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Assessing the impact of the economic complexity on the ecological footprint in G7 countries: Fresh evidence under human development and energy innovation processes

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A B S T R A C T

The G-7 economies include economically developed countries on a global scale. The high economic complexity and ecological behaviour of these countries have led to increased concern in other countries within the conjuncture. For this reason, this study investigates the impact of economic complexity, human development, high innovation processes, and renewable energy consumption on the ecological footprint, presenting as the main novelty the damper effect that human development and innovation processes exert on economic complexity and the global effect on the ecological footprint. This empirical evidence is analyzed under the validation of a U-inverted EKĆs behaviour between ecological footprint and economic complexity for 1991–2018. Our study follows a second-generation perspective that generates reliable and robust results using Cup-FMOLS, Konya panel bootstrap causality and panel VAR analyses under cross-sectional dependence and slope heterogeneity. The long-run elasticity estimates calculated with the Cup-FMOLS approach suggest that economic complexity, human development, high innovation process and interaction variables reduce the ecological footprint. The unidirectional causality from economic complexity and human development to ecological footprint, as well as from economic complexity and human development to the high innovation process, is part of the Konya bootstrap causality test. In addition, a bidirectional causality linkage is revealed between renewable energy consumption and ecological footprint, human development and high innovation process. In G-7 countries, where economic complexity is higher than in other countries, it is crucial to improve environmental quality to ensure sustainable development. The findings show that sustainable development in G-7 countries can be accelerated by improving renewable energy sources, R&D investments and social dimension.

1. Introduction

Despite the increasing level of productivity, pollution is increasing significantly due to human demand for natural resources and poses a danger to both human health and national economies (Yilanci & Pata, 2020). The accumulation of non-recyclable waste through pollution, depletion of natural resources, higher carbon emissions, global warming and economic growth has increased the importance of countries' environmental policies and encouraged countries to aim for sustainable development by reducing environmental degradation (Lee et al., 2022). In recent years, the linkage between environmental quality and economic development has been an important topic of debate and has received considerable attention (Liu et al., 2022; Akadiri et al., 2022; Rafique et al., 2022a, 2022b). Most studies have focused only on carbon dioxide (CO2) emissions as an indicator of air pollution. Rees (1992) and Wackernagel and Rees (1996) developed a more comprehensive indicator of environmental pollution called ecological footprint, which measures a population's demand on nature (Charfeddine & Mrabet, 2017; Yilanci & Pata, 2020). The ecological footprint variable is an accounting instrument that gauges a

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population's need for renewable energy. It applies to various industries and sociopolitical organizations, each with distinct cultures, natural systems, and methodological approaches to sustainability issues (Charfeddine & Mrabet, 2017; Lin et al., 2018; Kassouri & Altıntaş, 2020).

The ecological footprint is a suitable indicator of environmental degradation as it is consistent with the idea that human activities should not exceed the environment's capacity to replenish resources and can reveal the consequences of human activity on the environment in a country in terms of air, soil and water (Bostan et al., 2017; Charfeddine & Mrabet, 2017) (see Fig. 1).

On the other hand, it is also pointed out that the ecological footprint has limitations such as being a static measure, ignoring the role of technological change, not including some natural resources and representing a stock measure, not developing structural proposals for fair distribution and providing limited policy recommendations (Moffatt, 2000). The Environmental Kuznets Curve (EKC) hypothesis, proposed by Grossman & Krueger, has been used in numerous research to examine the relationship between economic growth and environmental quality (1991, 1995). Traditionally, the EKC hypothesis has assumed that environmental degradation increases with the level of per capita income and decreases when per capita income is large enough. Following the work of Grossman & Krueger (1991, 1995), many studies have been conducted to investigate the relationship between carbon emissions and income. Panayotou (1993), Shafik (1994) and Holtz-Eakin & Selden (1995) were among the first to identify an inverted U-shaped linkage between economic growth and environmental degradation. According to the inverted U-shaped relationship, environmental degradation will rise during the first stage of economic growth when it is low. In contrast, environmental degradation will decrease during the second stage of economic growth when it rises at a particular rate.

