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RESEARCH ARTICLE

Do demographic factors affect the environment? Empirical evidence from the Middle East and North African countries

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Abstract

Every country intends to enhance national production by achieving sustainable development. The purpose of this study is to examine whether there exists any long-run association among environmental deterioration measured by territorial emissions in CO_2, demographic factors (total population, population density, and urban population) and some other variables, namely, energy use, per capita income, energy intensity, and industrial value added for the 16 countries from the Middle East and North African (MENA) over 1990–2018. We implemented the generalized method of moments (GMM), fully modified ordinary least square (FMOLS), robust least square estimators, and panel Granger causality techniques for estimation. The empirical estimates reveal that there exists a long run cointegration among the series. Results also exhibit that energy use, per capita income, energy intensity, industrial value added, population density, total population, and urban population have positive effects on CO_2 emissions. Furthermore, in each panel, there is bi-directional causality between population density and CO_2 emissions, total population and CO_2 emissions, and urban population and CO_2 emissions. These findings suggest that the policymakers need not exclusively to focus on the transformation of rural labor from an agricultural-based model to urban regions with powerful, dominant industry and services sectors but also related to the changing of rural establishments into urban spaces is required. These changes in demographics involve changes in the demand for additional transportation services, food, shelter, clothing, and other necessities.

Keywords Population · Environmental degradation · MENA countries

JEL code : Q56 · Q5 · C2 · N55

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Introduction

Nowadays, the world is confronted with severe issues caused by the interplay among economic, societal, and environmental facets of evolution and growth. Environmental pollution is one of the most alarming problems to be addressed. The world is facing several environmental challenges, such as depletion of natural resources, lack of water in various regions, and poor soils that are no longer able to support various forms of life and fend off deforestation, suffocating pollution, and coastline degradation, which is all explicit evidence of environmental degradation. Particularly, global warming, driven by high CO_2 emissions, is one of the major environmental dangers. Climate change has prompted a greater focus and dialog on environmental factors. Higher temperatures in the air and the oceans lead to snow melting, which increases the average sea level and is thus a clear sign of global warming. Recent official estimates reveal that by the end of 2100, temperatures might rise by 1.1 to 6.4 °C, and sea levels can rise by 16.5–53.8 cm (Geneva 2013). It is believed that greenhouse gas (GHG) emissions, which are produced by fossil fuel combustion, are the leading source of global warming, especially GHGs. GHGs are also produced via traditional sources, such as petroleum, gas, and coal, and are large contributors to CO_2 emissions. As a result of increased urbanization and industrialization, practical realities and statistics show an upward trend in CO_2 emissions driven by the large usage of fossil fuels and nonrenewable energy. CO_2 emissions from the usage of nonrenewable energy are closely intertwined with pollution and global warming.

Many erstwhile studies including Haseeb et al. (2017), Liddle (2014), and Hunter and O'Neill (2014) have suggested that demographic changes, including population size, and density and urban population are leading sources of global warming. Individuals and households need energy for several reasons, such as food, clothing, shelter, and water. As a result, the higher their uses are, the higher their need for energy will be, which, in turn, increases environmental deterioration. However, some authors (Bradbury et al. 2014; López-Carr et al. 2014) have indicated that population growth (PG) and density and urbanization reduce the diverse effects on the environment. Malthus and Boserup constructed two theories about the effect of population on natural surroundings. In the eighteenth century, Malthus presented to the public his "Essay on the principle of population" (1798), which highlighted his perspective on PG. Malthus argued that in the case of a continued increase, the food supply would not be able to meet the rising demand, leading to a major crisis. In other words, Malthus emphasized the risk of depletion of the natural environment. On the same topic, Danish economist Boserup stated that population increase is bounded by the food volume it can produce. Furthermore, the spectrum of famine and the difficulties of ensuring food for a larger number of individuals challenge communities to improve their farming methods and create innovative technologies to prevent the degradation of the natural landscape.

There exists great confusion among policymakers about the arguments of Malthus and Boserup. Hence, the objective of the current study is to explore the effect of PG on the environment at the global level. The current section further explains the contemporary trends of population increase, density, and urbanization and their relationship with the environment. By the end of the twentieth century, the spectacular increase in the world population has reshaped the physical and societal boundaries of our planet. The rise in the world population accounts for approximately seventy-five million annually, which is a 1.1% growth per annum, from one billion in 1800 to 7.5 billion in 2016. Experts forecast an 8.4 billion population by mid-2030 and 9.6 billion by mid-2050 (United Nations 2017). The impressive progress in the past 50 years was enhanced, inter alia, by a large decrease in mortality rates that occurred even earlier in the 1920s and 1930s. In addition, urbanization is about economic and social development. It is not solely about the transformation of a rural worker from an agrarian model to metropolitan regions with powerful, dominant industry and services sectors but is also related to the changing of rural establishments into urban spaces. Urbanization has accelerated during the previous 20 years.

According to a report United Nations (2017), the worldwide urban population grew from 0.746 billion people in 1950 to 3.9 billion people in 2014. Nowadays, the world is witnessing an unprecedented wave of urban rise. Over 50% of the planet's population live in towns and cities, and according to research outlets, this number will exceed five billion by 2030. This phenomenon will be particularly sharp in Africa and Asia, leading to major social, economic, and environmental changes. Given that urbanism is an outcome of economic development, it can increase energy usage. Rapid urbanization requires more energy for consumption, which puts more pressure on the already vulnerable environment. In 2014, we consumed 66% more energy, and urban cities accounted for almost 70% of all contaminants (International Energy Agency 2020). Although the ecological modernization and urban environmental transformation hypothesis identify the positive and negative effects of urbanization on the ecosystems, any preliminary finding is difficult to describe (Sadorsky 2014).

The population density in the world follows an upward trend. In 1980, only 34.20 people were living per km2; in 2015, that number had risen to 56.62 people per km2. The nexus between population density and environmental degradation is a controversial topic. Some scholars (Saidi and Hammami 2015); Liddle 2004) have argued that energy demand is determined by per capita energy use and that urbanization has a significant influence on per capita consumption. The more thickly urbanized a nation turns into, the greater its energy usage will be, which thus increases CO2 emissions. From a different perspective, other researchers have suggested that highly exceptionally metropolitan urban communities show lower interest in individual transport; consequently, energy utilization and CO_2 emissions can decrease (Shafiei and Salim 2014). This analysis enriches the literature on environmental economics with empirical and contextual findings. To the best of our knowledge, this work is the first to explore the interplay among CO_2 emissions, demographic factors (population density and urban population) for 16 countries with various income levels from Middle East and North Africa (MENA) during 1990–2018.

This study covers MENA countries because being one of the driest and hottest regions, concerns about climate change are more concentrated throughout the MENA region. Even water shortage, without drought limits social and economic development in the MENA region (Bazza et al. 2018). The trend of rising temperature in many countries of MENA is excruciating (Giovanis and Ozdamar 2022). Soil erosion, alterations in seasonal rainfall, and increasing sea levels in coastal regions have exposed MENA to a variety of climatological risks, particularly drought, dust, and floods. Taken together, these changes indicate that the region is extremely vulnerable to many of the negative health impacts of climate changes, such as food instability, child malnutrition, and vector-borne illnesses such as dengue and zika fever among others (Atwoli et al. 2022; Karthik et al. 2014). MENA region has been suffering rapid population growth of 1.70%, urbanization of 66.00% in 2021 (Takian et al. 2022), dependency on food imports, population displacement, inequitable access to education and healthcare, and inadequate access to clean water (Waha et al. 2017).

Moreover, in their study, Makdisi et al. (2006) reveals that in general the growth performance of the MENA region (1960–2000) has been observed both mixed and described by a higher degree of instability if matched to the other regions in the globally. The comparatively sound growth performance of the MENA region during 1960s, 1970s and the 1st half of the 1980s is mainly ascribed to an encouraging external environment in the form of high energy price, whereas this situation has been overturned in the 2nd half of the 1980s and the early 1990s ensuing in sharp drops in local investment, savings and economic growth. Moreover, the whole growth performance of the MENA region has been mixed and more volatile compared with other regions of the globe. Devising effective and prudent policies required to boost economic growth with a minimum cost of environmental degradation in the MENA region, though empirical analysis is yet scarce. Moreover, the characteristics of the MENA region are very suitable for this type of study because it has the largest share of the world's energy reserve. The region is also trying to modernize and industrialize its economies facing great challenges of environmental degradation. Furthermore, this region is the highest carbon emission per output and 2nd most polluted region after South Asia (Omri et al. 2015). Along with these, this study also contributes to the existing literature in many ways, like, first, this study considers the cross-sectional dependency among countries and used 2nd-generation techniques for estimation. Secondly, this study used three estimation techniques to give a robust outcome like the panel generalized method of moments (GMM), robust least squares (RLS), and the fully modified ordinary least squares (FMOLS) approach applied to discover any potential long-term relationships among the selected variables, and Dumitrescu and Hurlin (D-H) panel causality tests were used to determine the direction of causality. Thirdly, this study used the three variables for demographic and survey the effect of carbon emissions in different ways like whole, developed, and developing countries panel for robustness which were not consider by prior studies. Like Dimnwobi et al. (2021) considered population growth and density and urban population as an explanatory variables but used only five countries data which is insufficient. Furthermore, no updated empirical studies are available in the same area for MENA countries on this important topic.

The remainder of this work is organized as follows. The second section includes a review of past studies. The third section describes the data and the methodology. The fourth section presents the analysis and the results. S\The fifth section concludes this study, and the sixth section provides some policy recommendations.

Literature review

Population size and CO_2 emissions

Past research notes that PG has detrimental and positive effects on ecosystems. As indicated by Dietz and Rosa (1997), PG is the main cause of higher global CO_2 emissions. Malthus and Hollingsworth (1973) indicated the existence of obvious effects of PG on the health of the natural surroundings. Everyone creates a demand for energy to serve his/her various needs. All other things being equal, the greater the population is, the higher the amount of energy will be required. The study of Bidsall (1992) described how a larger population contributes to CO_2 emissions. First, PG leads to additional energy consumption, which increases fossil fuel emissions. Second, it can cause deforestation, coupled with other modifications in land and resource use. These phenomena might create more dangerous emission volumes (Fan et al. 2006; Hang and Yuan-sheng 2011; Knapp and Mookerjee 1996; Lantz and Feng 2006; Liddle 2013, 2015; van Ypersele and Bartiaux 1995; You et al. 2015). On the opposite, according to Boscrup (1965), population growth enhances technological innovations, which can protect the environment. Similarly, various research demonstrates that the larger the population increases, the more rapid the growth of innovations will be, as well as better skill to propose fresh environmental solutions (Dasgupta 2000; Ravallion et al. 2000; Urry 2011).

To analyze the PG–CO_2 emission nexus globally, You et al. (2015) used quantile regression approach and basic least squares method. The results indicated that PG translates into superior levels of GHGs all over the world during the period of 1985–2005. In addition, Liddle (2013) documented the influence of PG on the environment and concluded that this growth affects environment quality via a higher demand for transportation services, housing, food, and energy utilization. Likewise, Hang and Yuan-sheng (2011) initiated to shed light on the major determinants of

CO_2 emissions by using an influence, population, affluence, and technology (IPAT) equation and emphasized that PG is the key driver of CO_2 emissions in China between 1980 and 2006. Puliafito et al. (2008) reveals that PG is strongly associated with CO_2 emissions in a wider context between 1850 and 2150. Fan et al. (2006) studied the effect factors of CO_2 emissions from 1975 to 2000 and confirmed the Malthusian hypothesis, noting that a population increase leads to higher CO_2 emissions. On the basis of the provincial level panel data for 1970–2000, Lantz and Feng (2006) showed that a series of macroeconomic and demographic forces stimulate CO_2 emissions in Canada. The authors stressed that PG puts pressure on CO_2 emissions.

