used in different studies and has been proven to be efficient in cases of small sample sizes (Pesaran et al., 2001). It also removes the problems of omission bias and autocorrelation (Salahuddin et al., 2018). The ARDL bounds testing approach has various advantages compared to other co-integration models; therefore, it is considered superior and preferable, particularly for small samples (Shahbaz et al., 2012). The ARDL model uses more appropriate considerations than the Johansen–Juselius (J-J) (Johamen and Jtiselius, 1990) and Engle and Granger (2015) models to test the co-integration among variables in a small sample (Ghatak and Siddiki, 2010) unlike the J-J co-integration model, which requires a large data sample for validity (Bekhet et al., 2017). Furthermore, the ARDL model can be applied if the underlying variables are purely I (0), purely I (1), or mixed, whereas other models require that all the underlying variables are integrated in the same order (Pesaran et al., 2001). Another advantage of the ARDL model is that it allows the variables to have different optimal lags that are not available when using conventional cointegration procedures (Ozturk and Acaravci, 2011). Therefore, ARDL bounds testing uses a proper lag order to capture the data-generating procedure and is considered sufficient to simultaneously correct for residual correlation and endogeneity problems. Furthermore, the ARDL model provides unbiased estimates of long-term and short-term models and valid t-statistics, even in the presence of endogeneity problems

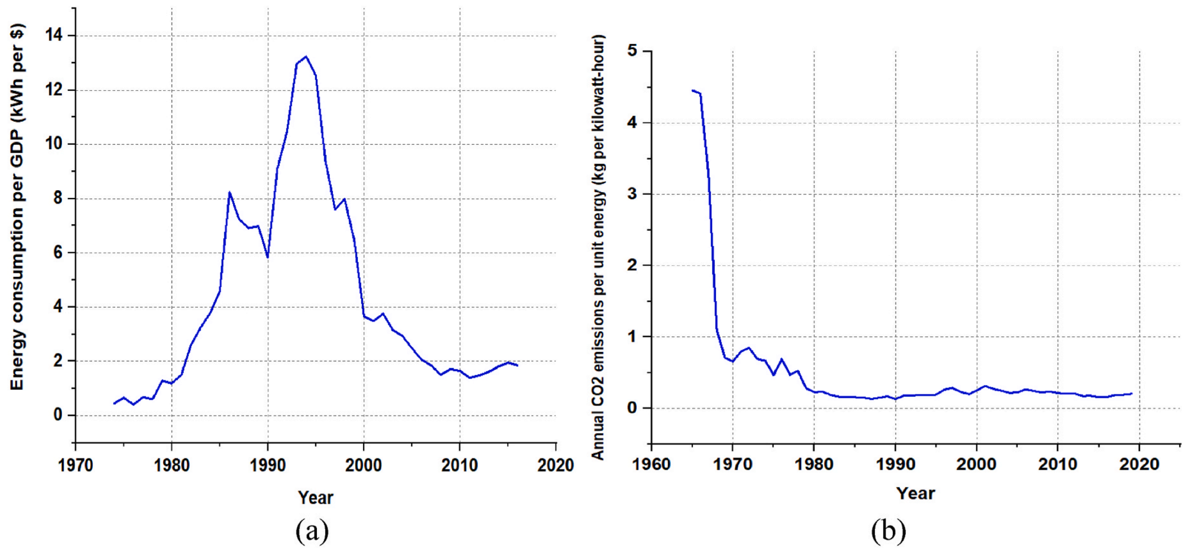

Fig. 6. (a) Energy consumption, (b) annual CO_2 emissions per unit energy.

Table 2
Dependent variables used in this study.

Variable	Unit	Definition
CO_2 emissions (CO_2)	Metrics tonnes per capita	CO_2 are the primary driver of global climate change and is the most dominant GHG produced by land use change, industrial production, and burning of fossil fuels.
Greenhouse gas emissions (GHG)	metrics tonnes per capita	Other GHG includes F-gases (hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF6)). These gases are summed and used in this study as other GHGs emissions. These gases contributed significantly in global climate change. The sources of these emissions are mainly from refrigeration/AC, aerosols, and semiconductors.
Methane emissions (CH_4). In this study, ME is used to denote Methane.	metrics tonnes per capita	The main source of ME is the agricultural emissions, produced by aerobic and anaerobic decomposition processes in crop and livestock production and management activities. The subdomains of the agricultural emissions that produce Methane include enteric fermentation, manure management, and burning-crop residues.
Nitrous oxide emissions (N_2O). In this study, NO will be used to denote Nitrous oxide	metrics tonnes per capita	The main source of NO is the agricultural emissions, produced by aerobic and anaerobic decomposition processes in crop and livestock production and management activities. The subdomains of the agricultural emissions that produce NO include agriculture soils, manure applied to soils, manure management, synthetic fertilizers, burning-crop residues, and crop residues.

(Harris and Sollis, 2003). This method enables the convenient use of a single reduced-form equation, long-term equilibrium, and estimation of short-term dynamics simultaneously within a dynamic unrestricted error correction model (UECM) (Shahbaz et al., 2012). Therefore, this study employs the ARDL bounds model to investigate the equilibrium relationships among variables. The empirical formulation of the ARDL equations for the models is as follows:

$$\begin{aligned}\Delta lnCO_2Q_{nt} &= \beta_0 + \alpha_1 lnCO_2Qn_{t-1} + \alpha_2 lnGDP_{t-1} + \alpha_3 lnELEC_{t-1} \\ &+ \alpha_4 lnENER_{t-1} + \alpha_5 CPI_{t-1} + \sum_{i=1}^{n}\beta_{1i}\Delta lnCO_2Q(n)_{t-i} + \sum_{i=0}^{n}\beta_{2i}\Delta lnGDP_{t-i} \\ &+ \sum_{i=0}^{n}\beta_{3i}\Delta lnELEC_{t-i} + \sum_{i=0}^{n}\beta_{4i}\Delta lnENER_{t-i} + \sum_{i=0}^{n}\beta_{5i}\Delta lnCPI_{t-i} + \mu_t\end{aligned} \tag{6}$$

$$\begin{aligned}\Delta lnMEQ_{nt} &= \beta_0 + \alpha_1 lnMEQn_{t-1} + \alpha_2 lnGDP_{t-1} + \alpha_3 lnELEC_{t-1} \\ &+ \alpha_4 lnENER_{t-1} + \alpha_5 CPI_{t-1} + \sum_{i=1}^{n}\beta_{1i}\Delta lnMEQ(n)_{t-i} + \sum_{i=0}^{n}\beta_{2i}\Delta lnGDP_{t-i} \\ &+ \sum_{i=0}^{n}\beta_{3i}\Delta lnELEC_{t-i} + \sum_{i=0}^{n}\beta_{4i}\Delta lnENER_{t-i} + \sum_{i=0}^{n}\beta_{5i}\Delta lnCPI_{t-i} + \mu_t\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta lnNOQ_{nt} &= \beta_0 + \alpha_1 lnNOQn_{t-1} + \alpha_2 lnGDP_{t-1} + \alpha_3 lnELEC_{t-1} \\ &+ \alpha_4 lnENER_{t-1} + \alpha_5 CPI_{t-1} + \sum_{i=1}^{n}\beta_{1i}\Delta lnNOQ(n)_{t-i} + \sum_{i=0}^{n}\beta_{2i}\Delta lnGDP_{t-i} \\ &+ \sum_{i=0}^{n}\beta_{3i}\Delta lnELEC_{t-i} + \sum_{i=0}^{n}\beta_{4i}\Delta lnENER_{t-i} + \sum_{i=0}^{n}\beta_{5i}\Delta lnCPI_{t-i} + \mu_t\end{aligned} \tag{8}$$

$$\begin{aligned}\Delta lnGHGQ_{nt} &= \beta_0 + \alpha_1 lnGHGQn_{t-1} + \alpha_2 lnGDP_{t-1} + \alpha_3 lnELEC_{t-1} \\ &+ \alpha_4 lnENER_{t-1} + \alpha_5 CPI_{t-1} + \sum_{i=1}^{n}\beta_{1i}\Delta lnGHGQ(n)_{t-i} + \sum_{i=0}^{n}\beta_{2i}\Delta lnGDP_{t-i} \\ &+ \sum_{i=0}^{n}\beta_{3i}\Delta lnELEC_{t-i} + \sum_{i=0}^{n}\beta_{4i}\Delta lnENER_{t-i} + \sum_{i=0}^{n}\beta_{5i}\Delta lnCPI_{t-i} + \mu_t\end{aligned} \tag{9}$$

where β_{1i} - β_{5i} , α_1-α_5 are coefficient, β_0 is a constant and, μ_t is white noise error term. The error correction models for the above models are specified as follows:

$$\begin{aligned}\Delta lnGHG_sQ_{nt} &= \beta_0 + \sum_{i=1}^{n}\beta_{1i}\Delta lnGHQ_sQn_{t-i} + \sum_{i=0}^{n}\beta_{2i}\Delta lnGDP_{t-i} \\ &+ \sum_{i=0}^{n}\beta_{3i}\Delta lnELEC_{t-i} + \sum_{i=0}^{n}\beta_{4i}\Delta lnENER_{t-i} + \sum_{i=0}^{n}\beta_{5i}\Delta lnCPI_{t-i} + \mu_t\end{aligned} \tag{10}$$