Empirical studies have generally analyzed the impact of economic activities on the environment with economic growth and per capita income variables. Although these variables provide a fundamental economic indicator, they do not cover structural changes in the economy and the direction of technological development (Chu, 2021; Arnaut & Dada, 2022; Balsalobre-Lorente et al., 2022: Taskin et al., 2022). Hidalgo & Hausmann (2009) and Hidalgo (2011) argue that the production process requires not only capital and labour but also capabilities. Hidalgo & Hausmann were the ones who initially developed the idea of economic complexity (2009). Economic complexity includes all elements of the production process, like proficiency, advanced understanding, and abilities (Khan et al., 2022). In other words, a country's knowledge- and skill-based production structure with an adequate output level can be used to characterize economic complexity (Can & Gozgor, 2017). There is a correlation between complexity levels and energy demand. Depending on their natural resources and import prospects, countries must build an acceptable energy mix from various sources to deliver the necessary energy while minimizing environmental damage. A country's productive system will impact the environment (Neagu, 2020). As countries' economies become more complex, environmental degradation will increase as more efficient processes are required to create a consumption product. According to the logic of the EKC hypothesis, economic complexity will positively impact the environmental footprint up to a certain point, but this impact should decrease after a certain point (Alvarado et al., 2021). The EKC hypothesis can be confirmed by an increase in environmental degradation as a result of an increase in economic growth without changes in its structure and technology, followed by a gradual increase in economic growth, a more skilled workforce and a limitation of the level of pollution thanks to a development in the direction of technological-energy efficient industries (Balsalobre-Lorente et al., 2022). On the first side, where economic complexity increases, product diversification accelerates, and extra investment and production entail higher energy demand, accompanied by an increase in the overall level of environmental pollution. In turn, economic complexity has a more remarkable ability to maintain environmental quality (Huang et al., 2022a, 2022b), as it includes more technological equipment, research and development (R&D) activities, environmentally friendly goods and services, and the ability to sustain the installation of cleaner technologies (see Fig. 2).

By putting money towards the growth of human capital, knowledge, and technology, higher economic complexity can safeguard the environment. With the emergence of environmentally friendly technology, structural changes are replacing outdated technology that harms environmental quality (Khan et al., 2022). Increasing environmental awareness encourages policymakers and industries

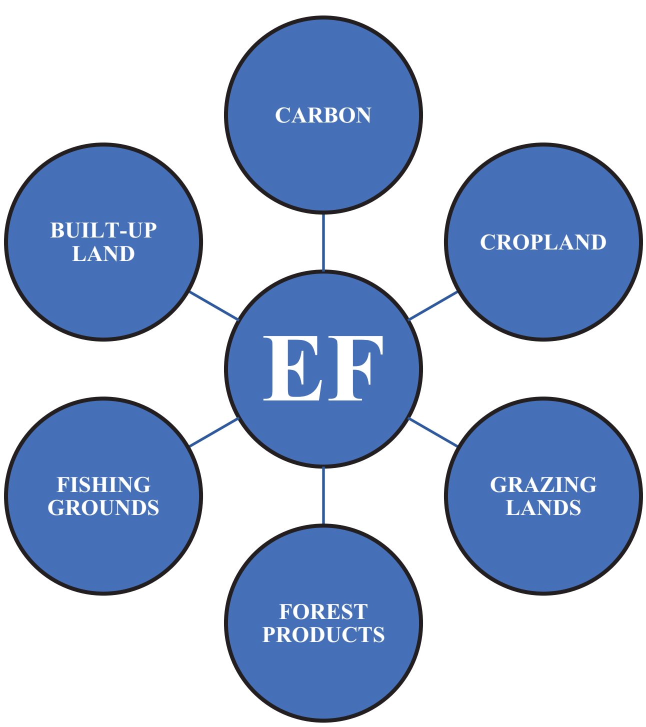

Fig. 1. The components of ecological footprint.

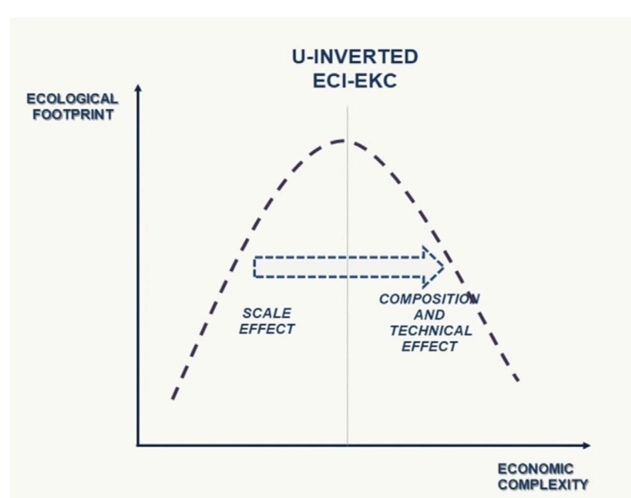

Fig. 2. Graphical presentation of EKC relationship.