Conversely, there seems to be little evidence of the absence of a link between PG and CO_2 emissions. Liddle (2015) observed the sensitivity of CO_2 for income and PG using the stochastic impacts by regression on population, affluence and technology (STIRPAT) system and panel data of 26 OECD and fifty-four non-OECD countries from 1971 to 2011. The FMOLS estimates exhibit an insignificant link between PG and CO_2 emissions. Thus, in most OECD and non-OECD nations, population increase is not a factor of contaminants. In Malaysia, Begum et al. (2015) studied the effect of PG on hazardous emissions between 1980 and 2009. According to the findings of ARDL and dynamic ordinary least squares (OLS) test, PG had no substantial influence on the CO_2 level. Furthermore, the study showed no evidence of a nexus between PG and CO_2 levels in low-, middle-, or high-income nations.

The study of Rehman et al. (2021) found that forestry, temperature, and rainfall have positive while livestock, population growth, crop production, and energy consumption have negative effect on carbon emissions in Pakistan from 1970 to 2017. Similarly, Chen et al. (2022) used the data for BRICS countries from 1990 to 2019 and AMG and CCEMG techniques for estimation and found that population growth and urbanization have an insignificant effect on carbon emissions.

Urbanization and CO_2 emissions

Numerous studies (Li and Yao 2009; Al-mulali et al. 2013; Ghosh and Kanjilal 2014; Li and Yao 2009) argued that demographic elements, such as urbanization, PG, and population density, increase CO_2 emissions. Several studies have investigated the link among energy utilization, urbanization, and CO_2 emissions (Al-mulali et al. 2013; Chikaraishi et al. 2015; Gholipour Fereidouni 2013; Kasman and Duman 2015; Parikh and Shukla 1995; Zhang and Lin 2012) by applying various quantitative techniques that yield different results. Kasman and Duman (2015) investigated the nexus between urbanization and environmental deterioration in the case of 15 Eurozone countries and candidates from 1992 to 2010 and highlighted that urbanization increases the CO_2 emissions in all countries subjected to analysis. Yuan et al. (2015) reported that urbanization boosts household food demand, clothing, education, transportation, and cultural activities in China. CO_2 emissions have changed as the structure and usage rate of energy demand changed. Sadorsky (2014) examined the urbanization implications on CO_2 for sixteen emerging states covering the period of 1971–2009 and claimed that urbanization in emerging states is one of the major drivers of GHGs.

Similarly, in the United Arab Emirates, Shahbaz et al. (2014) investigated the connection between urbanization and environmental deterioration from 1975 to 2011 and confirmed empirically the presence of cointegration and a long-term positive association between the two variables. Shafiei and Salim (2014) also documented the interlinkages between the two in the context of OECD countries during the period of 1980–2011. They applied a VECM to verify the link in the STIRPAT framework and suggested that urbanization is an important measure of CO_2 emissions in OECD states. Under this context, urbanists should improve public transit networks, energy efficiency, and the use of renewable energy sources to prevent ecological changes. Wang et al. (2014) studied the factors of CO_2 emissions in 30 Chinese provinces from 1995 to 2011 and highlighted a bidirectional significant association between urbanization and CO_2 emissions. Al-mulali et al. (2013) also found a positive and significant link between the two variables in the case of the MENA region and showed that increasing urbanization boosts energy utilization, resulting in increased CO_2 levels in the MENA region. Likewise, in their study, Gholipour Fereidouni (2013) indicated that urbanization is a vital factor in CO_2 discharges in 31 emerging countries during 2000–2008.

Furthermore, Al-mulali et al. (2012) investigated a detailed study on this topic in seven distinct countries from 1980 to 2008. The results from 184 countries underlined a significantly positive long-run relationship in 84% of nations, and mixed results for the remaining 16%. The findings suggested a general need for saving energy, efficiency, and conservation programs to mitigate its carbon footprint. Sharma (2011) revealed similar outcomes in sixty-nine lower-, middle-, and high-income nations between 1985 and 2005. In 99 different nations, Poumanyvong and Kaneko (2010) scanned the effect of urbanism on CO_2 emissions from 1975 to 2005 and stressed a significantly positive stimulus of urbanization on CO_2 emissions in middle-income economies. Alam et al. (2007) analyzed the nexus between the two during the period of 1971–2005 in Pakistan and indicated that a 1% rise in urbanization would augment CO_2 emissions by 0.81% in the long term. Likewise, Cole and Neumayer (2004) applied a STIRPAT framework for the period of 1975–1998 and asserted that urbanization drives CO_2 emissions in 86 countries. For less-developed nations during the period of 1980–2015, Ehrhardt-Martinez et al. (2002) used panel data and obtained similar findings.

Based on the above findings, rapid urbanization is a major determinant of contaminants that damages the environment of various states. Only a few researchers (Chikaraishi et al. 2015; Shafiei and Salim 2014; Sharma 2011; Xu and Lin 2015) claimed that urbanization protects the ecosystem. These works have suggested that urban cities have better infrastructure, which may lead to lower energy usage, and as a result, lower CO_2 emissions compared with rural regions. Moreover, urban population management is more intentional than rural population; thus, cities and towns can enjoy the advantage of rising economies in energy utilization, such as centralized energy distribution. Households in urban regions can use alternative energy fuels, such as natural gas, which generate fewer CO_2 emissions. Chikaraishi et al. (2015) reviewed the nature of the nexus between urbanization and CO_2 emissions in 140 nations from 1980 to 2008 using a STIRPAT framework and concluded that the evolution of urbanization can increase the environmental friendliness when the country's per capita GDP and proportion of service sector in national income are relatively high. Xu and Lin (2015) used panel data from 1990 to 2011 to analyze the urbanization–CO_2 pollution relationships in several areas of China, showing that urbanization curbs the GHG levels in China's eastern, western, and central areas.

In their study, for OECD nations, Shafiei and Salim (2014) applied a STIRPAT model to study this connection between 1980 and 2011. The panel VECM approach indicated that the greater the proportion of urbanism is, the smaller the incidence of the GHG level will be. These findings indicate that CO_2 can be controlled in some way by developing urbanization. Overcrowding and physical intensity limit the use of personal vehicles and support fewer mortised transit. If a country can improve the condition of public conveyance, then it will diminish its reliance on personal vehicle use, increase energy efficiency, and diminish CO_2 emissions. Sharma (2011) sought to identify the sources of CO_2 emissions in 69 countries from 1985 to 2005 by applying a GMM testing approach and highlighted that urbanization has an adverse influence on CO_2 in the global panel and all three subpanels. Fan et al. (2006) also found a similar relationship for a group of high-income countries in 1975–2000. Although a considerable amount of literature has investigated the causality between the two variables, some studies (Du et al. 2012; Zhu et al. 2012) have noted an insignificant relationship or no relation between urbanization and CO_2 discharges. In 30 provinces of China, Du et al. (2012) reviewed the determinants of CO_2 from 1995 to 2009 and found that the influence of urbanism on CO_2 emissions is negligible in selected areas. Zhu et al. (2012) used semi-parametric FEM to analyze panel data of 20 emerging nations from 1992 to 2008 and underlined no evidence of urbanization–CO_2 emission nexus. Azam et al. (2022) observed a two-way correlation among growth, energy usage, urbanization, industrialization, trade, and CO_2 in OPEC in the period 1975–2018.

In their study, Sun and Huang (2020) found an inverted U-shape relationship between urbanization and carbon emission in China and used data from 2000 to 2016. Similarly, Wang et al. (2021) used the panel ARDL technique in the case OECD countries and found that urbanization negatively related to carbon emissions. However, Awan et al. (2022) found that carbon emission increases with urbanization in thirty-three high income countries during 1996–2014 by novel quantile and robust techniques for estimation. Similarly, Sun et al. (2022) reveals that rapid urbanization significantly contributed in carbon emission in MENA region from 1991 to 2019 by using FMOLS techniques for estimation. However, Liu et al. (2023) investigate the effect of urbanization and other macroeconomic variables on carbon emissions in China from 1995 to 2020 and used PMG techniques for estimation. They found that urbanization has no effect on carbon emissions.

Population density and CO_2 emissions

According to the literature findings, the population is a major factor of development, and at the same time, the main driver of CO_2 emissions when exceeding the thresholds of the underlying mechanism. PG initially affects the environmental quality via the consumption of natural resources and the production of wastes, which leads to environmental stress in the form of biodiversity loss, pollution, and additional pressures on arable lands. Trainer (1990) argued that most developing economies are hurt by the sharp increase in population density, which determines the depletion of natural resources, water contaminations, massive deforestation, soil erosion, and damages to the marine and coastal landscapes. Moreover, Cropper and Griffiths (1994) highlighted that by raising the demand for arable land, population density enhances the transformation of forests into areas serving agricultural practices. Given that communities living in rural areas heavily rely on agriculture, deforestation might increase, driven by higher population densities, which is similar to the demand for wood used for timber and fuel. Reardon and Vosti (1995) documented a downward trend in food productivity, PG, and natural resources that reduce soil productivity, which leads to a vicious circle of density, poverty, and CO_2 emissions. Ayres and Miller (1980) claimed that if worldwide trends in PG, food production, industrialization, pollution, and resource exhaustion persist, the most credible outcome would be a drop in population density and

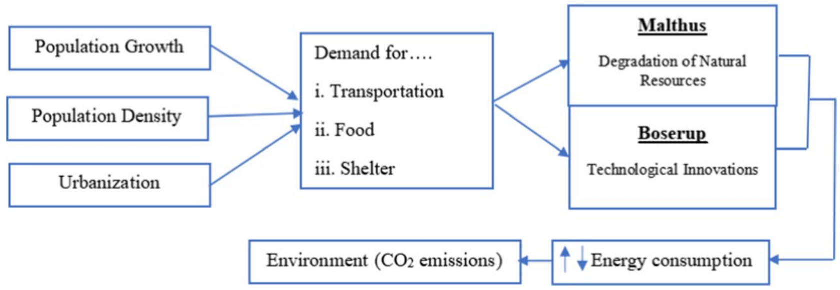

Fig. 1 Conceptual framework. Source: Author' perspective

industrial capacity beyond any control possibility. Higher population density is the major driver of pollution and other resources issues in advanced and poor countries (Ehrlich and Holdren 1971).

Dasgupta et al. (2000) empirical study on the nexus between population density and CO_2 emissions in the USA showed a positive association between the two variables. Kafka et al. (2009) examined the interplay among natural hazards, environmental degradation, and population density and highlighted the complexity of these issues, which is not going to lead to straightforward scientific answers about the timing and magnitude of the attached harmful implications. More recent works by Shafiei and Salim (2014) and Haseeb et al. (2017), who used a STRIPAT model, suggested that population density contributes to larger CO_2 emissions. Ribeiro et al. (2019) revealed the joining role of population and density in the increase of carbon emissions in the USA by using different econometrics techniques. Rahman (2020) found that energy consumption and population density have positive, while, GDP growth has negative effect on carbon emissions in India from 1971 to 2011. Wang and Li (2021) found the nonlinear relationship between population density and carbon emissions by using a panel of 154 countries. Azam and Raza (2022) found that the influence of PG on environmental pollution is mixed (positive/negative) in full and subsample analyses in a panel of 125 countries over the period of 1990–2018.