The cointegrating relationship is examined by conducting a Wald test

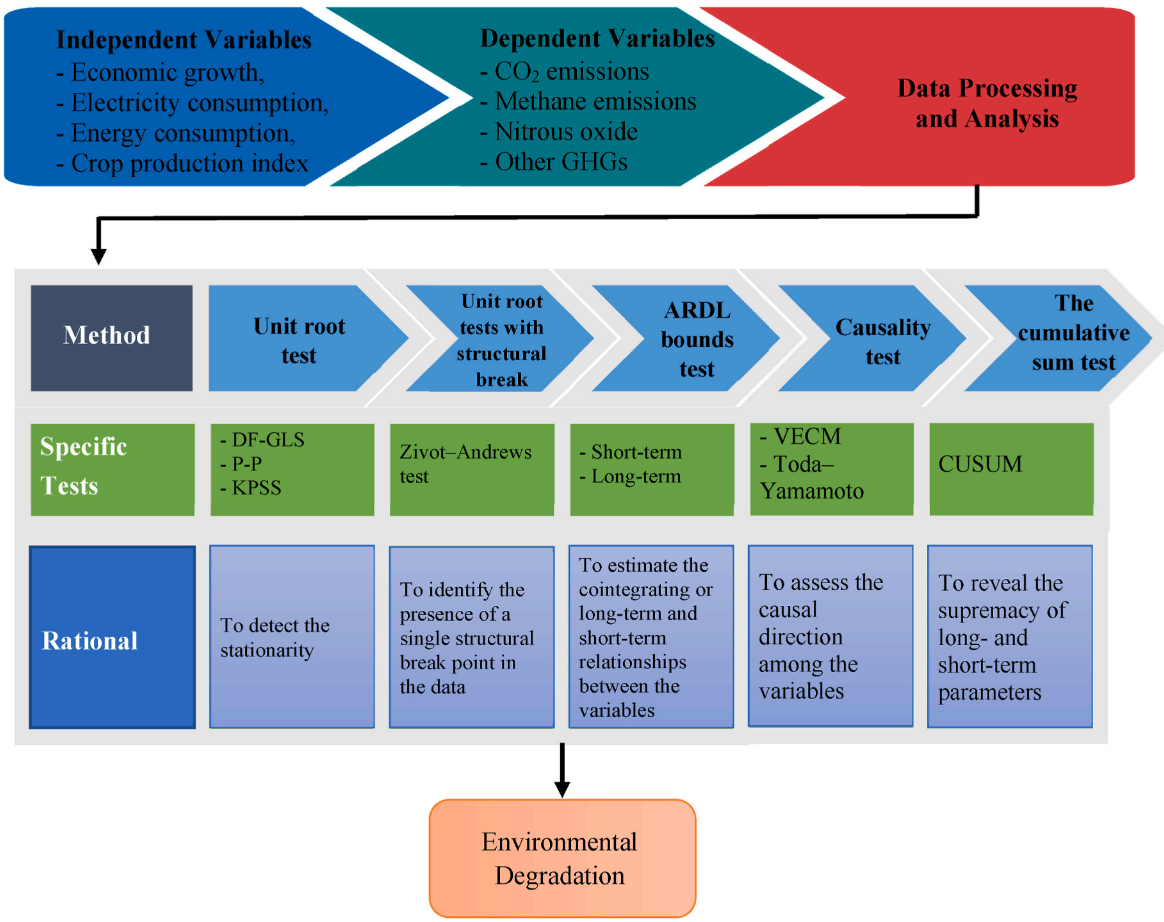

Fig. 7. Proposed methodology flowchart to assess the environmental degradation in Qatar.

and an F-test for the joint significance of the coefficients of the lagged variables, assuming the null hypothesis, as there is no cointegration among the variables against the alternative hypothesis of the presence of cointegration among variables. The short-term, long-term, and ECT–1 (error correction term that shows the speed of adjustment of short-term deviations towards the long-term equilibrium) are estimated using the ARDL method.

4.4. Causality test

The Toda–Yamamoto (TY) causality analysis and the vector error correction model (VECM) short-term Granger causality test were performed to assess the causal direction among the variables to provide a better understanding of the policy implications of the empirical findings. The VECM test is efficient and appropriate for estimating causal link variables once they are integrated in the same order (Salahuddin et al., 2018), (Granger, 1969). One of the main advantages of the TY test is that it is insensitive to the order of integration. In this study, the VECM short-term Granger causality test is represented according to Equation (11).

$$\Delta lnGHG_t = \beta_{0i} + \sum_{i=1}^{n} \beta_{1i}\Delta GHG_{t-i} + \sum_{i=0}^{n} \beta_{2i}\Delta lnGDP_{t-i} + \sum_{i=0}^{n} \beta_{3i}\Delta lnELEC_{t-i} + \sum_{i=0}^{n} \beta_{4i}\Delta lnENER_{t-i} + \sum_{i=0}^{n} \beta_{5i}\Delta lnCPI_{t-i} + \varepsilon_t \quad 11$$

5. Results and discussion

5.1. Descriptive statistics

To determine the nature of the data distribution, Table 3 provides the basic statistics and pre-estimation diagnostics for all the variables. The results indicate that Qatar's average CO_2 emissions are exceptionally high compared with the world average of 4.49 (Charfeddine, 2017). Overall, the mean and median results exhibit no large differences in their values for any of the variables. The standard deviation values reflect the volatile nature of the variables. Based on the standard deviation values, the data are homogeneous and are nearly normally distributed within a reasonable range. This is also shown by the kurtosis values, which indicate that the data are light-tailed to a normal distribution. The values in the table show that CO_2 emissions and CPI are negatively skewed. Fat tails are present for all the variables, as indicated by the excess kurtosis and Jarque–Bera statistics. This indicates that applying the standard estimation techniques is unlikely to provide spurious findings. This allowed us to conduct further statistical analyses and estimations.

A variance inflation factor (VIF) test was performed to examine the data multicollinearity. The test aims to quantify the extent to which the variance of the estimated coefficients is inflated when multicollinearity exists. The variance inflation factor for the nth predictor is

$$VIF_n = \frac{1}{1 - R_n^2} \quad 12$$

where R_n^2 is the R^2 value resulting from the regression of the nth predictor with the remaining predictors. The results (Table 4) of the

Table 3
Summary statistics of the data.

Definition	Variables	Mean	Median	Std. D.	Kurt.	Sk.	J-B	P-value
CO_2 emissions (metrics tonnes per capita)	CO2	51.36	54.82	11.78	2.0799	-0.43	1.70	0.43
Greenhouse gas emissions (metrics tonnes per capita)	GHG	39.76	38.28	5.59	2.262	0.427	1.34	0.511
Methane emissions (metrics tonnes per capita)	ME	3.38	3.43	0.40	1.576	0.19	2.43	0.297
Nitrous oxide emissions (metrics tonnes per capita)	NO	0.46	0.40	0.15	2.70	0.995	4.07	0.131
GDP (metric billion USD)	GDP	1.18e+11	0.39e+11	1.36e+11	2.247	0.94	4.6	0.100
Energy consumption (metric kg of oil equivalent per gdp)	ENER	4.9634	3.156	3.975	2.416	0.917	4.169	0.124
Electric power consumption (kWh per capita)	ELEC	13502.06	14153.71	2163.185	2.3205	-0.732	2.9317	0.230886
Crop Production Index	CPI	80.09926	82.65000	17.25923	2.3123	-0.2646	0.8472	0.6547

J-B is the Jarque Bera test statistic for normality hypothesis.
Std. D. Is the standard deviation.
Kurt. Is the Kurtosis.
Sk. Is the skewness.

Table 4
Multicollinearity Testing (among the independent variables): Variance Inflation Factor (VIF) results.

Feature	Variance Inflation Factor (VIF)	1/VIF
lnGDP	5.843865	0.171120
ENER	5.699187	0.175464
lnELEC	2.859047	0.349767
lnCPI	2.165853	0.461712

variance inflation factor (VIF) test suggest that the data were free from multicollinearity. The entries in the table show that there is no correlation between the predictors; therefore, the variances of the variables are not inflated.

5.2. Unit root tests analysis

The first step in the empirical analysis of the data is to conduct unit root tests to determine the order of integration of all the selected variables using three different standard unit root tests: DF-GLS, P–P, and KPSS. The results for the level and difference in the variables of these unit root tests for the State of Qatar are presented in Table 5. The results indicate that the three tests were in harmony. The table shows that most of the variables are stationary after the first difference by comparing the absolute terms of the observed values of the DF-GLS, P–P, and KPSS test statistics, with the critical values of the test statistics at the 1%, 5%, and 10% levels of significance. These results are strong indicators of stationarity at both the level and first difference. However, there are still unit roots in some variables based on the results of some tests at various levels; thus, the null hypothesis is accepted for these variables. Furthermore, the null hypothesis of non-stationarity is rejected, and it is safe to conclude that some variables are stationary at I (0), while other variables are stationary at I (1). This indicates that the variables are mutually integrated in the order of zero and one (I (0) and I (1)), which enables us to apply the ARDL test. However, these tests have been criticized for the lack of any indication or information related to the presence of structural breaks in the time series. Therefore, these tests may lead to biased results concerning the stationarity of variables (Mrabet and Alsamara, 2017).