to emphasize renewable energy sources, reducing environmental degradation (Destek & Sinha, 2020). Sustainable development links economic and environmental goals (Mrabet & Alsamara, 2017). In this context, how it is possible to use resources sustainably and how environmental quality can be improved are seen as the main problems of development (Ke et al., 2021). The Human Development Index is recommended as an output variable rich in meaning and suitable for sustainable development as it addresses the dimensions of education, life and economy together (Salman et al., 2022). However, it is possible to mention that progress in the essential elements of human development will increase environmental pressures with increasing resource demand, negatively affecting environmental quality, that is, increasing the ecological footprint. Since the Human Development Index does not directly address resource consumption and its impact on environmental quality, it is thought that using this variable together with the ecological footprint will provide a holistic perspective in terms of sustainability. In order to achieve sustainable development, the goal is to increase the Human Development Index and reduce the ecological footprint. One of the ways to reduce the ecological footprint is to meet increasing demands with green technologies. It is stated that using green technologies is essential to improve environmental quality (Usman & Hammar, 2020) and to ensure sustainable development (Ramdhani et al., 2017). In this context, it is stated that innovation generated by Research and Development investments can increase energy efficiency and reduce energy consumption (Wang et al., 2019). In recent years, there has been an increase in studies linking economic complexity and ecological footprint as the environmental footprint of countries has grown beyond the biosphere's production capacity (biocapacity) (Charfeddine & Mrabet, 2017). In general, the results of studies are ambiguous. Some studies (e.g., Pata (2021), Ahmad et al., 2021, 2022a, 2022b, Nguyen and Doytch (2022), Numan et al., (2022)) support the EKC hypothesis, while others (e.g., Yilanci & Pata (2020), Nathaniel et al., (2022)) do not. This study goals to empirically investigate the linkage between economic complexity, human development, innovation process and renewable energy consumption and ecological footprint for G-7 countries. While economic complexity is the primary explanatory variable, human development and innovation process are interaction variables. Thus, it will be possible to reveal the impact of the interaction between economic complexity and energy innovation and human development on the stage of sustainable development. The G-7 countries, which are economically complex countries, have grown remarkably with social change and automation. The demand for energy consumption has increased in these countries, which are known to consume a large share of the world's energy. Economic complexity in these economically developed countries is higher than in other countries (Khan et al., 2022). Developed economies are leading in innovation, green technology and environmental policies. Therefore, it is important to see how environmental quality can be improved in these countries to ensure sustainable development. The findings of the studies on G-7 countries in the literature differ according to methodology, period and variables. In addition, unlike the literature, this study examines the moderating role of human development and innovation process variables on ecological footprint. In this connection, the study will contribute to the environmental economics literature and provide comprehensive findings for sustainable development policies.

2. Literature review

The linkage between economic complexity and the environment has been examined in the literature in different periods, in different regions and with different variables. In this study, economic complexity, ecological footprint, human development, innovation process and renewable energy consumption variables are used.

The Environmental Kuznets Curve (EKC) theory has drawn much attention in the empirical literature since Grossman & Krueger's seminar works in 1991 and 1995. The traditional EKC hypothesis postulates that environmental pollution and economic growth are inversely U-shaped. Therefore, in the first stage, economic growth is expected to damage the environment due to increased economic activity. In contrast, in the second stage, if the economy grows appropriately, the previous environmental quality is expected to return (Balsalobre-Lorente et al., 2022). In the literature, many studies trying to provide evidence to support the EKC hypothesis have focused on variables in the air pollutant group as proxies for environmental degradation. Recently, a new body of literature has emerged that views the ecological footprint as a comprehensive and globally comparable indicator of the environmental degradation caused by human activity (Neagu, 2020). When the studies focusing on the direct determinants of ecological footprint are examined, Erdoğan et al. (2021) stated that globalization and human capital are the sources of cleaner and sustainable environment in Sub-Saharan African countries.