Theory and methodology

Conceptual framework

The effects of increases in population, density, and urbanization on the surroundings are a matter of discussion. These changes in demographics demand additional transportation services, food, shelter, clothing, and other necessities. According to Malthus (1798), this phenomenon can lead to the depletion of natural resources, which may increase energy consumption and, consequently, hurt the natural environment. Conversely, higher demand for transportation, food, shelter, clothing, and other necessities encourages technological innovation that may improve the efficiency of energy consumption. Carbon emissions is the main soucre of envirmental digradation (Chen et al. 2022). Ehrlich and Holdren (1971) present the model, namely, the influence, population, affluence, and technology (IPAT), to describe the impact of human activities on the carbon emission. They show the three main contributors of carbon emission are population, affluence, and economic activities especially production with the use of enviromental damaging technology, which shows that carbon emission increases with increase in population size, economic growth, and affluence. Moreover, York et al. (2002) argued that the population size, technology, and wealth have fluctuating effects on carbon emissions. Similarly, urbanization is also considered the major contributor of the carbon emission. The develoment of cities indicates the increase in the proportion of urban population and alters consumer markets, industrial sturcture, etc. (Li et al. 2020). Figure 1 shows the comparison between Malthus and Boserup's school of thought.

Data and data sources

Annual panel secondary data over the period ranging from 1990 to 2018 are used[1]. Urban population is the total population of a country residing in urban areas and population density is represented as the population per square kilometer; the data are gathered from the World Development Indicators (WDI) (2022) and the World Bank. Finally, data on CO_2 emissions, expressed in millions of metric tons (MT), GDP per capita, industry (including construction), value added measured in current US dollar, GDP per unit of energy use (PPP $ per kg of oil equivalent) used as proxy for energy intensity,[2] and energy use (kg of oil equivalent per capita) are also collected from the World Bank's online database.

[1] We intend to use more longer and updated data but consistent data on some variables especially CO_2 emissions are not available. Data used in this study for empirical examination have been obtained from the World Development Indicators (2022), the World Bank database https://data.worldbank.org/

[2] We intend to use energy price as a determinant of carbon emission in this study, but reliable and consistent balanced panel data on our sample countries were not available, while most of the prior studies used inflation, consumer price index, or GDP deflator as proxy for energy prices (Mahadevan and Asafu-Adjaye 2007; Tang and Tan 2013; Anton and Nucu 2020). Therefore, unlike the use of inflation as proxy for energy prices, we used the energy intensity instead of energy prices.

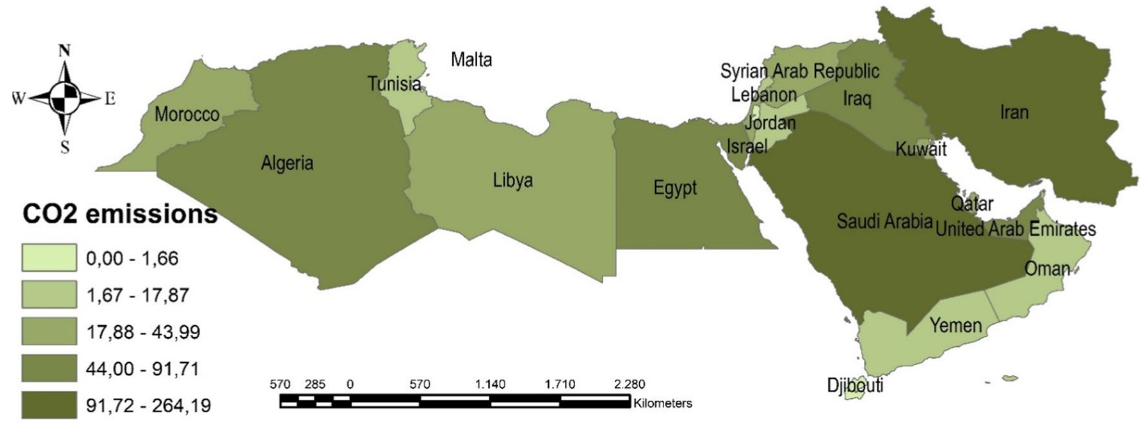

Fig. 2 CO_2 Emissions in MENA countries (average 1960–2016). Source: Salehnia et al. (2020)

Table 1 Description of variables and sources of data

Variables	Symbol	Definition	Measure	Expected sign	Variables used in literature
Carbon dioxide	ED	CO_2 produced during usage of liquid, solid, and gas fuels and gas flaring.	Million tons per capita.	–	
Population density	PD	"Population density is midyear population divided by land area in square kilometers.	persons/seq/km	+/–	Ohlan (2015) and Zarco-Periñán et al. (2021) and many others
Population size	TP	"The total population is calculated using the de-facto concept of population that includes all people notwithstanding position or citizenship. The data presented are midyear projections."	Millions of people.	+/–	Dietz and Rosa (1997) and Bidsall (1992) and many others
Urban population	UR	The term "urban population" refers to persons who live in cities as defined by national statistical bureaus. The United Nations Population Division gathers and smooths data.	Numbers	+/–	Kasman and Duman (2015), and Azam et al. (2022) and many others
GDP per capita	GDP	GDP per capita is gross domestic product divided by mid-year population.	Current US$	+/–	Wang et al. (2016) and Mikayilov et al. (2018) and many others
Industry, value added	IND	It comprises value added in mining, manufacturing, construction, electricity, water, and gas.	Current US$	+	Liu and Bae (2018) and Raheem and Ogebe (2017) and many others
Energy use	EC	Energy use refers to use of primary energy before transformation to other end-use fuels.	kg of oil equivalent per capita	+	Zhang and Lin (2012) and Wang et al. (2016) and many others

Source: Data collected from the World Development Indicators (2022) and the World Bank

Figure 2 shows the volume of carbon emissions in selected MENA countries. Variable definitions and data sources are given in Table 1.

Figure 2 shows the geographical distribution of CO_2 emanations in the 16 MENA countries included in the research. The data illustrated correspond to the average for the period. The two main economic powers in the region, Saudi Arabia and Iran, are the countries with the highest amount of CO_2 emissions, and, to a lesser extent, Egypt and Algeria.

Model specification

The main purpose of this work is to investigate the effects of population and population density on CO_2 in the MENA region, in which Algeria, Egypt, Iran, Iraq, Jordan, Lebanon, Morocco, Tunisia, and Yemen are developing (lower middle income and upper middle income) and Bahrain, Israel, Kuwait, Malta, Oman, Saudi Arabia, and UAE are developed countries (high income)[3]. The multivariate regression model used in many previous studies including Zhu et al. (2012), Shafiei and Salim (2014), Xu and Lin (2015), Awan et al. (2020), Awan and Azam (2021), Haseeb and Azam (2021), and Khan et al. (2021) is also used in this work, which can be expressed as follows:

$$ED_{it} = \beta_0 + \beta_1 EC_{it} + \beta_2 GDP_{it} + \beta_3 EI_{it} + \beta_4 IND_{it} + \beta_5 PD_{it} + \beta_6 UP_{it} + \beta_7 TP_{it} + \varepsilon_{it} \tag{1}$$

where ED refers to the amount of CO_2 emission per capita which represents environmental degradation, UP is the urban poplutaion, PD measures population density, GDP is GDP per capita, EI is energy intensity measured by GDP per unit of energy consuption, and IND measures industry (including construction) value added. The use of logarithms of the variables makes obtaining the elasticities directly in the econometric estimates easier. Table 1 reports the descriptive statistics on all variables, namely, CO_2 emissions, urban population, population density, GDP per capita, industry value added, GDP per unit of energy use, and energy use for 16 MENA countries over the period of 1990–2018. For the empirical analysis, data are transformed into log form to avoid any nonlinearity problem. Similarly, Table 2 contains the coefficients of the partial correlations between the pairs of variables.

Econometric strategy

The major target of this study is to determine whether there exists a long-term nexus among CO_2 emissions, population size, population density, and urban population of the MENA countries. This study selects MENA data to empirically investigate the Malthus and Boserup's school of thought. The four steps for the panel data analysis are as follows. We employ (i) the cross-sectional dependency test to check the independence between sections. If cross-section dependence exists then, we are required to apply the second-generation tests. (ii) The panel unit root test to check the stationarity between the variables. (iii) Panel cointegration approach is used to verify if cointegration exists between the variables. (iv) As per behavior of the data, we apply GMM, robust least squares (RLS), and FMOLS techniques to estimate the long-run elasticities and other more recent techniques. (v) Finally, the causal effect between the variables is explored using the Granger causality approach. However, the vector autoregressive (VAR) model is not appropriate in this case because the order of integration of the variables is mixed, while the VAR model required that all the variables are to be stationary at 1st difference. The panel VAR framework required the first difference ordered data of each variable included in the empirical model. Moreover, we apply GMM, robust least squares (RLS), and FMOLS techniques to reconfirm and give the robust and reliable results.

Cross-sectional dependence and panel unit root test

First, we execute the cross-sectional dependence test, which determines the application of the first- or second-generation cointegration approaches. We estimate the Pesaran (2015) test, in which the null hypothesis states that the variables are independent in the cross sections. Acceptance of the null hypothesis implies that what happens in any of the MENA countries does not affect the rest of the countries in this region. Second, we check the unit root of variables, which is a necessary condition for cointegration analysis. If the data series is nonstationary at the start, then it can be transformed to become stationary. Researchers have developed new unit root methods because the old unit root methods are too restricted and cannot detect the stationarity of the variables (Shahbaz et al. 2014). On the basis of previous empirical evidence, we apply the second-generation cointegration tests. In these tests, the null hypothesis (H0) is that every series inside the panel has a unit root (for all i); whereas the alternative hypothesis (H1) allows some (but not all) of the individual series to have unit roots. By using the series without the trend component obtained through the first difference, Eq. (2) specifies the unit root test in its standard form.

$$\Delta y_{it} = \alpha_i + \rho_i y_{it-1} + \varphi_0 \overline{y}_{t-1} + \sum_{j=0}^{p} \varphi_{j-1} \Delta \overline{y}_{t-1} + \sum_{k=1}^{p} c_k \Delta y_{it-k} + \varepsilon_{it} \tag{2}$$

[3] The World Bank assigns world economics to four income groups—low, lower-middle, upper-middle, and high income based on the Atlas GNI per capita (low income, less than USD 1085 GNI per capita; lower middle income range USD 1086–4255; upper middle income range USD 4256–13,205, and high income above USD 13,205). Source: https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2022-2023