***, **, * denotes the significant level of 1% 5% 10% respectively; Critical values for DF-GLS test are: −2.657(1%), −1.954(5%), −1.609 (10%); Critical values for PP test are: −3.711(1%), −2.981(5%), −2.630 (10%(; Critical values for KPSS test are: 0.739(1%), 0.463(5%), 0.347 (10%). For DF-GLS and PP tests, the null hypothesis H0 is that the series has a unit root (isn't stationary), while the null hypothesis for the KPSS test is that the series is stationary.

5.3. Unit root tests with structural break

Because the DF-GLS, P–P, and KPSS tests have been criticized for their poor explanatory power and inability to consider break(s) in the variables, to overcome this weakness, these variables were further examined using the Zivot–Andrews (Zivot and Andrews, 2012) structural break unit root test to allow for structural breaks in the series. The results are detailed in Table 6. The results further indicate that the null hypothesis cannot be rejected for all the variables. Most of the variables are stationary at the level and when considering the first difference stationary, that is, I (1), in the presence of single structural breaks in the variables; hence, they meet the pre-condition for cointegration. Therefore, it is safe to investigate the cointegrating relationships between the variables. The results also confirm that most of the variables are first-difference-stationary. Furthermore, the results indicate that the test detects numerous break points predominantly around two periods, the first half of the 1990s (1993, 1995) and in the 2000s (2003, 2004, 2005, 2006, and 2009), for some variables in level and first difference, as shown in the table. The break in 1993 may have been due to the first Gulf War in 1990, and the break in 2009 may be attributed to some effects of the global financial crisis. This indicates that the pattern of change in these variables is not characterized by significant volatility.

5.4. ARDL cointegration analysis

The unit root test demonstrates that most of the variables are stationary and integrated with the first order; therefore, the next step is to

Table 5
Standard unit root tests (checking for stationarity).

Variables	Level			First Difference		
	DF-GLS	P–P	KPSS	DF-GLS	P–P	KPSS
lnGDP	-0.9139	-0.5452	0.77***	-2.6781***	-2.9018*	0.1503
ENER	-2.8380***	-0.9361	0.6040**	-2.6810***	-3.9287***	0.1439
lnELEC	-1.0735	-2.0491	0.5136**	-1.9127*	-4.9106***	0.3925*
lnCPI	-1.6758*	-3.2072**	0.4900**	-4.3805***	-5.8707***	0.1743
lnCO_2	-1.6855*	-3.0424**	0.2710	-2.7840**	-4.4815***	0.4307*
lnGHG	-1.3252	-2.0537	0.2106	-3.5690***	-4.5110***	0.5599**
lnME	-1.2630	-1.2728	0.2873	-1.9336*	-1.9	0.4569*
lnNO	-0.9165	-3.0274**	0.6510**	-7.1702***	-18.1266***	0.2250

Table 6
Zivot–Andrews unit root test assuming a single break point in data.

Variables	Level			First Difference		
	T-statistic	**Time break**	**Decision**	**T-statistic**	**Time break**	**Decision**
lnGDP	-2.0898	2013	Unit root	-5.7043***	2010	Stationary
ENER	-5.5726***	1995	Stationary	-5.3526***	1992	Stationary
lnELEC	-5.5726***	1995	Stationary	-5.3526***	1992	Stationary
lnCPI	-5.246**	2000	Stationary	-6.9***	1996	Stationary
$lnCO_2$	-7.0175***	2006	Stationary	-5.6744***	1991	Stationary
lnGHG	-3.615	2007	Unit root	-6.7597***	2004	Stationary
lnME	-5.363***	2004	Stationary	-3.8196	2009	Unit root
lnNO	-5.9697***	2003	Stationary	-8.1301***	2005	Stationary

Note: ** and *** denote 5% and 1% levels of significance, respectively; the corresponding critical values: −5.34(1%), −4.8(5%), −4.58(10%).

estimate the short- and long-term coefficients of the variables. The ARDL cointegration approach was used to test for long-term relationships, and the results are listed in Table 6. The results of the Wald test F-statistics for the four models are statistically significant at 10% and 5%. Compared to the Pesaran et al. (2001) critical values, the calculated F-statistics indicate that strong cointegration exists among the variables, which in turn stimulates the ARDL procedures to continue to estimate the short- and long-term coefficients. Nevertheless, prior to such an estimation, prior information is necessary for the optimal lag length. The optimal lag was selected based on the Bayesian information criteria (BIC) for the four models, as listed in Table 7.

5.5. ARDL short-term analysis

The next step is to investigate the long- and short-term impacts of GDP, ELECT, ENE, and CPI on different types of GHGs. The short-term relationship between the dependent and independent variables was investigated using the ARDL model, and the results are presented in Tables 8–11. As indicated in the table, the short-term effects of GDP, ELECT, ENE, and CPI on all the indicators of environmental quality are statistically insignificant. This suggests that GDP has a negative but insignificant effect on CO_2, GHGs, and NO and a positive but insignificant effect on the other MEs. Electricity consumption was found to have negative but insignificant effects on CO_2, NO, and ME but positive and insignificant effects on the other GHGs. Furthermore, energy consumption has varying effects on GHG emissions. Energy consumption has a positive but insignificant effect on CO_2, GHGs, and NO, and a negative but insignificant effect on ME. CPI has a negative but insignificant effect on NO and a positive but insignificant effect on the other GHGs. Furthermore, the estimated coefficients associated with the error correction coefficients ECT (−1) for the four models have their expected negative sign, which implies that the disequilibrium can be adjusted to the long term with higher speed. Furthermore, ECT (−1) for CO_2 and NO was significant at the 10% and 1% levels, respectively. This result indicates that the speed of adjustment in CO_2 and NO from short-term toward the long-term equilibrium will occur by 0.57% and 1.67%, respectively, every year. The results affirm that in the short term, there is no causality in the independent variables for CO_2, ME, NO, or other GHG emissions. The R^2 values range between 33% and 68%, which confirms that the model has a moderately good fit.

Table 8
ARDL short-term analysis for model ($lnCO_2$) as Endogenous variable.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.045259	0.054447	0.831249	0.4174
$LNCO_2$(-1)	0.260085	0.298958	0.869970	0.3964
LNGDP (-2)	-0.251173	0.303425	-0.827793	0.4193
LNCPI(-2)	0.113246	0.144089	0.785946	0.4427
LNELEC (-1)	-0.611206	0.550786	-1.109697	0.2826
ENER(-2)	0.015226	0.015903	0.957424	0.3518
ECT (-1)	-0.574821	0.323662	-1.775991	0.0936

R-squared	0.336902	Mean dependent var	-0.014485
Adjusted R-squared	0.102868	S.D. dependent var	0.102763
S.E. of regression	0.097334	Akaike info criterion	-1.582846
Sum squared resid	0.161056	Schwarz criterion	-1.239247
Log likelihood	25.99415	Hannan-Quinn criterion	-1.491689
F-statistic	1.439542	Durbin-Watson stat	2.227118
Prob (F-statistic)	0.257086		

Table 9
ARDL short-term analysis for model (lnGHG) as Endogenous variable.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.014068	0.026186	0.537218	0.5981
LNGHG (-1)	0.169692	0.231878	0.731818	0.4742
LNGDP (-2)	-0.091109	0.140496	-0.648484	0.5253
LNCPI(-2)	0.078639	0.076065	1.033846	0.3157
LNELEC (-1)	0.103305	0.337001	0.306543	0.7629
ENER(-2)	0.002292	0.009007	0.254507	0.8022
ECT (-1)	-0.460391	0.269294	-1.709625	0.1055

R-squared	0.445810	Mean dependent var	0.001825
Adjusted R-squared	0.250213	S.D. dependent var	0.056462
S.E. of regression	0.048890	Akaike info criterion	-2.959974
Sum squared resid	0.040635	Schwarz criterion	-2.616375
Log likelihood	42.51969	Hannan-Quinn criterion	-2.868818
F-statistic	2.279231	Durbin-Watson stat	1.969280
Prob (F-statistic)	0.084875		

5.6. ARDL long-term analysis

The ARDL model was used to investigate the long-term impacts of the independent variables on the dependent variables; the estimation results are reported in Tables 12–15. Table 12 shows the ARDL long-term analysis for model $lnCO_2$ as an endogenous variable and provides the

Table 7
Walt test of the ARDL cointegrations

Models	Endogenous variables	Function	Optimal Lag lengths	Wald Test F-statistic	Cointegration Decision
1	$lnCO_2$	F (lnGDP, lnCPI, lnELEC, ENER)	(1,2,2,1,2)	4.816816[a]	Cointegrated
2	lnGHG	F (lnGDP, lnCPI, lnELEC, ENER)	(1,2,2,1,1)	3.482566**	Cointegrated
3	lnME	F (lnGDP, lnCPI, lnELEC, ENER)	(2,2,3,2,1)	4.349594[a]	Cointegrated
4	lnNO	F (lnGDP, lnCPI, lnELEC, ENER)	(1,2,2,2,2)	4.196223[a]	Cointegrated

[a] , and ** denote statistical significance at 5%, and 10% levels respectively.