Table 2 Descriptive statistics and correlation matrix of variables

	Variables/ statistics	ED_{it}	EC_{it}	GDP_{it}	EI_{it}	IND_{it}	PD_{it}	UP_{it}	TP_{it}
Whole penal	Mean	0.7329	3.2509	3.7363	0.8835	10.2480	1.9165	6.7839	6.8919
	Median	0.6598	3.1477	3.7272	0.9144	10.3330	1.8162	6.8068	6.8942
	Maximum	1.5017	4.0937	4.7443	1.2851	11.6641	3.3037	7.7872	8.9843
	Minimum	0.0023	2.2589	1.3578	0.1761	8.3184	0.7675	5.5053	4.1541
	Std. Dev.	0.4247	0.4878	0.5672	0.1632	0.6807	0.6344	0.5734	0.7360
	Skewness	0.1979	0.1888	− 0.4026	− 0.9026	− 0.2308	0.3987	− 0.4385	− 0.1229
	Kurtosis	1.8622	2.0805	3.2320	3.9643	2.2319	2.4771	2.4915	3.8464
	ED_{it}	1							
	EC_{it}	0.7752	1						
	GDP_{it}	0.8126	0.8189	1					
	EI_{it}	− 0.2619	− 0.2882	0.1172	1				
	IND_{it}	0.3336	0.3396	0.3823	0.2439	1			
	PD_{it}	0.1748	0.2123	0.3297	− 0.2237	− 0.4060	1		
	UP_{it}	− 0.4066	− 0.3820	− 0.4053	0.1902	0.6117	− 0.5495	1	
	TP_{it}	− 0.4245	− 0.4196	− 0.4401	0.1655	0.4336	− 0.4554	0.8107	1
Developing countries panel	Mean	0.4176	2.8975	3.3278	0.8934	10.1563	1.7864	7.0846	7.2410
	Median	0.4160	2.9525	3.3448	0.9293	10.1518	1.7800	7.1537	7.2909
	Maximum	0.8967	3.4858	4.0152	1.1548	11.4445	2.8264	7.7872	8.9843
	Minimum	0.0023	2.2589	1.3578	0.1761	8.3184	1.0340	6.3673	4.5902
	Std. Dev.	0.2177	0.2613	0.3753	0.1645	0.6018	0.3803	0.3843	0.6182
	Skewness	0.0398	− 0.3728	− 1.4651	− 1.1604	− 0.1318	0.7185	− 0.0553	0.1752
	Kurtosis	2.5370	2.8982	7.9971	4.6502	2.6046	4.1389	1.7957	4.9589
	ED_{it}	1							
	EC_{it}	0.9079	1						
	GDP_{it}	0.4584	0.5176	1					
	EI_{it}	− 0.3252	− 0.3645	0.3307	1				
	IND_{it}	0.3273	0.3933	0.5016	0.2452	1			
	PD_{it}	0.1594	0.1576	0.3580	0.0246	− 0.2672	1		
	UP_{it}	0.2731	0.3617	0.1474	0.0352	0.8729	− 0.3710	1	
	TP_{it}	0.0018	0.0165	− 0.0674	0.0329	0.4894	− 0.0944	0.5705	1
Developed countries panel	Mean	1.1383	3.7053	4.2616	0.8707	10.3660	2.0838	6.3973	6.4430
	Median	1.1841	3.7437	4.2937	0.9020	10.5541	2.1245	6.3489	6.4722
	Maximum	1.5017	4.0937	4.7443	1.2851	11.6641	3.3037	7.4511	7.5277
	Minimum	0.4720	3.1048	3.7340	0.4056	8.9868	0.7675	5.5053	4.1541
	Std. dev.	0.2423	0.2976	0.2515	0.1610	0.7557	0.8285	0.5446	0.6244
	Skewness	− 0.4200	− 0.2320	− 0.2323	− 0.5740	− 0.4744	− 0.1610	0.0630	− 0.4927
	Kurtosis	2.1363	1.5962	2.0451	3.2309	2.0625	1.6189	2.1066	3.1279
	ED_{it}	1							
	EC_{it}	0.9350	1						
	GDP_{it}	0.3280	0.3683	1					
	EI_{it}	0.4450	− 0.4602	0.2610	1				
	IND_{it}	0.4391	0.3694	0.4310	0.2758	1			
	PD_{it}	0.1504	− 0.0219	0.2360	− 0.3842	− 0.5724	1		
	UP_{it}	0.1794	0.1372	0.2432	0.3321	0.8965	− 0.6047	1	
	TP_{it}	0.1405	0.0843	0.1285	0.3085	0.7590	− 0.6277	0.8816	1

Source: authors’ compilation

The fraction of the individual time series that are stationary should be nonzero, such as $\lim_{n\to\infty}(n1/n) = \delta$, where $1 < \delta \leq 1$. This condition is necessary for the consistency of the panel unit root test.

Panel cointegration test

Numerous cointegration tests are used in the empirical literature on environmental degradation. However, the possible existence of dependency in the cross sections conditions the application of second-generation cointegration techniques. Westerlund (2007) verified the null hypothesis of no cointegration between the series in 16 countries of the MENA region. One advantage of this cointegration test is that it does not impose restrictions on the common factors and includes the model's structural dynamics and dependence on the cross sections. The residual series $\hat{e}_{it}$ is stationary when all the variables cointegrated are included in the model. Thus, to test the H_0 of no cointegration is equal to testing the residuals of the regrression for a unit root with authoregression. Then Eq. (3) proposes the Westerlund (2005) simple panel cointegration test-based residuals used for this study. However, we cannot use the panel cointegration test based on error-correction because the order of integration of the variables of this study is mixed. The panel cointegration test based on error correction required that all the variables are integrated of order one $I(1)$ (Persyn and Westerlund 2008). Furthermore it is needed that the series needs to be integrated at the first order (I(1)) for employing the Bootstrap panel cointegration approach (Azam and Haseeb 2021). All the variables are assumed to be stationary at level by applying the ECM-based cointegration test (Catia 2013). We also apply the Kao residual cointegration test to reverify the cointegration in the among the variables.

$$\hat{e}_{it} = \rho_i \hat{e}_{it-1} + \mu_{it} \tag{3}$$

The GMM estimation

The generalized method of moments (GMM) is famous estimation technique to avoid the endogeneity problem. The GMM technique is the extension of instrumental variable (IV) technique. GMM techniques have many advantages like the model is not required to be homoscedastic and serially independent and to overcome the problem of endogeneity as well. Empirical results obtained employing the GMM techniques are more robust if compared with other approaches (Ahmad and Khan 2019). Especially, the developing economies differ in several observable like consumption, saving, per capita income, etc., and unobservable characteristic like stages of development, culture, etc., while estimating the panel data, concerns such as endogeneity and reverse casualty may arise. The dynamic panel system GMM technique significantly tackles the problem of autocorrelation, reverse causation, and endogeneity and to acquire the consistent, efficient, and unbiased estimates (Ahmad and Khan 2019).

The FMOLS estimation

After establishing that the series is cointegrating, this study proceeds to evaluate the long-run coefficients using Pedroni (2001) FMOLS technique, which enables for the estimation of heterogeneous co-integrated vectors for the panel members. This technique has the advantage of correcting autocorrelation and simultaneity biases. One more reason that OLS is ineffective is that its estimation generates skewed results because the explanatory variables determined are endogenously in case I(1).

The panel Granger causality

The presence of a causal association between variables, at least in one way, is indicated by the cointegration relation. It does not, however, provide details on the causal links. This study describes a panel-based ECM with a dynamic error correction illustration to examine the direction of short- and long-term causal associations between the variables. Generally, we use the Engle and Granger (1987) two-sequence technique. To obtain the residuals, we initially estimate the long-run parameters via the GMM, RLS, and FMOLS techniques. The residuals are then used as a right-hand-side parameter to estimate the short-run error correction model in the second step. The Akaike information criterion is used to determine the optimal lag length. Along with the estimating short- and long-run coefficients, we also used the pairwise Dumitrescu-Hurlin (D-H) (2012) panel causality test to examine the direction of a causal link between the variables included in the model of the study.

Results and discussions

The results of the cross-sectional dependence test in the series are presented in Table 3. To verify the estimated consistency of the parameters, we report the results of Pesaran (2015) with their respective ρ-values. From the ρ-value of the CD values, evidence indicates to reject the null hypothesis of cross-sectional independence. Consequently, the series contains cross-sectional dependence in the series. These results occur due to the relationship that exists between the countries of the MENA region. Furthermore, the results in Table 3 justify the unit root and second-generation cointegration procedures. The existence of

Table 3 Cross-sectional dependence test analysis

	Tests	ED_{it}	EC_{it}	GDP_{it}	EI_{it}	IND_{it}	PD_{it}	UP_{it}	TP_{it}
Whole panel	Breusch-Pagan LM	1180.75* (0.0000)	1182.6* (0.0000)	2657.9* (0.0000)	1703.43* (0.0000)	2150.4* (0.0000)	3284.6* (0.0000)	3294.5* (0.0000)	1907.5* (0.0000)
	Pesaran scaled LM	68.471* (0.0000)	68.59* (0.0000)	163.82* (0.0000)	102.210* (0.0000)	131.06* (0.0000)	204.27* (0.0000)	204.91* (0.0000)	115.38* (0.0000)
	Pesaran CD	7.1046* (0.0000)	18.580* (0.0000)	51.289* (0.0000)	34.9635* (0.0000)	42.678* (0.0000)	57.282* (0.0000)	57.372* (0.0000)	30.615* (0.0000)
Developing countries panel	Breusch-Pagan LM	328.76* (0.0000)	440.32* (0.0000)	740.07* (0.0000)	565.82* (0.0000)	726.87* (0.0000)	1031.6* (0.0000)	1027.8* (0.0000)	105.26* (0.0000)
	Pesaran scaled LM	34.503* (0.0000)	47.650* (0.0000)	82.976* (0.0000)	62.440* (0.0000)	81.420* (0.0000)	117.33* (0.0000)	116.88* (0.0000)	8.1628* (0.0000)
	Pesaran CD	9.9201* (0.0000)	16.370* (0.0000)	27.023* (0.0000)	21.705* (0.0000)	26.728* (0.0000)	32.118* (0.0000)	32.058* (0.0000)	2.6654* (0.0077)
Developed countries panel	Breusch-Pagan LM	187.27* (0.0000)	134.62* (0.0000)	515.97* (0.0000)	246.17* (0.0000)	345.35* (0.0000)	547.18* (0.0000)	552.45* (0.0000)	411.95* (0.0000)
	Pesaran scaled LM	25.6558* (0.0000)	17.532* (0.0000)	76.376* (0.0000)	34.7452* (0.0000)	50.049* (0.0000)	81.192* (0.0000)	82.004* (0.0000)	60.3246* (0.0000)
	Pesaran CD	0.5845* (0.5589)	2.5994* (0.0093)	22.679* (0.0000)	11.5626* (0.0000)	15.028* (0.0000)	23.379* (0.0000)	23.493* (0.0000)	13.9058* (0.0000)