Table 10
ARDL short-term analysis for model (lnME) as Endogenous variable.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009796	0.018494	0.529678	0.6036
LNME (-2)	0.467663	0.260469	1.795468	0.0915
LNGDP (-2)	-0.072553	0.091329	-0.794414	0.4386
LNCPI(-2)	0.012297	0.047783	0.257357	0.8002
LNELEC (-1)	-0.086857	0.176549	-0.491968	0.6294
ENER(-2)	-0.000155	0.006532	-0.023774	0.9813
ECT (-1)	-0.454848	0.296126	-1.535994	0.1441

R-squared	0.342140	Mean dependent var	-0.005616
Adjusted R-squared	0.095442	S.D. dependent var	0.033774
S.E. of regression	0.032122	Akaike info criterion	-3.792772
Sum squared resid	0.016509	Schwarz criterion	-3.447187
Log likelihood	50.61687	Hannan-Quinn criterion	-3.705858
F-statistic	1.386878	Durbin-Watson stat	1.281853
Prob (F-statistic)	0.278937		

Table 11
ARDL short-term analysis for model (lnNO) as Endogenous variable.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.017243	0.111567	0.154557	0.9790
LNNO(-1)	0.330236	0.224011	1.474198	0.1587
LNGDP (-2)	0.143997	0.565122	0.254806	0.8019
LNCPI(-2)	-0.079449	0.316680	-0.250880	0.8049
LNELEC (-2)	-0.757842	0.956003	-0.792719	0.4389
ENER(-2)	0.011847	0.034128	0.347147	0.7327
ECT (-1)	-1.670209	0.363623	-4.593241	0.0003

R-squared	0.681230	Mean dependent var	0.020713
Adjusted R-squared	0.568723	S.D. dependent var	0.322425
S.E. of regression	0.211742	Akaike info criterion	-0.028407
Sum squared resid	0.762187	Schwarz criterion	0.315192
Log likelihood	7.340879	Hannan-Quinn criterion	0.062750
F-statistic	6.055000	Durbin-Watson stat	2.148547
Prob (F-statistic)	0.001537		

Table 12
ARDL Long-term analysis for model ($lnCO_2$) as endogenous variable.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-11.99555	2.140509	-5.604061	0.0000
LNGDP	-0.110877	0.036227	-3.060635	0.0057
LNELEC	1.781649	0.217682	8.184625	0.0000
ENER	0.057618	0.013423	4.292550	0.0003
LNCPI	0.327423	0.140958	2.322847	0.0298

R-squared	0.828540	Mean dependent var	3.910081
Adjusted R-squared	0.797366	S.D. dependent var	0.253185
S.E. of regression	0.113971	Akaike info criterion	-1.340170
Sum squared resid	0.285767	Schwarz criterion	-1.100200
Log likelihood	23.09229	Hannan-Quinn criterion	-1.268814
F-statistic	26.57747	Durbin-Watson stat	1.470067
Prob (F-statistic)	0.000000		

Table 13
ARDL Long-term analysis for model (lnGHG) as Endogenous variable.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.894478	1.257173	-3.0997806	0.0053
LNGDP	-0.083962	0.021277	-3.946175	0.0007
LNELEC	0.969783	0.127850	7.585305	0.0000
ENER	-0.002267	0.007884	-0.287567	0.7764
LNCPI	0.099757	0.082788	1.204974	0.2410

R-squared	0.803933	Mean dependent var	3.673526
Adjusted R-squared	0.768285	S.D. dependent var	0.139058
S.E. of regression	0.066938	Akaike info criterion	-2.404526
Sum squared resid	0.098575	Schwarz criterion	-2.164556
Log likelihood	37.46110	Hannan-Quinn criterion	-2.333170
F-statistic	22.55165	Durbin-Watson stat	1.025732
Prob (F-statistic)	0.000000		

Table 14
ARDL Long-term analysis for model (lnME) as Endogenous variable.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.002116	0.471047	-10.61914	0.0000
LNGDP	-0.104101	0.007972	-13.05800	0.0000
LNELEC	0.869099	0.047904	18.14256	0.0000
ENER	0.005853	0.002954	1.981418	0.0602
LNCPI	0.005853	0.031020	3.638685	0.0014

R-squared	0.962281	Mean dependent var	1.211770
Adjusted R-squared	0.955423	S.D. dependent var	0.118792
S.E. of regression	0.025081	Akaike info criterion	-4.367851
Sum squared resid	0.013839	Schwarz criterion	-4.127882
Log likelihood	63.96599	Hannan-Quinn criterion	-4.296496
F-statistic	140.3162	Durbin-Watson stat	1.696399
Prob (F-statistic)	0.000000		

Table 15
ARDL Long-term analysis for model (lnNO) as Endogenous variable.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.943123	3.893762	-2.039961	0.0535
LNGDP	0.243897	0.065899	3.701052	0.0012
LNELEC	0.190638	0.395982	0.481431	0.6350
ENER	0.039957	0.024417	1.636451	0.1160
LNCPI	-0.199366	0.256414	-0.777515	0.4451

R-squared	0.596383	Mean dependent var	-0.803535
Adjusted R-squared	0.522998	S.D. dependent var	0.300183
S.E. of regression	0.207323	Akaike info criterion	-0.143506
Sum squared resid	0.945618	Schwarz criterion	0.096464
Log likelihood	6.937329	Hannan-Quinn criterion	-0.072150
F-statistic	8.126764	Durbin-Watson stat	2.475617
Prob (F-statistic)	0.000350		

long-term coefficients from the ARDL estimates. The results suggest that ENER, ELECT, and CPI cause a deterioration in environmental quality and that there is a highly significant, at the 1% level of significance, long-term relationship between GDP, ELEC, and ENER as well as a highly significant, at the 5% level of significance, long-term relationship between CPI and CO_2 emissions. However, GDP has a significantly negative association with CO_2 emissions. A 1% increase in GDP causes a 0.11% decline in CO_2 emissions. In contrast, ENER, ELECT, and CPI have a significant positive association with CO_2 emissions. A 1% increase in ELECT, ENER, and CPI leads to 1.78%, 0.058%, and 0.33% increases in CO_2 emissions, respectively. Although these coefficients are still small, their magnitudes and effects must not be undermined, indicating that a substantial reduction in emissions is still far from reality.

The results illustrated in Table 13 reveal a negative relationship between GDP and per capita GHG emissions. These results imply that a 0.084% decrease in the per capita GHG emissions is linked to a 1% increase in GDP. This relationship is statistically significant at the 1% level. However, the results show a positive and statistically significant effect of ELEC on the per capita GHG emissions. This indicates that this variable plays a substantial role in increasing GHG emissions in the country in the long term. Keeping the other factors constant, a 1% increase in ELEC increases GHG emissions by 0.97%. ENER and CPI have no significant impact on GHG emissions.

Table 14 suggests a negative and statistically significant relationship at the 1% level between GDP and per capita ME emissions. These results imply that a 0.104% decrease in the per capita ME emissions is linked to a 1% increase in GDP. In contrast, the results suggest a positive relationship between the other independent variables (ENER, ELEC, and CPI) and the per capita ME emissions. This indicates that these variables play a critical role in increasing ME emissions in a country in the long term. The results identify a positive and statistically significant effect of ENER on the per capita ME emissions at the 10% level. Keeping the other factors constant, a 1% increase in ENER increases the ME emissions by 0.0058%. Moreover, ELEC and CPI have positive and significant relationships with the per capita ME emissions at the 1% significance level, implying that 0.869% and 0.0058% of per capita ME emissions increased by a 1% increase in ELEC and CPI, respectively.

The long-term relationship between the per capita NO emissions and the independent variables was investigated and the results are provided in Table 15. The results suggest a positive and significant impact of GDP at the 1% level on the per capita NO emissions, and a 0.244% increase in the per capita NO emissions is linked to a 1% increase in GDP. This implies that economic growth plays a vital role in increasing NO emissions in the country. However, ELEC and ENER have positive but insignificant impacts on the per capita NO emissions, while CPI has a negative but insignificant impact.

The negative long-term relationship between GDP and CO_2, ME, and GHGs indicates that this relationship is U-shaped, which means that the Environmental Kuznets Curve (EKC) hypothesis is not valid for Qatar when using CO_2, ME, and GHGs as indicators of environmental degradation when considering only GDP. This can be attributed to the fact that these types of GHG emissions to real GDP per capita ratios were smaller compared to the same ratio after a certain point of economic development in Qatar. This reflects the importance of the other variables because Qatar is practicing a long-term transition toward significantly increasing industrial activities related to the energy sector to diversify its economy as well as increase gas and oil production. This result agrees with the findings of Mrabet and Alsamara (2017). These results reflect the dramatic rise in the production and demand for energy and electricity in the country in recent decades. For example, in 2016, the electricity demand in the country increased by 2.3% compared to 2015, reaching 7435 MW, and the electricity transmitted in 2016 was 39,667 GWH (Abulibdeh, 2021a), (Khalifa et al., 2019). Furthermore, natural gas is used for electricity and energy production, and there is no intention to transition to renewable energy sources in the short term in the country. This is expected because Qatar has the third largest natural gas reserve in the world. However, authorities in the State of Qatar recently launched a strategy to minimize the negative impact of economic development, including energy production and consumption, on the environment in the long term.