Asterisk * denote the significance level of 1%

Table 4 Panel unit root tests analysis

	Tests	Lag	ED_{it}	EC_{it}	GDP_{it}	EI_{it}	IND_{it}	PD_{it}	UP_{it}	TP_{it}
Whole panel	L.L.C (p-value)	1(0)	− 1.038 (0.1497)	− 1.55*** (0.0606)	− 2.18** (0.0147)	− 3.52* (0.0002)	− 2.24** (0.0125)	6.177 (1.0000)	3.535 (0.9998)	1.609 (0.9462)
		1(1)	− 7.072* (0.0000)	− 7.057* (0.0000)	---	---	---	− 15.17* (0.0000)	− 13.52* (0.0000)	− 13.92* (0.0000)
	CIPS	1(0)	− 1.397	− 2.385*	− 2.719*	− 2.591*	− 2.400*	− 3.081*	− 2.635*	− 2.25**
		1(1)	− 5.019*	---	---	---	---	---	---	---
Developing countries panel	L.L.C (p-value)	1(0)	− 1.2539 (0.1049)	− 1.0395 (0.1493)	− 2.450* (0.0072)	− 3.333* (0.0004)	− 2.781* (0.0027)	7.0011 (1.0000)	4.0819 (1.0000)	2.3943 (0.9917)
		1(1)	− 7.383* (0.0000)	− 4.3467* (0.0000)	---	---	---	− 13.42* (0.0000)	− 12.27* (0.0000)	− 12.80* (0.0000)
	CIPS	1(0)	− 1.202	− 1.646	− 2.45**	− 2.668*	− 1.953	− 2.806*	− 3.101*	− 4.593*
		1(1)	− 5.157*	− 5.222*	----	----	− 4.188*	-----	-----	-----
Developed countries panel	L.L.C (p-value)	1(0)	0.0789 (0.5314)	− 1.51*** (0.0650)	− 0.2549 (0.3994)	− 1.34*** (0.0899)	0.3451 (0.6350)	− 1.0056 (0.1573)	− 0.5871 (0.2786)	− 1.0510 (0.1466)
		1(1)	− 2.386* (0.0085)	− 5.791* (0.0000)	− 8.409* (0.0000)	− 5.0322* (0.0000)	− 6.247* (0.0000)	− 4.507* (0.0000)	− 4.772* (0.0000)	− 4.127* (0.0000)
	CIPS	1(0)	− 1.782	− 2.780*	− 2.28**	− 2.349**	− 2.540*	− 2.641*	− 0.491	0.633
		1(1)	− 5.168*	----	----	----	----	----	− 2.37*	− 2.2***

Asterisks *, **, and *** indicated the level of significance at 1%, 5%, and 10%, respectively, and value inside circle parenthesis () is *p*-value. Critical values for CIPS test are − 2.07, − 2.15, and − 2.32 and 1%, 5%, and 10%, respectively

heterogeneity in the slope and the transversal dependence determines the estimation of techniques that implicitly incorporate both aspects and obtain reliable estimators. Several empirical investigations have used the cross-sectional dependence and the slope's homogeneity tests.

Panel unit root test results

Table 4 shows the results of the first-generation unit root test L.L.C by Levin et al. (2002) and the second-generation unit root test CIPS by Pesaran et al. (2013). First, we apply both unit root tests on the whole panel. The L.L.C results show that the series energy use, GDP, GDP per unit of energy use,

Table 5 Cointegration tests results

Test	Whole panel		Developing countries panel		Developed countries panel	
	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Westerlund test for cointegration	1.8477**	0.0323	1.8595**	0.0315	1.5606***	0.0593
Kao Residual Cointegration Test	– 3.0250*	0.0012	– 2.5218*	0.0058	– 2.9515*	0.0016

Asterisks *, **, and *** indicated the level of significance at 1%, 5%, and 10%, respectively

and industry are stationary at level, while CO_2 emissions, population density, total population, and urban population have stationary at first difference. Similarly, the CIPS test results indicated that the series ED (CO_2) is stationary at the first difference, while the remainder of the series are stationary at level. In developing countries, the L.L.C test results show that GDP per capita income (GDP), energy intensity, and industrial value added are stationary at level, while the rest of the variables are stationary at the first difference. Similarly, the CIPS test results show that the series CO2, energy use, and industry are stationary at first difference, while the remaining are stationary at level. Furthermore, in the case of developed countries, the L.L.C test results show that GDP per unit of energy use and industry are stationary at level, while the rest of the variables are stationary at the first difference. Similarly, the CIPS test results show that the series such as CO_2, total population, and urban population are stationary at the first difference, while the remaining are stationary at level.

Panel cointegration test results

The panel unit root result reveals that all series have the mixed integration order and suggest using the simple panel cointegration approach based on residuals to test the variables' long-run association, but cannot apply the panel cointegration test based on error correction. Therefore, we initially use the Kao residual cointegration test, and Westerlund residual cointegration test results are shown in Table 5. Both tests support the existence of cointegration among the variables by rebuffing the null hypothesis of no cointegration in each panel.

Regression results

We implemented the GMM, FMOLS, and RLS techniques to estimate the coefficient of the variables for whole/full, developing countries and developed countries panel. Table 6 indicates the regression results of all estimators for the whole panel/full sample. The results of all the estimators indicated that energy use has a positive and significant effect on CO_2 emissions. The MENA region is abundant with natural resources and huge consumption of energy leads to carbon emissions (Muhammad 2019). Our results were in line with Zhang and Lin (2012) and Wang et al. (2016). Similarly, the GDP also has positive and significant effect on CO2 emissions. Energy usage is the main input in the production process like transport and public sector activities. It indicated that energy usage has a direct effect on GDP. Furthermore, the GDP also affects carbon emissions directly (Saboori et al. 2012). Similar results were given by Wang et al. (2016) and Mikayilov et al. (2018). The EI has positive and significant effect on CO_2 emissions. The opposite results were given by Li et al. (2020). Similarly, the industry also has a positive and significant effect on CO_2

Table 6 The GMM, RLS, and FMOLS estimates (full sample- 16)

Variables	GMM	RLS	FMOLS
EC_{it}	0.0524* [0.0190] (0.0062)	0.4067* [0.0134] (0.0000)	0.6286* [0.0517] (0.0000)
GDP_{it}	0.0259* [0.0096] (0.0071)	0.2518* [0.0153] (0.0000)	0.2302* [0.0291] (0.0000)
EI_{it}	0.0878* [0.0195] (0.0000)	0.6000* [0.0236] (0.0000)	0.1464* [0.0528] (0.0063)
IND_{it}	0.0297** [0.0127] (0.0199)	0.1387* [0.0123] (0.0000)	0.7883* [0.0629] (0.0000)
PD_{it}	0.0146* [0.0038] (0.0001)	0.1503* [0.0052] (0.0000)	0.4794* [0.0059] (0.0000)
TP_{it}	0.1220* [0.0460] (0.0083)	0.0203* [0.0065] (0.0018)	0.6368* [0.0303] (0.0000)
UP_{it}	0.0722** [0.0324] (0.0263)	0.3347* [0.0135] (0.0000)	0.2592* [0.0049] (0.0000)

Asterisks *, **, and *** indicated the level of significance at 1%, 5%, and 10%, respectively

The value inside square parenthesis [] is standard deviation and circle parenthesis () is *p*-value emissions. Because China is the biggest and most newly industrilized and 2nd-largest economy in the world, the huge rise in the GDP growth in the past few decades also rises carbon emissions (Liu and Bae 2018). Similar results were given by Liu and Bae (2018), while dissimilar results were given by Raheem and Ogebe (2017). The population density has positive and significant effect on CO_2 emissions. The same result was given by Ohlan (2015) and Zarco-Periñán et al. (2021). Similarly, the urban population has positive and significant effect on CO_2 emissions. The urbanization will boost the economic growth by increaseing consumption and output. The rise in urbanization will increase the demand for infrastructure, such as transportation, building, and other facilities as well as the environmental pollution, particularly, GHG emissions (Liu and Bae 2018). Similar results that urban population has significantly contributed to the CO_2 emissions were given Alam et al. (2007), Al-mulali et al. (2012), Kasman and Duman (2015), and Azam et al. (2022), but contradictory to the findings by Fan et al. (2006) and Shafiei and Salim (2014). Similarly, the total population has a positive and significant effect on CO_2 emissions. When the population size increases, ultimately, the population increases and causes environmental damage. The population growth increases the demand for energy utilization and consequently higher atmospheric pollution, and will exacerbate environmental issues (Haddian 2018). Several prior studies, including Dietz and Rosa (1997), suggest that one of the central causes of higher global CO_2 emissions is population growth. In a study, Bidsall (1992) also claimed that a larger population enhances CO_2 emissions because population growth leads to an upsurge in demand for energy usage, thereby growing fossil fuel emissions. Likewise, it can cause deforestation and some other negative influence on the environment.

Table 7 depicts the regression results of all estimators for the developing countries panel. The results indicated that energy use, GDP, industry, population density, and urban population have positive and significant effect on CO_2 emissions. However, GMM technique results show that EI has an insignificant effect on CO_2 emissions, while RLS and FMOLS results show that EI has significant and positive effects on CO_2 emissions. Similarly, the GMM and RLS technique results show that the total population has an insignificant effect on CO_2 emissions, while FMOLS technique results show that total population has a positive and significant effect on CO_2 emissions.

Similarly, Table 7 indicates the regression results of all estimators for the developed countries panel. The results displayed that energy use, GDP, population density, industry, and urban population have positive and significant effect on ED. However, GMM technique results show that EI and the total population have an insignificant effect on CO_2 emissions, while RLS and FMOLS results show that EI and the total population have significant and positive effects on CO_2 emissions. Table 7 shows results on the developing MENA countries, and Table 8 results on developed MENA countries.

Table 7 The GMM,RLS, and FMOLS estimates (developing MENA countries-09)

Variables	GMM	RLS	FMOLS
EC_{it}	0.2437* [0.0412] (0.0000)	0.8962* [0.0258] (0.0000)	0.5356* [0.0682] (0.0000)
GDP_{it}	0.0491** [0.0211] (0.0210)	0.0537** [0.0255] (0.0352)	0.1836* [0.0319] (0.0000)
EI_{it}	0.0281 [0.0218] (0.1979)	0.0657** [0.0335] (0.0494)	0.1144** [0.0545] (0.0378)
IND_{it}	0.0388* [0.0148] (0.0093)	0.0868* [0.0243] (0.0004)	0.1699** [0.0729] (0.0214)
PD_{it}	0.4753* [0.1050] (0.0000)	0.0390* [0.0138] (0.0047)	0.3674* [0.0061] (0.0000)
TP_{it}	0.0010 [0.0033] (0.7699)	0.0101 [0.0083] (0.2240)	0.2732* [0.0374] (0.0000)
UP_{it}	0.3448* [0.0839] (0.0001)	0.1110* [0.0316] (0.0004)	0.3338* [0.0051] (0.0000)

Asterisks *, **, and *** indicated the level of significance at 1%, 5%, and 10%, respectively

The value inside square parenthesis [] is standard deviation and circle parenthesis () is *p*-value

Nine (09) developing (lower middle income and upper middle income) MENA countries anemlyAlgeria, Egypt, Iran, Iraq, Jordan, Lebanon, Morocco, Tunisia, and Yemen

Granger causality tests results

After finding the effects of population density, urban population, and other macroeconomic variables on CO_2 emission, we further implement the D–H causality tests to examine the path of causality between the variables used in this study. Table 9 shows the results of D-H Granger causality techniques among the variables.