5.7. VECM cranger and Toda–Yamamoto causality testing results

An appropriate assessment of environmental degradation in Qatar depends on the nature of the causal relationship between the dependent and independent variables. Therefore, the final step in investigating the impact of GDP, ELEC, ENER, and CPI on CO_2, GHG, NO, and ME is to test the existence of a causal relationship between these variables using Toda–Yamamoto and VECM Cranger causality testing. Because most of the variables are first difference stationary, VECM Cranger and Toda–Yamamoto (TY) causality analyses are suitable tests to assess the causal direction among the variables. Tables (16 and 17) present the empirical causality relationships between dependent and independent variables. The two tests identified different causal relationships between the variables. The TY causality analysis (Table 16) indicates a bidirectional causal relationship between the independent variables GDP, ELEC, ENER, CPI, and the dependent variable ME, and between GPD, ELEC, CPI, and NO. Furthermore, the test suggests a bidirectional causal relationship between GDP, ELEC, CPI, and NO. There is also unidirectional causality from GDP to CO_2, GHG to ELEC, and GHG to ENER. However, the VECM Cranger-causality analysis (Table 17) shows only a unidirectional causality relationship running from CPI, ELEC, ENER, and GHGs; ELEC and ME; ENER and NO; and CO_2 and ELEC.

5.8. The cumulative sum (CUSUM) test

The cumulative sum (CUSUM) is a stability analysis test that reveals the supremacy of long- and short-term parameters. If the graph of this test crosses the critical bounds (red lines), we may reject the hypothesis of misspecification of the empirical model (Shahbaz et al., 2012).

Table 16
Toda–Yamamoto Causality test.

	Chi-sq	Prob.		Chi-sq	Prob.
ΔlnGDP–> Δ$lnCO_2$	11.21033*	0.0008	Δ$lnCO_2$–> ΔlnGDP	0.014844	0.9030
ΔlnCPI–> Δ$lnCO_2$	0.104320	0.7467	Δ$lnCO_2$–> ΔlnCPI	0.183727	0.6682
ΔlnELEC–> Δ$lnCO_2$	0.805477	0.3695	Δ$lnCO_2$–> ΔlnELEC	0.233759	0.6288
Δ ENER–> Δ$lnCO_2$	1.282560	0.2574	Δ$lnCO_2$–> Δ ENER	0.067642	0.795
ΔlnGDP–> ΔlnGHG	2.558	0.4649	ΔlnGHG–> ΔlnGDP	5.029	0.170
ΔlnCPI–> ΔlnGHG	3.821	0.282	ΔlnGHG–> ΔlnCPI	0.326307	0.5678
ΔlnELEC–> ΔlnGHG	2.281	0.5161	ΔlnGHG–> ΔlnELEC	35.777*	0.000
Δ ENER–> ΔlnGHG	3.457	0.326	ΔlnGHG–> Δ ENER	139.3862*	0.000
ΔlnGDP–> ΔlnME	601.553*	0000	ΔlnME–> ΔlnGDP	17.4511*	0.0006
ΔlnCPI–> ΔlnME	48.002*	0.000	ΔlnME–> ΔlnCPI	41.7211*	0.000
ΔlnELEC–> ΔlnME	192.425*	0.000	ΔlnME–> ΔlnELEC	1767.678*	0.000
Δ ENER–> ΔlnME	107.495*	0.000	ΔlnME–> Δ ENER	7.5274***	0.0569
ΔlnGDP–> ΔlnNO	477.053*	0.000	ΔlnNO–> ΔlnGDP	99.367*	0.000
ΔlnCPI–> ΔlnNO	519.401*	0.000	ΔlnNO–> ΔlnCPI	23.4025*	0.000
ΔlnELEC–> ΔlnNO	182.520*	0.000	ΔlnNO–> ΔlnELEC	58.355*	0.000
Δ ENER–> ΔlnNO	497.654*	0.000	ΔlnNO–> Δ ENER	2.71734	0.3766

Note: * and *** show significance at 1% and 10% levels respectively.

Table 17
VECM cranger-causality analysis.

	Chi-sq	Prob.		Chi-sq	Prob.
ΔlnGDP–> Δ$lnCO_2$	0.196447	0.6576	Δ$lnCO_2$–> ΔlnGDP	0.171449	0.6788
ΔlnCPI–> Δ$lnCO_2$	0.166898	0.6829	Δ$lnCO_2$–> ΔlnCPI	0.157851	0.6911
ΔlnELEC–> Δ$lnCO_2$	0.235059	0.6278	Δ$lnCO_2$–> ΔlnELEC	2.977281***	0.0844
ΔlnENER–> Δ$lnCO_2$	0.848049	0.3571	Δ$lnCO_2$–> ΔlnENER	2.274734	0.1315
ΔlnGDP–> ΔlnGHG	7.538323	0.0054	ΔlnGHG–> ΔlnGDP	0.193018	0.6604
ΔlnCPI–> ΔlnGHG	7.754302**	0.0303	ΔlnGHG–> ΔlnCPI	0.326307	0.5678
ΔlnELEC–> ΔlnGHG	4.692768**	0.0014	ΔlnGHG–> ΔlnELEC	0.012261	0.9118
ΔlnENER–> ΔlnGHG	10.18380*	0.0060	ΔlnGHG–> ΔlnENER	0.031283	0.8596
ΔlnGDP–> ΔlnME	0.470113	0.4929	ΔlnME–> ΔlnGDP	0.503590	0.4779
ΔlnCPI–> ΔlnME	0.023975	0.8769	ΔlnME–> ΔlnCPI	0.588699	0.4429
ΔlnELEC–> ΔlnME	3.784971***	0.0517	ΔlnME–> ΔlnELEC	0.013635	0.9070
ΔlnENER–> ΔlnME	0.243587	0.6216	ΔlnME–> ΔlnENER	0.002258	0.9621
ΔlnGDP–> ΔlnNO	0.195136	0.6587	ΔlnNO–> ΔlnGDP	0.030634	0.8611
ΔlnCPI–> ΔlnNO	1.999195	0.1574	ΔlnNO–> ΔlnCPI	0.011271	0.9155
ΔlnELEC–> ΔlnNO	0.590979	0.4420	ΔlnNO–> ΔlnELEC	0.063616	0.8009
ΔlnENER–> ΔlnNO	14.88132*	0.0001	ΔlnNO–> ΔlnENER	0.781769	0.3766

Note: *, ** and *** show significance at 1%, 5% and 10% levels respectively.

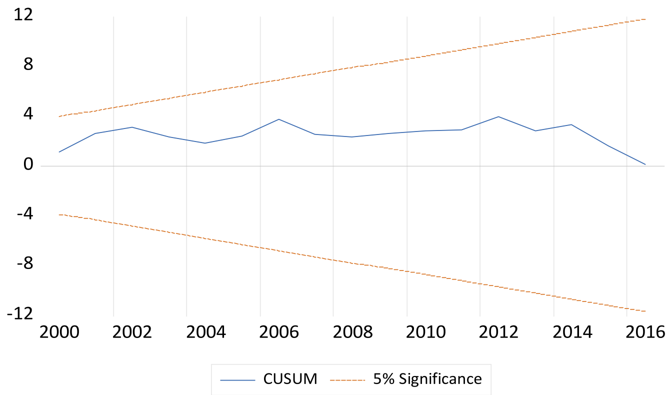

Fig. 8. The plot of the cumulative sum of recursive residuals of the first model ($lnCO_2$).

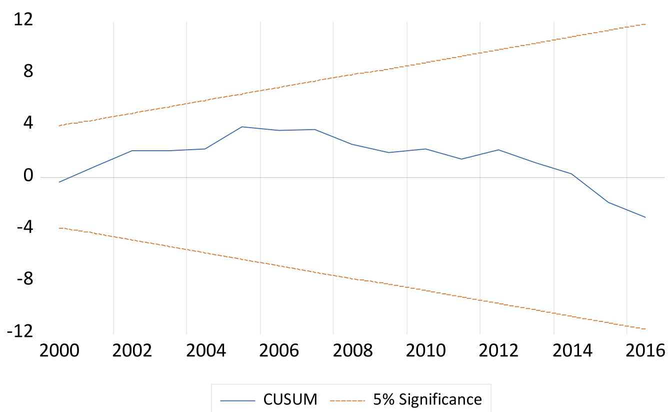

Fig. 9. The plot of the cumulative sum of recursive residuals of the second model (lnGHG).

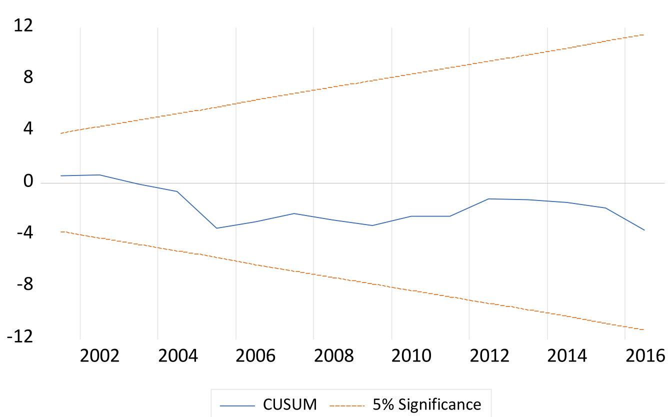

Fig. 10. The plot of the cumulative sum of recursive residuals of the third model (lnME).

Figs. 8–11 display the CUSUM plots for the four models. These figures illustrate that the ARDL parameters in all the models are stable at the 5% significance level. The graphical plots of CUSUM examine the stability of the short- and long-term estimates over time. The figure indicates that the estimated coefficients lie between the upper and lower critical bounds at a 5% significance level.

Comparing the outcomes of this research with the outcomes of other studies reveals the congruence and similarity with some findings and inconsistency with others. On the national scale, few studies investigated the factors that may degrade the environmental quality in Qatar.

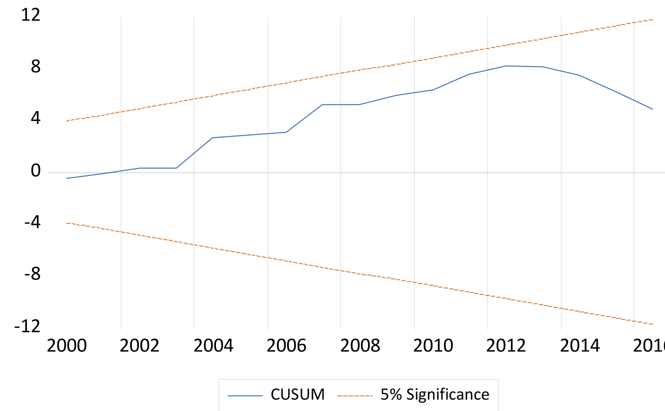

Fig. 11. The plot of the cumulative sum of recursive residuals of the fourth model (lnNO).

Salahuddin and Gow (2014) investigated the effects of energy consumption, financial development, economic growth, and foreign direct investment on environmental quality in the country. They conclude that energy consumption have an injurious long-term effects on the indicators of environmental quality, which aligns with the findings of this research. Mrabet and Alsamara (2017) examined the effect of energy use, real gross domestic product, the square of real gross domestic product, the trade openness, and the financial development on the CO_2 and ecological footprint. When we use the CO_2 emissions, the found that there is a long-term relationship among the variables and that the inverted U-shaped hypothesis is not valid. Charfeddine (2017) also investigate the factors that contribute to environmental degradation in Qatar. The study used trade openness, economic growth, urbanization, and energy consumption as indicators of environmental degradation. They found that EKC hypothesis holds for the CO_2 emissions under the condition of controlling for breaks and that the electricity consumption is negatively correlated to CO_2 emissions and to Ecological Carbon Footprint. On the regional level, Zmami and Ben-Salha (2020) studied the environmental degradation in the GCC countries. They investigate the impact of energy consumption, foreign direct investments, urbanization, per capita GDP, and international trade on CO_2 emissions. They conclude that energy consumption has a negative impact on environmental degradation and that energy consumption is the most variable that effect environmental degradation on the short-term. Magazzino (Magazzino) investigate the impact of energy use and economic growth on CO_2 emissions in the Middle East countries. The study found a negative correlation between economic growth and CO_2 emissions and a positive correlation between energy use and CO_2 emissions. Salahuddin and Gow (El-Montasser and Ben-Salha, 2019) found a positive and significant relation between CO2 emissions and energy consumption as well as between energy consumption and economic growth in the GCC countries both in the short- and the long-run. They also found no significant relation between CO2 emissions and economic growth in this region.

6. Conclusion and policy implications and recommendations

The aim of this study was to examine the effects of economic growth, electricity consumption, energy consumption, and the crop production index on different types of GHG emissions, including CO_2, methane, nitrogen oxide, and other types of GHG gases, using time series data for the State of Qatar between 1990 and 2019. The results from the ARDL technique illustrate that electricity consumption, energy consumption, and the crop production index have a positive and significant relationship in the long term. The VECM Cranger and Toda–Yamamoto causality tests identify different causality relationships between the variables. It is critical to understand the causal relationship (U-shaped or inverted U-shaped) between the variables considered in this study to formulate effective environmental policies and strategies to reduce environmental degradation in the country. Several key policy implications can be derived from the findings of this research to sustain environmental quality in Qatar. The existence of an inverted U-shape between GDP and CO_2, ME, and GHGs indicates that Qatar's policy to reduce GHG emissions must continue to consider environmental factors. This negative relationship implies that the high economic growth achieved thus far in the country is insufficient to achieve a sustainable reduction in per capita GHG emissions. This further implies that Qatar may witness a sustainable increase in GHG emissions in the long term but with a high cost associated with the negative externalities on the economy. Nevertheless, since the 2000s, Qatar has started a significant long-term economic development diversification plan aimed at diversifying its economy by involving more sectors, such as the industrial and service sectors, rather than depending on the oil and natural gas sector alone.

These findings illustrate the challenges for Qatar in pursuing an energy conservation policy in the time of enormous growing energy demand in the country and globally. Qatar depends on fossil fuel sources to generate its growing needs from electricity; hence, there is a need for the country to seek alternative sources of electricity generation, such as renewable energy sources associated with electricity generation efficiency, other potential mitigation measures, and additional resources and logistics to reduce the GHG emissions in the country.

The findings of this study are relevant to energy and environmental experts and policymakers in Qatar. Energy and electricity production and consumption are the main contributors to GHG emissions. The electricity in Qatar is highly subsidized, which encourages massive and sprawling consumption, as well as wasting electricity, and is considered a substantial handicap to improving energy efficiency and reducing energy use. Therefore, the country needs to increase its efforts to rationalize its electricity consumption to reduce the social and environmental costs of a highly subsidized policy. In this sense, achieving electricity use efficiency is essential for reducing consumption and, hence, emissions from this sector.

The authorities must promote and rely more on renewable energy sources as clean and green alternatives to traditional energy sources. Qatar is exceptionally rich in renewable resources owing to its geographical location and the abundant natural resources available to generate electricity, such as solar and wind resources, which can significantly help improve the quality of the environment. The country is characterized by its high average daily irradiation and ambient temperatures and is rated excellent in terms of solar energy. Qatar can also accelerate the development of a cleaner energy sector to sustain long-term economic growth and environmental protection, as well as reduce the amount of GHGs emitted from oil and gas production. Water- and electricity-subsidized tariff systems should be revised, because they are a considerable obstacle to promoting renewable energy. Therefore, the country should follow a comprehensive strategy that encourages investments in environmentally friendly ecosystems and innovative planning in a green economy.

Key policies may include encouraging technological innovation and development as well as further investments in research and development on developing low-carbon technologies and renewable sources of energy, which could be useful in reducing GHG emissions without any detrimental effects on Qatar's economic growth. Furthermore, the transport sector in the country has expanded rapidly over the last decade, driven by population growth, rapid urbanization, and the preparation for the FIFA 2022 World Cup; therefore, this sector is responsible for a substantial proportion of emissions. However, emissions from this sector cannot be eliminated for countries where cars are essential for commuting, particularly in hot weather. Qatari policymakers aimed to spread awareness among the Qatari population regarding the negative effects of environmental degradation on the Qatari economy, quality of life, and health. Therefore, there is a need to conduct additional campaigns to increase awareness.

The heavy reliance on the conventional sources of energy in the country results in increasing economic and environmental costs (Charfeddine et al., 2018). Therefore, as part of its vision statement, Qatar consider the environmental objectives and the promotion of environmental stewardship and alternative sources of energy as one of its top priorities. The country has the opportunity to reduce carbon emissions and develop strategies and technologies that can play a major part in achieving global emissions-reduction targets without a major structural change to its economy. These opportunities mainly depend on improved management systems in using renewable energy, adoption new technologies, and the shift to zero-carbon energy systems. Through the transition to zero-carbon energy technologies and systems, Qatar has the ability to apply best practice in energy efficiency, reduce its carbon-emission profile at low net cost, and to serve as a platform for global development of zero-carbon energy technologies. Despite the increase on energy demand in Qatar, the country is working on reducing its carbon emission. This ambition gives the country the desire to adapt and develop new energy technologies and strategies that will provide a source of long-term economic growth. Therefore, the development of policies that encourage the transformation to and integration of zero-carbon energy systems and technologies enable Qatar to meet its own economic and environmental objectives and stay at the center of energy economy. However, the transition toward zero-carbon emissions is a very challenging issue since it involves the interaction between a large set of factors affecting both energy demand side and supply side. The identification and analysis of these factors is particularly important because the transition to zero-carbon emissions cannot be implemented through large and centralized zero-carbon energy projects.