In the whole panel/full sample, there is bi-directional causality that exists between energy use and ED, GDP and ED, EI and ED, industry and ED, population density and ED, urban population and ED, total population and CO_2 emissions, total population and EI, total population and population density, total population and urban population, population density and energy use, urban population and energy use, GDP and EI, GDP and population density, GDP and urban population, EI and industry, EI and population density, EI and urban

Table 8 The GMM, RLS, and FMOLS estimates (developed MENA countries-07)

Variables	GMM	RLS	FMOLS
EC_{it}	0.0854***	0.6175*	0.2599*
	[0.0482]	[0.0003]	[0.0254]
	(0.0777)	(0.0000)	(0.0000)
GDP_{it}	0.1297*	0.1386*	0.2244*
	[0.0381]	[0.0004]	[0.0167]
	(0.0008)	(0.0000)	(0.0000)
EI_{it}	0.0209	0.2783*	0.1379*
	[0.0657]	[0.0006]	[0.0333]
	(0.7511)	(0.0000)	(0.0010)
IND_{it}	0.0369**	0.0660*	0.0579*
	[0.0163]	[0.0002]	[0.0044]
	(0.0244)	(0.0000)	(0.0000)
PD_{it}	0.9125***	0.0774*	3.4623*
	[0.4921]	[0.0001]	[0.1878]
	(0.0653)	(0.0000)	(0.0000)
TP_{it}	0.0202	0.0139*	0.0016***
	[0.0240]	[0.0002]	[0.0009]
	(0.4018)	(0.0000)	(0.0975)
UP_{it}	0.8100***	0.1285*	2.9493*
	[0.4545]	[0.0003]	[0.1690]
	(0.0764)	(0.0000)	(0.0000)

Asterisks *, **, and *** indicated the level of significance at 1%, 5%, and 10%, respectively

The value inside square parenthesis [] is standard deviation and circle parenthesis () is *p*-value

Seven (07) developed (high income) MENA countries namely Bahrain, Israel, Kuwait, Malta, Oman, Saudi Arabia, and the UAE

population, population density and industry, and urban population and population density. Furthermore, there is uni-directional casualty running from GDP to energy use, energy use to EI, industry to energy use, industry to GDP, energy use to the total population, and GDP to the total population.

In the developing countries panel, there is bidirectional causality that exists among the energy use and ED, GDP and ED, EI and ED, industry and ED population density and ED, urban population and ED, GDP and energy use, population density and energy use, urban population and energy use, EI and GDP, EI and industry, population density and EI, EI and urban population, population density and total population, urban population and total population, and urban population and population density. However, there is a unidirectional casualty running from energy use to EI, industry to energy use, industry to GDP, GDP to population density, GDP to urban population, industry to population density, energy use to total population, GDP to total population, EI to total population, and industry to the urban population.

In the developed countries panel, there is a one-way casualty exist running from ED to energy use, GDP to ED, EI to ED, industry to ED, industry to energy use, population density to energy use, urban population to energy use, population density to EI, energy use to total population, population density to total population, urban population to total population, and urban population to EI. However, there is two-way causality exist between population density and ED, urban population and ED, GDP and EI, population density and GDP, urban population and GDP, industry and EI, industry and population density, industry and urban population, ED to total population, GDP and total population, industry and ED, and population density and urban population. Furthermore, there is no causality that exists between GDP and energy use, EI and energy use, and industry and GDP.

Conclusion and policy implications

The central aim of this study is to analyze the relationship among demographic factors (population density and urban population) and other macroeconomic variables and CO2 emissions for the sixteen countries from the MENA region over the period of 1990 to 2018. After checking the data cross-sectional dependency, we use appropriate and broadly used panel unit root test, namely, LLC and CIPS. As per the behavior of the data, we use GMM, FMOLS, and RLS techniques to estimate the coefficients of the variables. We also use Kao and Westerlund residual cointegration tests to examine long-run cointegration among the variables. In addition, we applied the D-H causality test to examine the direction of the variables.

We found that there exists long-run cointegration among the variables in each panel. We also found that energy use, GDP, EI, population density, urban population, and the total population have a positive and significant effect on ED. In the case of developing countries panel, the energy use, GDP, industry, population density, and urban population have positive and significant effect on ED. Similarly, in the developed countries panel, energy use, GDP, population density, industry, EI, and total population and urban population have positive and significant effect on ED.

In the whole panel, there is a bi-directional causality that exists between energy use and ED, GDP and ED, EI and ED, industry and ED, population density and ED, urban population and ED, total population and ED, total population and EI, total population and population density, total population and urban population and population density and energy use, urban population and energy use, GDP and EI, GDP and population density, GDP and urban population, EI and industry, EI and population density, EI and urban population, population density and industry, and urban population and population density. Furthermore, there is uni-directional casualty running from GDP to energy use, energy use to EI,

Table 9 Panel Granger causality (D-H) test results

		ED it	EC it	GDP it	EI it	IND it	PD it	UP it	TP it
Full sample-16	ED_{it}	----	10.1818* (0.0000)	4.5202* (0.0001)	3.8940* (0.0053)	3.5458** (0.0269)	15.1517* (0.0000)	9.8304* (0.0000)	6.7866* (0.0000)
	EC_{it}	3.3894*** (0.0505)	----	2.6570 (0.4523)	3.6138** (0.0201)	2.1526 (0.9379)	8.3847* (0.0000)	4.4126* (0.0003)	4.8203* (0.0000)
	GDP_{it}	7.2595* (0.0000)	4.7574* (0.0000)	----	4.8129* (0.0000)	2.3097 (0.8568)	20.6435* (0.0000)	15.6557* (0.0000)	7.7982* (0.0000)
	EI_{it}	4.8398* (0.0000)	2.7784 (0.3415)	4.8527* (0.0000)	----	5.8671* (0.0000)	10.4709 (0.0000)	6.6130* (0.0000)	4.0868* (0.0019)
	IND_{it}	6.7252* (0.0000)	5.1537* (0.0000)	7.6807* (0.0000)	4.0202* (0.0028)	----	16.8060* (0.0000)	11.9985* (0.0000)	6.7837* (0.0000)
	PD_{it}	10.1679* (0.0000)	6.5619* (0.0000)	3.6615** (0.0162)	6.3899* (0.0000)	3.9109* (0.0049)	----	30.7430* (0.0000)	6.6060* (0.0000)
	UP_{it}	10.2746* (0.0000)	6.0828* (0.0000)	3.9187* (0.0047)	6.4460* (0.0000)	4.2705* (0.0007)	41.7017* (0.0000)	----	8.9991* (0.0000)
	TP_{it}	4.1008* (0.0018)	2.1802 (0.9741)	3.0140 (0.1807)	3.4354** (0.0422)	4.0202* (0.0028)	3.9798* (0.0034)	6.8741* (0.0000)	----
Developing countries Panel-07	ED_{it}	----	12.1481* (0.0000)	5.4455* (0.0000)	4.6011* (0.0031)	4.2061* (0.0133)	12.9012* (0.0000)	3.9489* (0.0310)	8.0767* (0.0000)
	EC_{it}	4.2632** (0.0109)	----	5.3548** (0.0527)	5.3548* (0.0001)	2.6923 (0.5437)	13.2897* (0.0000)	5.0936* (0.0004)	6.7490* (0.0000)
	GDP_{it}	5.6396* (0.0000)	5.6011* (0.0000)	----	5.1023* (0.0003)	2.2817 (0.9197)	25.4841* (0.0000)	17.4832* (0.0000)	12.4055* (0.0000)
	EI_{it}	4.1501* (0.0162)	2.4069 (0.7986)	5.2906* (0.0001)	----	6.2179* (0.0000)	15.9931* (0.0000)	9.7686* (0.0000)	4.5039* (0.0045)
	IND_{it}	4.9369* (0.0007)	5.7396* (0.0000)	12.3440* (0.0000)	4.5880* (0.0032)	----	23.8778* (0.0000)	14.5202 (0.0000)	9.9856* (0.0000)
	PD_{it}	5.4316* (0.0000)	6.0635* (0.0000)	3.0696 (0.2835)	6.3277* (0.0000)	2.6711 (0.5811)	----	38.2494* (0.0000)	8.4661* (0.0000)
	UP_{it}	5.8961* (0.0000)	5.6109* (0.0000)	3.2606 (0.1908)	6.0151* (0.0000)	3.0730 (0.2816)	58.9781* (0.0000)	----	12.2555* (0.0000)
	TP_{it}	2.9018 (0.3867)	2.7083 (0.5306)	2.2555 (0.9455)	2.9436 (0.3590)	2.1299 (0.9311)	5.1815* (0.0002)	10.9319* (0.0000)	----
Developed countries panel -09	ED_{it}	----	7.6536* (0.0000)	3.3306 (0.2188)	2.9846 (0.3934)	2.6969 (0.5889)	18.0453* (0.0000)	17.3924* (0.0000)	9.9904* (0.0000)
	EC_{it}	2.2659 (0.9429)	----	1.2252 (0.2890)	1.3754 (0.3697)	1.4587 (0.4200)	2.0782 (0.8946)	3.5371 (0.1458)	3.5371* (0.0000)
	GDP_{it}	9.3423* (0.0000)	3.6727 (0.1092)	----	4.4409** (0.0148)	2.3457 (0.8741)	14.4199* (0.0000)	13.3059* (0.0000)	11.8985* (0.0000)
	EI_{it}	5.7266* (0.0001)	3.2560 (0.2507)	4.2897** (0.0230)	----	5.4162* (0.0005)	3.3710 (0.2027)	2.5559 (0.6987)	4.7413* (0.0057)
	IND_{it}	9.0245* (0.0000)	4.4004* (0.0167)	1.6850 (0.5753)	3.2903 (0.2356)	----	7.7138* (0.0000)	8.7564* (0.0000)	6.5362* (0.0000)
	PD_{it}	16.2575* (0.0000)	7.2028* (0.0000)	4.4226** (0.0156)	6.4698* (0.0000)	5.5050* (0.0003)	----	21.0917* (0.0000)	10.9299* (0.0000)
	UP_{it}	15.9040* (0.0000)	6.6895* (0.0000)	4.7648* (0.0053)	6.9999* (0.0000)	5.8101* (0.0000)	19.4892* (0.0000)	----	11.4783* (0.0000)
	TP_{it}	5.6587* (0.0002)	2.1717 (0.9754)	5.1672* (0.0012)	2.7077 (0.5807)	4.7002* (0.0065)	3.3787 (0.1998)	3.1288 (0.3123)	----

Followed W-statistics and asterisks *, **, and *** indicated the level of significance at 1%, 5%, and 10%, respectively. The value inside circle parenthesis () is *p*-value

industry to energy use, industry to GDP, energy use to the total population, and GDP to the total population.