Qatar is also testing the idea of sustainable communities – The Msheireb Downtown Doha district is under construction to be fitted with solar panels, solar water heaters and overhangs designed to shade the surrounding sidewalks. While these pioneering initiatives are encouraging, the problem of zero-carbon transition remains very challenging and requiring transformational changes at larger societal levels. Except for few, these projects focus on capacity building of clean energy production, including community level shared energy assets. The Stockholm project seems to be the only which is taking a more comprehensive and integrated approach, e.g., managing waste, Electric Vehicles (EVs) and energy all together. There are a number of commonly made assumptions that can potentially distort results and outcomes for typical large-scale projects. The usual cost and benefit models relay on stationary data on technology and demand without much provisions for drastic behavioral, demand or other external changes. Furthermore, a common assumption for lifecycle assessment is that the installed system will be used at around its optimal operational parameter. For example, a smart building design will always stay smart irrespective of how its occupants behave or use it. Furthermore, in many of the existing initiatives, year 2050 targets are set to 50% or slightly more renewable energy production at city levels. It is not clear how these projects tend to deal with the Demand Side Management (DSM) and changing social landscape over time. Neither it is clear how these projects take into account carbon footprints from other sectors of the economy.

CRediT authorship contribution statement

Ammar Abulibdeh: Conceptualization, Resources, Formal analysis, Methodology, Writing – original draft, Funding acquisition.

Declaration of competing interest

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

Acknowledgement

This publication was made possible by an NPRP award [NPRP13S-0206–200272] from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors. The open access publication of this article was funded by the Qatar National Library (QNL).

References

Abulibdeh, A.O., 2019. Water-energy Nexus Challenges and Opportunities in Qatar.
Abulibdeh, A., Nov. 2021. Modeling electricity consumption patterns during the COVID-19 pandemic across six socioeconomic sectors in the State of Qatar. Energy Strategy Rev. 38, 100733 https://doi.org/10.1016/J.ESR.2021.100733.
Abulibdeh, A., Apr. 2021. Analysis of urban heat island characteristics and mitigation strategies for eight arid and semi-arid gulf region cities. Environ. Earth Sci. 80 (7), 259. https://doi.org/10.1007/s12665-021-09540-7.
Abulibdeh, A., Dec. 2021. Spatiotemporal analysis of water-electricity consumption in the context of the COVID-19 pandemic across six socioeconomic sectors in Doha City, Qatar. Appl. Energy 304, 117864. https://doi.org/10.1016/J.APENERGY.2021.117864.
Abulibdeh, A., Al-Awadhi, T., Al-Barwani, M., 2019. Comparative analysis of the driving forces and spatiotemporal patterns of urbanisation in Muscat, Doha, and Dubai. Dev. Pract. 29 (5), 606–618. https://doi.org/10.1080/09614524.2019.1598335.
Al-Awadhi, T., Abulibdeh, A., Al-Masri, A.N., Bin Touq, A., Al-Barawni, M., El Kenawy, A.M., May 2022. Spatial and temporal changes in electricity demand regulatory during pandemic periods: the case of COVID-19 in Doha, Qatar. Energy Strategy Rev. 41, 100826 https://doi.org/10.1016/J.ESR.2022.100826.
Al-Maamary, H.M.S., Kazem, H.A., Chaichan, M.T., Sep. 2017. Climate change: the game changer in the gulf cooperation council region. Renew. Sustain. Energy Rev. 76, 555–576. https://doi.org/10.1016/J.RSER.2017.03.048.
Al-Marri, W., Al-Habaibeh, A., Watkins, M., 2018. An Investigation into Domestic Energy Consumption Behaviour and Public Awareness of Renewable Energy in Qatar. https://doi.org/10.1016/j.scs.2018.06.024.
M. S. Alam and S. R. Paramati, "Do oil consumption and economic growth intensify environmental degradation? Evidence from developing economies," https://doi.org/10.1080/00036846.2015.1044647, vol. 47, no. 48, pp. 5186–5203, Oct. 2015, doi: 10.1080/00036846.2015.1044647..
Ali, R., Bakhsh, K., Yasin, M.A., Jul. 2019. Impact of urbanization on CO2 emissions in emerging economy: evidence from Pakistan. Sustain. Cities Soc. 48, 101553 https://doi.org/10.1016/J.SCS.2019.101553.
Arvin, M.B., Pradhan, R.P., Norman, N.R., Aug. 2015. Transportation intensity, urbanization, economic growth, and CO2 emissions in the G-20 countries. Util. Pol. 35, 50–66. https://doi.org/10.1016/J.JUP.2015.07.003.
Bekhet, H.A., Matar, A., Yasmin, T., Apr. 2017. CO2 emissions, energy consumption, economic growth, and financial development in GCC countries: dynamic simultaneous equation models. Renew. Sustain. Energy Rev. 70, 117–132. https://doi.org/10.1016/J.RSER.2016.11.089.
Chang, T., Fang, W., Wen, L.F., 2001. Energy consumption, employment, output, and temporal causality: evidence from Taiwan based on cointegration and error-correction modelling techniques. Appl. Econ. 33 (8), 1045–1056. https://doi.org/10.1080/00036840122484.
Charfeddine, L., Jun. 2017. The impact of energy consumption and economic development on ecological footprint and CO2 emissions: evidence from a markov switching equilibrium correction model. Energy Econ 65, 355–374. https://doi.org/10.1016/J.ENECO.2017.05.009.
Charfeddine, L., Yousef Al-Malk, A., Al Korbi, K., Feb. 2018. Is it possible to improve environmental quality without reducing economic growth: evidence from the Qatar economy. Renew. Sustain. Energy Rev. 82, 25–39. https://doi.org/10.1016/J.RSER.2017.09.001.
Chen, J., Wang, P., Cui, L., Huang, S., Song, M., Dec. 2018. Decomposition and decoupling analysis of CO2 emissions in OECD. Appl. Energy 231, 937–950. https://doi.org/10.1016/J.APENERGY.2018.09.179.
Clayton, S., Kals, E., Feygina, I., Jan. 2016. Justice and environmental sustainability. Handb. Soc. Justice Theory Res. 369–386. https://doi.org/10.1007/978-1-4939-3216-0_20.
Danish, Baloch, M.A., Mahmood, N., Zhang, J.W., Aug. 2019. Effect of natural resources, renewable energy and economic development on CO2 emissions in BRICS countries. Sci. Total Environ. 678, 632–638. https://doi.org/10.1016/J.SCITOTENV.2019.05.028.
Dauda, L., et al., Jan. 2021. Innovation, trade openness and CO2 emissions in selected countries in Africa. J. Clean. Prod. 281, 125143 https://doi.org/10.1016/J.JCLEPRO.2020.125143.
Demirel, M., Demirel, D.H., Isik, U., May 2017. Environmental sustainability for future generations (A comparison of 2020's candidate cities). Kamla Raj Enterp 24 (2), 652–656. https://doi.org/10.1080/09720073.2016.11892060.
El-Montasser, G., Ben-Salha, O., Aug. 2019. A new methodology for assessing the energy use–environmental degradation nexus. Environ. Monit. Assess. 191 (9), 1–12. https://doi.org/10.1007/S10661-019-7761-0, 2019 1919.
Engle, R.F., Granger, C.W.J., 2015. Co-integration and error correction: representation, estimation, and testing. Appl. Econ. 39 (3), 107–135. https://doi.org/10.2307/1913236.
Foley, J.A., et al., Jul. 2005. Global consequences of land use. Science (80-.) 309 (5734), 570–574. https://doi.org/10.1126/SCIENCE.1111772.
S. Ghatak and J. U. Siddiki, "The use of the ARDL approach in estimating virtual exchange rates in India," https://doi.org/10.1080/02664760120047906, vol. 28, no. 5, pp. 573–583, 2010, doi: 10.1080/02664760120047906..
Ghofrani, A., Zaidan, E., Abulibdeh, A., Nov. 2021. Simulation and Impact Analysis of Behavioral and Socioeconomic Dimensions of Energy Consumption. Energy, 122502. https://doi.org/10.1016/J.ENERGY.2021.122502.
Granger, C.W.J., Aug. 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37 (3), 424. https://doi.org/10.2307/1912791.
Grossman, G.M., Krueger, A.B., May 1995. Economic growth and the environment. Q. J. Econ. 110 (2), 353–377. https://doi.org/10.2307/2118443.
Harris, R.I.D., Sollis, R., 2003. Applied Time Series Modelling and Forecasting, p. 302.
He, Z., Xu, S., Shen, W., Long, R., Chen, H., Jan. 2017. Impact of urbanization on energy related CO2 emission at different development levels: regional difference in China based on panel estimation. J. Clean. Prod. 140, 1719–1730. https://doi.org/10.1016/J.JCLEPRO.2016.08.155.
Hu, M., Li, R., You, W., Liu, Y., Lee, C.C., Dec. 2020. Spatiotemporal evolution of decoupling and driving forces of CO2 emissions on economic growth along the Belt and Road. J. Clean. Prod. 277, 123272 https://doi.org/10.1016/J.JCLEPRO.2020.123272.
Hunt, R.A., Fund, B.R., Jul. 2016. Intergenerational fairness and the crowding out effects of well-intended environmental policies. J. Manag. Stud. 53 (5), 878–910. https://doi.org/10.1111/JOMS.12202.
Johamen, S., Jtiselius, K., 1990. Maximum likelihood estimation and inference ON cointegration-with APPLICATIONS to the demand for money. BUtXETlN Econ. Stat. 52.
Khalifa, A., Caporin, M., Di Fonzo, T., Apr. 2019. "Scenario-based forecast for the electricity demand in Qatar and the role of energy efficiency improvements. Energy Pol. 127, 155–164. https://doi.org/10.1016/j.enpol.2018.11.047.
Khan, M.K., Teng, J.Z., Khan, M.I., Khan, M.O., Oct. 2019. Impact of globalization, economic factors and energy consumption on CO2 emissions in Pakistan. Sci. Total Environ. 688, 424–436. https://doi.org/10.1016/J.SCITOTENV.2019.06.065.
Koçak, E., Ulucak, R., Ulucak, Z.Ş., Jan. 2020. The impact of tourism developments on CO2 emissions: an advanced panel data estimation. Tourism Manag. Perspect. 33, 100611 https://doi.org/10.1016/J.TMP.2019.100611.
Lau, L.S., Choong, C.K., Eng, Y.K., May 2014. Investigation of the environmental Kuznets curve for carbon emissions in Malaysia: do foreign direct investment and trade matter? Energy Pol. 68, 490–497. https://doi.org/10.1016/J.ENPOL.2014.01.002.
Ma, X.W., Ye, Y., Shi, X.Q., Le Zou, L., Sep. 2016. Decoupling economic growth from CO2 emissions: a decomposition analysis of China's household energy consumption. Adv. Clim. Change Res. 7 (3), 192–200. https://doi.org/10.1016/J.ACCRE.2016.09.004.
C. Magazzino and G. Cerulli, "The determinants of CO2 emissions in MENA countries: a responsiveness scores approach," https://doi.org/10.1080/13504509.2019.1606863, vol. 26, no. 6, pp. 522–534, Aug. 2019, doi: 10.1080/13504509.2019.1606863..
Mrabet, Z., Alsamara, M., 2017. Testing the Kuznets Curve hypothesis for Qatar: a comparison between carbon dioxide and ecological footprint. Renew. Sustain. Energy Rev. 70, 1366–1375, Apr. https://doi.org/10.1016/J.RSER.2016.12.039.
Omri, A., Nguyen, D.K., Rault, C., Oct. 2014. Causal interactions between CO2 emissions, FDI, and economic growth: evidence from dynamic simultaneous-equation models. Econ. Modell. 42, 382–389. https://doi.org/10.1016/J.ECONMOD.2014.07.026.
Ozturk, I., Acaravci, A., Aug. 2011. Electricity consumption and real GDP causality nexus: evidence from ARDL bounds testing approach for 11 MENA countries. Appl. Energy 88 (8), 2885–2892. https://doi.org/10.1016/J.APENERGY.2011.01.065.
R. K. Pachauri et al., "Climate change 2014: synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change," Epic. Switzerland, IPCC, 151 *p., pp.* 151, ISBN 978-92-9169-143-2, 2014, Accessed: Dec. 10, 2021. [Online]. Available: https://www.ipcc.ch/pdf/assessment-report/ar5/syr/SYR_AR5_FINAL_full_wcover.pdf..
Pesaran, M.H., Shin, Y., Smith, R.J., May 2001. Bounds testing approaches to the analysis of level relationships. J. Appl. Econom. 16 (3), 289–326. https://doi.org/10.1002/JAE.616.
Sadorsky, P., Jan. 2014. The effect of urbanization on CO2 emissions in emerging economies. Energy Econ 41, 147–153. https://doi.org/10.1016/J.ENECO.2013.11.007.
Saidi, K., Omri, A., Aug. 2020. Reducing CO2 emissions in OECD countries: do renewable and nuclear energy matter? Prog. Nucl. Energy 126, 103425. https://doi.org/10.1016/J.PNUCENE.2020.103425.
Salahuddin, M., Gow, J., Aug. 2014. Economic growth, energy consumption and CO2 emissions in Gulf Cooperation Council countries. Energy 73, 44–58. https://doi.org/10.1016/J.ENERGY.2014.05.054.
Salahuddin, M., Gow, J., 2019a. Effects of energy consumption and economic growth on environmental quality: evidence from Qatar, 2618 Environ. Sci. Pollut. Res. 26 (18), 18124–18142. https://doi.org/10.1007/S11356-019-05188-W. Apr. 2019.
Salahuddin, M., Gow, J., 2019b. Effects of energy consumption and economic growth on environmental quality: evidence from Qatar, 2618 Environ. Sci. Pollut. Res. 26 (18), 18124–18142. https://doi.org/10.1007/S11356-019-05188-W. Apr. 2019.
Salahuddin, M., Alam, K., Ozturk, I., Sohag, K., Jan. 2018. The effects of electricity consumption, economic growth, financial development and foreign direct investment on CO2 emissions in Kuwait. Renew. Sustain. Energy Rev. 81, 2002–2010. https://doi.org/10.1016/J.RSER.2017.06.009.
Shahbaz, M., Zeshan, M., Afza, T., Nov. 2012. Is energy consumption effective to spur economic growth in Pakistan? New evidence from bounds test to level relationships