In the developing countries panel, there is bidirectional causality that exists among the energy use and ED, GDP and ED, EI and ED, industry and ED, population density and ED, urban population and ED, GDP and energy use, population density and energy use, urban population and energy use, EI and GDP, EI and industry, population density and

EI, EI and urban population, population density and total population, urban population and total population, and urban population and population density. However, there is unidirectional casualty running from energy use to EI, industry to energy use, industry to GDP, GDP to population density, GDP to urban population, industry to population density, energy use to total population, GDP to total population, EI to total population, and industry to urban population. In the developed countries panel, there is one-way casualty that exists running from ED to energy use, GDP to ED, EI to ED, industry to ED, industry to energy use, population density to energy use, urban population to energy use, population density to EI, energy use to total population, population density to total population, urban population to total population, and urban population to EI. However, there is two-way causality that exists between population density and ED, urban population and ED, GDP and energy intensity, population density and GDP, urban population and GDP, industry and energy intensity, industry and population density, industry and urban population, ED to total population, GDP and total population, industry and ED, and population density and urban population. Furthermore, there is no causality that exists between GDP and energy use, energy intensity, and energy use, and industry and GDP. The empirical findings of the study suggest some policy measures to maintain such an environment that is free of any type of pollution. The benefits of a clean environment would be better health, more productivity, and thereby a higher level of economic growth and improved level of socioeconomic condition of the society. The policymakers of the MENA region need to formulate effective policies to avoid rapid population growth and implement family planning programs. Moreover, effective planning is required to accommodate people moving from rural to urban areas because it increases CO_2 emissions in the region. The policy of a clean and green environment is desirable. Therefore, policymakers need to formulate effective policies for adopting appropriate and clean and green technology that is environmentally friendly. These measures will undeniably not only boost economic growth but will also reduce CO_2 emissions, thereby helping attain sustainable economic development in the MENA region. Aggregate and disaggregate data covering the whole world panel should also be used for analysis to compare the effects of these regressors on the response variable. Furthermore, energy consumption is one of the main drivers of carbon emissions; therefore, this study recommended the use of energy which has low carbon emissions. Similarly, the population density of a city suggests the distribution of business activities and residents' distribution and optimize the urban organizing and layouts. A fair level of population density, in particular, can lower fiscal spending and time wastage in public transit, such as buses and subways. A balanced population distribution can increase energy efficiency and further reduce carbon emissions in energy supply infrastructures such as heating and gas. The proper management and remedial measures reduce carbon emissions from industries because the MENA region has been rising vulnerable to the health impact of climate change due to the industrial revolution. The empirical results covering large panels and comparative analysis will certainly yield more robust findings and will largely help policymakers.

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Data availability World Development Indicators (2022), the World Bank. Available at https://databank.worldbank.org/source/world-development-indicators

Declarations

Ethical approval and consent to participate The authors declare that they have no conflict of interest.

Consent for publication We all authors agree to publish our research work with your journal.

Competing interests
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References

Ahmad M, Khan R (2019) Does demographic transition with human capital dynamics matter for economic growth? A dynamic panel data approach to GMM. Soc Indic 14:753–772

Alam S, Fatima A, Butt MS (2007) Sustainable development in Pakistan in the context of energy consumption demand and environmental degradation. J Asian Econom 18(5):825–837

Al-mulali U, Sab BC, C. N., & Fereidouni, H. G. (2012) Exploring the bi-directional long run relationship between urbanization, energy consumption, and carbon dioxide emission. Energy 46(1):156–167. https://doi.org/10.1016/j.energy.2012.08.043

Al-mulali U, Fereidouni HG, Lee JYM, Sab CNBC (2013) Exploring the relationship between urbanization, energy consumption, and CO2 emission in MENA countries. Renew Sustain Energy Rev 23:107–112. https://doi.org/10.1016/j.rser.2013.02.041

Atwoli L, Erhabor GE, Gbakima A, Haileamlak A, Ntumba JMK, Kigera J, . . . Mulaudzi FM (2022) Climate Change Conference: urgent action needed for Africa and the world. Panamer J Public Health (PAHO) 46:1-3. https://doi.org/10.26633/RPSP.2022.214

Awan AM, Azam M, Saeed IU, Bakhtyar B (2020) Does globalization and financial sector development affect environmental quality? A panel data investigation for the Middle East and North African countries. Environ Sci Pollut Res 27(36):45405–45418

Awan A, Alnour M, Jahanger A, Onwe JC (2022) Do technological innovation and urbanization mitigate carbon dioxide emissions from the transport sector? Technol Soc 71:102128. https://doi.org/10.1016/j.techsoc.2022.102128

Awan AM, Azam M (2021) Evaluating the impact of GDP per capita on environmental degradation for G-20 economies: does N-shaped environmental Kuznets curve exist? Environ Dev Sustain. https://doi.org/10.1007/s10668-021-01899-8

Ayres RU, Miller SM (1980) The role of technological change. J Environ Econ Manag 7(4):353–371

Azam M, Haseeb M (2021) Determinants of foreign direct investment in BRICS- does renewable and non-renewable energy matter? Energy Strat Rev 35:1–10. https://doi.org/10.1016/j.esr.2021.100638

Azam M, Raza A (2022) Does foreign direct investment limit trade-adjusted carbon emissions: fresh evidence from global data. Environ Sci Pollut Res 29(25):37827–37841

Azam M, Rehman ZU, Ibrahim Y (2022) Causal nexus in industrialization, urbanization, trade openness, and carbon emissions: empirical evidence from OPEC economies. Environ , Dev Sustain. https://doi.org/10.1007/s10668-021-02019-2

Bazza M, Kay M, Knutson C (2018) Drought characteristics and management in North Africa and the Near East. FAO Water Rep 45. https://www.cabdirect.org/cabdirect/abstract/20193257679

Begum RA, Sohag K, Abdullah SMS, Jaafar M (2015) CO2 emissions, energy consumption, economic and population growth in Malaysia. Renew Sustain Energy Rev 41:594–601. https://doi.org/10.1016/j.rser.2014.07.205

Bidsall N (1992) Another look at population and global warming. In: Population, health and nutrition policy research. Working Paper, WPS 1020 World Bank, Washington DC

Boscrup E (1965) The conditions of agricultural growth: the economics of agrarian change under population pressure. Aldine, New Yoik

Bradbury M, Peterson MN, Liu J (2014) Long-term dynamics of household size and their environmental implications. Populat Environ 36(1):73–84

Catia C (2013) CO2 emissions, GDP and trade: a panel cointegration approach. Working Papers In Transport, Tourism Information Technology And Microdata

Chen H, Tackie EA, Ahakwa I, Musah M, Salakpi A, Alfred M, Atingabili S (2022) Does energy consumption, economic growth, urbanization, and population growth influence carbon emissions in the BRICS? Evidence from panel models robust to cross-sectional dependence and slope heterogeneity. Environ Sci Pollut Res 29(25):37598–37616. https://doi.org/10.1007/s11356-021-17671-4

Chikaraishi M, Fujiwara A, Kaneko S, Poumanyvong P, Komatsu S, Kalugin A (2015) The moderating effects of urbanization on carbon dioxide emissions: a latent class modeling approach. Technol Forecast Soc Change 90:302–317

Cole MA, Neumayer E (2004) Examining the impact of demographic factors on air pollution. Populat Environ 26(1):5–21

Cropper M, Griffiths C (1994) The interaction of population growth and environmental quality. Am Econ Rev 84(2):250–254

Dasgupta P (2000) Population and resources: an exploration of reproductive and environmental externalities. Populat Dev Rev 26(4):643–689

Dasgupta P, Levin S, Lubchenco J (2000) Economic pathways to ecological sustainability. BioScience 50(4):339–345

Dietz T, Rosa EA (1997) Effects of population and affluence on CO2 emissions. Proc Nat Acad Sci 94(1):175–179

Dimnwobi SK, Ekesiobi C, Madichie CV, Asongu SA (2021) Population dynamics and environmental quality in Africa. Sci Total Environ 797:149172. https://doi.org/10.1016/j.scitotenv.2021.149172

Du L, Wei C, Cai S (2012) Economic development and carbon dioxide emissions in China: provincial panel data analysis. China Econ Rev 23(2):371–384. https://doi.org/10.1016/j.chieco.2012.02.004

Ehrhardt-Martinez K, Crenshaw EM, Jenkins JC (2002) Deforestation and the environmental Kuznets curve: a cross-national investigation of intervening mechanisms. Soc Sci Quart 83(1):226–243. https://doi.org/10.1111/1540-6237.00080

Ehrlich PR, Holdren JP (1971) Impact of population growth. Science 171(3977):1212–1217. https://doi.org/10.1126/science.171.3977.1212

Engle RF, Granger CW (1987) Co-integration and error correction: representation, estimation, and testing. Econ : J Econ Soc 55(2):251–276

Fan Y, Liu L-C, Wu G, Wei Y-M (2006) Analyzing impact factors of CO2 emissions using the STIRPAT model. Environ Impact Assess Rev 26(4):377–395

Geneva, S. (2013). Intergovernmental Panel on Climate Change, 2014. Working Group I Contribution to the IPCC Fifth Assessment Report. Climate Change, 8.

Gholipour Fereidouni H (2013) Foreign direct investments in real estate sector and CO2 emission. Manag Environ Quality: An Int J 24(4):463–476. https://doi.org/10.1108/MEQ-04-2012-0032

Ghosh, S., & Kanjilal, K. (2014). Long-term equilibrium relationship between urbanization, energy consumption and economic activity: empirical evidence from India. Energy, 66(0), 324-331. doi: https://doi.org/10.1016/j.energy.2013.12.052

Giovanis E, Ozdamar O (2022) The impact of climate change on budget balances and debt in the Middle East and North Africa (MENA) region. Climatic Change 172(3):1–27. https://doi.org/10.1007/s10584-022-03388-x

Haddian A (2018) The effect of population growth on environment in Iran and other countries in the MENA region. Quart J Macro Strat Pol 6(21):40–60

Hang G, Yuan-sheng J (2011) The relationship between CO2 emissions, economic scale, technology, income and population in China. Proc Environ Sci 11:1183–1188. https://doi.org/10.1016/j.proenv.2011.12.178

Haseeb M, Azam M (2021) Dynamic nexus among tourism, corruption, democracy and environmental degradation: a panel data investigation. Environ , Dev Sustain 23(4):5557–5575

Haseeb M, Hassan S, Azam M (2017) Rural–urban transformation, energy consumption, economic growth, and CO2 emissions using STRIPAT model for BRICS countries. Environ Progr Sustain Energy 36(2):523–531

Hunter LM, O'Neill BC (2014) Enhancing engagement between the population, environment, and climate research communities: the shared socio-economic pathway process. Populat Environ 35(3):231–242

International Energy Agency. (2020). World energy outlook 2020: OECD Publishing, Retrieved from https://www.iea.org/reports/world-energy-outlook-2020.

Kafka, A. L., Frapper, A., & Synder, N. (2009). Natural hazards, environmental degradation, and the urbanization of planet Earth. Paper presented at the Proceedings of the International Conference on Ethics and Sustainability of the Earth, Boston College.