and Granger causality tests. Econ. Modell. 29 (6), 2310–2319. https://doi.org/10.1016/J.ECONMOD.2012.06.027.

Shahbaz, M., Solarin, S.A., Mahmood, H., Arouri, M., Sep. 2013. Does financial development reduce CO2 emissions in Malaysian economy? A time series analysis. Econ. Modell. 35, 145–152. https://doi.org/10.1016/J.ECONMOD.2013.06.037.

Shahbaz, M., Solarin, S.A., Sbia, R., Bibi, S., Mar. 2015. Does energy intensity contribute to CO2 emissions? A trivariate analysis in selected African countries. Ecol. Indicat. 50, 215–224. https://doi.org/10.1016/J.ECOLIND.2014.11.007.

Uddin, G.S., Sjö, B., Shahbaz, M., Sep. 2013. The causal nexus between financial development and economic growth in Kenya. Econ. Modell. 35, 701–707. https://doi.org/10.1016/J.ECONMOD.2013.08.031.

Wu, S., Li, S., Lei, Y., Li, L., Jun. 2020. Temporal changes in China's production and consumption-based CO2 emissions and the factors contributing to changes. Energy Econ 89, 104770. https://doi.org/10.1016/J.ENECO.2020.104770.

Zaidan, E., Abulibdeh, A., 2018. Modeling ground access mode choice behavior for hamad international airport in the 2022 FIFA world Cup city, Doha, Qatar. J. Air Transport. Manag. 73, 32–45. https://doi.org/10.1016/j.jairtraman.2018.08.007.

Zaidan, E., Abulibdeh, A., 2020. Master planning and the evolving urban model in the gulf cities: principles, policies, and practices for the transition to sustainable urbanism. Plann. Pract. Res. https://doi.org/10.1080/02697459.2020.1829278.

Zaidan, E., Abulibdeh, A., Alban, A., Jabbar, R., May 2022. Motivation, preference, socioeconomic, and building features: new paradigm of analyzing electricity consumption in residential buildings. Build. Environ., 109177 https://doi.org/10.1016/J.BUILDENV.2022.109177.

Zambrano-Monserrate, M.A., Carvajal-Lara, C., Urgilés-Sanchez, R., Ruano, M.A., Jul. 2018. Deforestation as an indicator of environmental degradation: analysis of five European countries. Ecol. Indicat. 90, 1–8. https://doi.org/10.1016/J.ECOLIND.2018.02.049.

Zhang, Y.J., Bin Da, Y., 2015. The decomposition of energy-related carbon emission and its decoupling with economic growth in China. Renew. Sustain. Energy Rev. 41, 1255–1266, Jan. https://doi.org/10.1016/J.RSER.2014.09.021.

Zhang, D., Alhorr, Y., Elsarrag, E., Marafia, A.H., Lettieri, P., Papageorgiou, L.G., Jan. 2017. Fair design of CCS infrastructure for power plants in Qatar under carbon trading scheme. Int. J. Greenh. Gas Control 56, 43–54. https://doi.org/10.1016/J.IJGGC.2016.11.014.

E. Zivot and D. W. K. Andrews, "Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis," https://doi.org/10.1198/073500102753410372, vol. 20, no. 1, pp. 25–44, Jan. 2012, doi: 10.1198/073500102753410372..

M. Zmami and O. Ben-Salha, "An empirical analysis of the determinants of CO2 emissions in GCC countries," https://doi.org/10.1080/13504509.2020.1715508, vol. 27, no. 5, pp. 469–480, Jul. 2020, doi: 10.1080/13504509.2020.1715508..