Karthik L, Kumar G, Keswani T, Bhattacharyya A, Chandar SS, Bhaskara Rao K (2014) Protease inhibitors from marine actinobacteria as a potential source for antimalarial compound. PloS One 9(3):1–13. https://doi.org/10.1371/journal.pone.0090972

Kasman A, Duman YS (2015) CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: a panel data analysis. Econ Model 44:97–103

Khan S, Azam M, Ozturk I, Saleem SF (2021) Analysing association in environmental pollution, tourism and economic growth: empirical evidence from the commonwealth of independent states. J

Asian Afr Studies 1-18. https://doi.org/10.1177/00219096211058881

Knapp T, Mookerjee R (1996) Population growth and global CO2 emissions: a secular perspective. Energy Pol 24(1):31–37. https://doi.org/10.1016/0301-4215(95)00130-1

Lantz V, Feng Q (2006) Assessing income, population, and technology impacts on CO2 emissions in Canada: where's the EKC? Ecol Econ 57(2):229–238. https://doi.org/10.1016/j.ecolecon.2005.04.006

Levin A, Lin CF, Chu CSJ (2002) Unit root tests in panel data: asymptotic and finite-sample properties. J Econ 108(1):1–24

Li B, Yao R (2009) Urbanisation and its impact on building energy consumption and efficiency in China. Renew Energy 34(9):1994–1998

Li Y, Wei Y, Zhang D, Huo Y, Wu M (2020) Impacts of demographic factors on carbon emissions based on the stirpat model and the pls method: a case study of Shanghai. Environ Eng Manag J(EEMJ) 19(8):1443–1458

Liddle B (2004) Demographic dynamics and per capita environmental impact: using panel regressions and household decompositions to examine population and transport. Populat Environ 26(1):23–39

Liddle B (2013) Population, affluence, and environmental impact across development: evidence from panel cointegration modeling. Environ Model Software 40:255–266. https://doi.org/10.1016/j.envsoft.2012.10.002

Liddle B (2014) Impact of population, age structure, and urbanization on carbon emissions/energy consumption: evidence from macro-level, cross-country analyses. Populat Environ 35(3):286–304

Liddle B (2015) What are the carbon emissions elasticities for income and population? Bridging STIRPAT and EKC via robust heterogeneous panel estimates. Global Environ Change 31:62–73

Liu X, Bae J (2018) Urbanization and industrialization impact of CO2 emissions in China. J Clean Prod 172:178–186. https://doi.org/10.1016/j.jclepro.2017.10.156

Liu H, Wong W-K, The Cong P, Nassani AA, Haffar M, Abu-Rumman A (2023) Linkage among urbanization, energy consumption, economic growth and carbon emissions. Panel data analysis for China using ARDL model. Fuel 332:126122. https://doi.org/10.1016/j.fuel.2022.126122

López-Carr D, Pricope NG, Aukema JE, Jankowska MM, Funk C, Husak G, Michaelsen J (2014) A spatial analysis of population dynamics and climate change in Africa: potential vulnerability hot spots emerge where precipitation declines and demographic pressures coincide. Populat Environ 35(3):323–339

Makdisi S, Fattah Z, Limam I (2006) Chapter 2 Determinants of growth in the MENA Countries. In: Nugent JB, Pesaran MH (eds) Contributions to Economic Analysis, vol 278. Elsevier, pp 31–60

Malthus T (1798) An essay on the principle of population. Printed for J. Johnson. St. Paul's church-yard, London, pp 1–126

Malthus TR, Hollingsworth T (1973) An essay on the principle of population, Dent London

Mikayilov JI, Galeotti M, Hasanov FJ (2018) The impact of economic growth on CO2 emissions in Azerbaijan. J Clean Prod 197:1558–1572. https://doi.org/10.1016/j.jclepro.2018.06.269

Muhammad B (2019) Energy consumption, CO2 emissions and economic growth in developed, emerging and Middle East and North Africa countries. Energy 179:232–245. https://doi.org/10.1016/j.energy.2019.03.126

Ohlan R (2015) The impact of population density, energy consumption, economic growth and trade openness on CO2 emissions in India. Nat Hazards 79(2):1409–1428

Omri A, Daly S, Rault C, Chaibi A (2015) Financial development, environmental quality, trade and economic growth: what causes what in MENA countries. Energy Econ 48:242–252. https://doi.org/10.1016/j.eneco.2015.01.008

Parikh J, Shukla V (1995) Urbanization, energy use and greenhouse effects in economic development: results from a cross-national study of developing countries. Global Environ Change 5(2):87–103

Pedroni P (2001) Purchasing power parity tests in cointegrated panels. Rev Econ Stat 83(4):727–731

Persyn D, Westerlund J (2008) Error-correction–based cointegration tests for panel data. STATA J 8(2):232–241

Pesaran MH (2015) Testing weak cross-sectional dependence in large panels. Econ Rev 34(6-10):1089–1117

Pesaran MH, Vanessa S, L. & Takashi, Y. (2013) Panel unit root tests in the presence of a multifactor error structure. J Econ 175(2):94–115

Poumanyvong P, Kaneko S (2010) Does urbanization lead to less energy use and lower CO2 emissions? A cross-country analysis. Ecol Econ 70(2):434–444. https://doi.org/10.1016/j.ecolecon.2010.09.029

Puliafito SE, Puliafito JL, Grand MC (2008) Modeling population dynamics and economic growth as competing species: an application to CO2 global emissions. Ecol Econ 65(3):602–615. https://doi.org/10.1016/j.ecolecon.2007.08.010

Raheem ID, Ogebe JO (2017) CO emissions, urbanization and industrialization. Manag Environ Quality: An Int J 28(6):851–867. https://doi.org/10.1108/MEQ-09-2015-0177

Rahman MM (2020) Exploring the effects of economic growth, population density and international trade on energy consumption and environmental quality in India. Int J Energy Sector Manag 14(6):1177–1203. https://doi.org/10.1108/IJESM-11-2019-0014

Ravallion M, Heil M, Jalan J (2000) Carbon emissions and income inequality. Oxford Econ Papers 52(4):651–669

Reardon T, Vosti SA (1995) Links between rural poverty and the environment in developing countries: asset categories and investment poverty. World Dev 23(9):1495–1506

Rehman A, Ma H, Ahmad M, Irfan M, Traore O, Chandio AA (2021) Towards environmental sustainability: devolving the influence of carbon dioxide emission to population growth, climate change, forestry, livestock and crops production in Pakistan. Ecol Ind 125(107460):1–11. https://doi.org/10.1016/j.ecolind.2021.107460

Ribeiro HV, Rybski D, Kropp JP (2019) Effects of changing population or density on urban carbon dioxide emissions. Nat Commun 10(1):3204. https://doi.org/10.1038/s41467-019-11184-y

Saboori B, Sulaiman J, Mohd S (2012) Economic growth and CO2 emissions in Malaysia: a cointegration analysis of the environmental Kuznets curve. Energy Pol 51:184–191. https://doi.org/10.1016/j.enpol.2012.08.065

Sadorsky P (2014) The effect of urbanization on CO2 emissions in emerging economies. Energy Econ 41:147–153

Saidi K, Hammami S (2015) The impact of CO2 emissions and economic growth on energy consumption in 58 countries. Energy Rep 1:62–70. https://doi.org/10.1016/j.egyr.2015.01.003

Salehnia N, Karimi Alavijeh N, Salehnia N (2020) Testing Porter and pollution haven hypothesis via economic variables and CO2 emissions: a cross-country review with panel quantile regression method. Environ Sci Pollut Res 27(25):31527–31542. https://doi.org/10.1007/s11356-020-09302-1

Shafiei S, Salim RA (2014) Non-renewable and renewable energy consumption and CO2 emissions in OECD countries: a comparative analysis. Energy Pol 66:547–556. https://doi.org/10.1016/j.enpol.2013.10.064

Shahbaz M, Sbia R, Hamdi H, Ozturk I (2014) Economic growth, electricity consumption, urbanization and environmental degradation relationship in United Arab Emirates. Ecol Ind 45:622–631. https://doi.org/10.1016/j.ecolind.2014.05.022

Sharma SS (2011) Determinants of carbon dioxide emissions: empirical evidence from 69 countries. Appl Energy 88(1):376–382
Sun W, Huang C (2020) How does urbanization affect carbon emission efficiency? Evidence from China. J Clean Prod 272(1). https://doi.org/10.1016/j.jclepro.2020.122828
Sun Y, Li H, Andlib Z, Genie MG (2022) How do renewable energy and urbanization cause carbon emissions? Evidence from advanced panel estimation techniques. Renew Energy 185:996–1005. https://doi.org/10.1016/j.renene.2021.12.112
Takian A, Mousavi A, McKee M, Yazdi-Feyzabadi V, Labonté R, Tangcharoensathien V, . . . Engebretsen E (2022) COP27: The prospects and challenges for the Middle East and North Africa (MENA). Int J Health Pol Manag 11(12):2776-2779
Trainer F (1990) Environmental significance of development theory. Ecol Econ 2(4):277–286
United Nations. (2017). World population projected to reach 9.8 billion in 2050, and 11.2 billion in 2100. UN DESA| United Nations Department of Economic and Social Affairs, News, June, 21. https://www.un.org/development/desa/en/news/population/world-population-prospects-2017.html
Urry, J. (2011). Climate change and society: Polity.
van Ypersele JP, Bartiaux F (1995) The role of population growth in global CO2 emissions. In: Studies in Environmental Science, vol 65. Elsevier, pp 669–674
Waha K, Krummenauer L, Adams S, Aich V, Baarsch F, Coumou D, . . . Schleussner CF (2017) Climate change impacts in the Middle East and Northern Africa (MENA) region and their implications for vulnerable population groups. Reg Environ Change 17(6):1623-1638. https://doi.org/10.1007/s10113-017-1144-2
Wang Q, Li L (2021) The effects of population aging, life expectancy, unemployment rate, population density, per capita GDP, urbanization on per capita carbon emissions. Sustain Prod Consump 28:760–774. https://doi.org/10.1016/j.spc.2021.06.029
Wang S, Fang C, Guan X, Pang B, Ma H (2014) Urbanisation, energy consumption, and carbon dioxide emissions in China: a panel data analysis of China's provinces. Appl Energy 136:738–749. https://doi.org/10.1016/j.apenergy.2014.09.059
Wang S, Li Q, Fang C, Zhou C (2016) The relationship between economic growth, energy consumption, and CO2 emissions: empirical evidence from China. Sci Total Environ 542:360–371. https://doi.org/10.1016/j.scitotenv.2015.10.027
Wang W-Z, Liu L-C, Liao H, Wei Y-M (2021) Impacts of urbanization on carbon emissions: an empirical analysis from OECD countries. Energy Pol 151:112171. https://doi.org/10.1016/j.enpol.2021.112171
Westerlund J (2005) New simple tests for panel cointegration. Econ Rev 24(3):297–316
Westerlund J (2007) Testing for error correction in panel data. Oxford Bull Econ Stat 69(6):709–748
World Development Indicators (WDI) (2022). World Development Indicators, the World Bank.
Xu B, Lin B (2015) How industrialization and urbanization process impacts on CO 2 emissions in China: evidence from nonparametric additive regression models. Energy Econ
York R, Rosa EA, Dietz T (2002) Bridging environmental science with environmental policy: plasticity of population, affluence, and technology. Soc Sci Quart 83(1):18–34
You W-H, Zhu H-M, Yu K, Peng C (2015) Democracy, financial openness, and global carbon dioxide emissions: heterogeneity across existing emission levels. W Dev 66:189–207. https://doi.org/10.1016/j.worlddev.2014.08.013
Yuan B, Ren S, Chen X (2015) The effects of urbanization, consumption ratio and consumption structure on residential indirect CO2 emissions in China: a regional comparative analysis. Appl Energy 140:94–106. https://doi.org/10.1016/j.apenergy.2014.11.047
Zarco-Periñán PJ, Zarco-Soto IM, Zarco-Soto FJ (2021) Influence of population density on CO2 emissions eliminating the influence of climate. Atmosphere 12(9):1–20. https://doi.org/10.3390/atmos12091193
Zhang C, Lin Y (2012) Panel estimation for urbanization, energy consumption and CO2 emissions: a regional analysis in China. Energy Pol 49:488–498. https://doi.org/10.1016/j.enpol.2012.06.048
Zhu H-M, You W-H, Zeng ZF (2012) Urbanization and CO2 emissions: a semi-parametric panel data analysis. Econ Lett 117(3):848–850. https://doi.org/10.1016/j.econlet.2012.09.001

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