Similarly, Ilkay et al. (2021) showed that globalization and human capital help protect the environment and create sustainable plans in BRICS group countries. Yılancı et al. (2022a) investigated the impact of policy shocks on ecological footprints on sustainability in Mediterranean countries and stated that stricter policies are needed for environmental sustainability. In another study, Yilanci et al. (2022b) examined the relationship between development changes and forest footprint for China over the period 1961–2017 and found that urbanization, human capital and total factor productivity reduce forest footprint. Different studies have proposed per capita income as an indicator of economic development. However, this indicator does not fully capture the structural changes in an economy and sustainable development processes (Chu, 2021). Hidalgo & Hausmann (2009) and Hausmann & Hidalgo (2011) provide evidence that the level of development is related to the economic complexity of a country. Economic complexity reflects a country's productive structure and leads to a specific energy consumption pattern and environmental quality (Chu, 2021). In this context, when studies examine the relationship between economic complexity and ecological footprint (Huang et al., 2022a, 2022b; Kazemzadeh et al., 2022; Ghosh et al., 2022a, 2022b). For example, Mrabet and Alsamara (2017) discovered that there is a long-run relationship between the selected variables with a change in the cointegration vector in 1991 and 2000, but that the inverse U-shape hypothesis is invalid when utilizing CO2 emissions for the period 1980–2011 in Qatar. However, the inverse U-shape is valid when using ecological footprint. Ulucak & Bilgili (2018) confirmed the EKC hypothesis in low-, high- and middle-income countries for 1961–2013 by using the ecological footprint variable as an indicator of environmental degradation. Yilanci & Pata (2020) investigated the validity of the EKC hypothesis for China for the period 1965–2016. They found that economic complexity significantly increases the ecological footprint, and the EKC hypothesis is invalid for China in the relevant period. In another study, In order to demonstrate that there is an inverted U-shaped EKC link, Pata (2021) looked at how economic complexity, globalization, and the use of renewable and non-renewable energy in the United States from 1980 to 2016. On the contrary, Shahzad et al. (2021), who investigated the relationship between economic complexity and ecological footprint, reveal that economic complexity and fossil fuel energy consumption increased the ecological footprint due to their application in the United States during the period 1965–2017.

For the top 10 countries in terms of economic complexity from 1980 to 2017, Rafique (2021) found that economic complexity increases ecological footprint. Similarly, Ikram et al. (2021) analyzed the link between economic complexity and ecological footprint for Japan for the period 19655–2017, and Nathaniel (2021) examined the relationship between economic complexity and ecological footprint for the Association of Southeast Asian Nations (ASEAN) for the period 1990–2016 and found that the variables are positively related to one another. Alvarado et al. (2021) investigated the relationship between economic complexity and rents from natural resources and the ecological footprint of Latin America from 1980 to 2016 and found that the influence varied across the distribution. Ahmad et al. (2021) examined how economic development, institutional strength, energy consumption breakdown, and economic complexity affected environmental degradation in emerging nations between 1984 and 2017. They found a positive relationship between economic complexity and ecological footprint, thus increasing environmental degradation, while a high level of economic complexity reduces ecological footprint. In addition, it was also shown that there is an inverted U-shaped relationship between ecological footprint and economic growth. Huang et al. (2022a, 2022b) examined the relationship between renewable energy, human capital, economic complexity, financial development and ecological footprint for G-7 and E-7 countries from 1995 to 2018. They found that economic complexity and human capital increase pollution in E-7 countries, while renewable energy significantly reduces it. In G-7 countries, all potential factors except financial development significantly improve environmental quality.

Similarly, Ahmed et al. found that economic complexity reduces ecological footprint, and there is an inverted U-shaped relationship between economic growth and ecological footprint in G-7 countries in the period 1985–2017. In another study for G-7 countries, Ghosh et al. (2022a, 2022b) found that economic complexity reduces ecological footprint in the long run but increases carbon dioxide emissions in the 1990–2018 period. On the contrary, Rafei et al. (2022) examined the effects of economic complexity, renewable energy consumption, natural resources and foreign direct investment on the ecological footprint in countries with poor, medium and high institutional quality in 1995–2017. They concluded that economic complexity positively affects the ecological footprint in all countries. Nguyen & Doytch (2022) examined the effects of economic complexity on ecological footprints for a global sample of 30 low- and middle-low-income economies, 27 upper-middle-income economies and 38 high-income economies over the period 1995–2013. In the whole sample, an inverted U-shaped relationship between economic complexity and ecological footprints was found, and this relationship was supported in middle-low-income countries but not in upper-middle-income economies.

Similarly, Numan et al. (2022) examined the impact of economic complexity on the ecological footprint for 85 countries grouped as high-income, lower-middle-income, upper-middle-income and the whole sample for 2001–2020. The N-shaped EKC hypothesis was confirmed in all groups except upper-middle-income countries. In another sample, Nathaniel et al. (2022) examined the relationship between economic complexity and environmental degradation for 11 developing countries in the period 1995–2016 and found that the EKC between environmental degradation and energy use in economies which are developing is unacceptable, the EKC between environmental degradation and economic development is acceptable for Egypt, Indonesia and Vietnam. The EKC hypothesis between population and environmental degradation is valid for the Republic of Korea, Turkey, Mexico and Iran. Kazemzadeh et al. (2022) examined the impact of economic complexity and income inequality on the ecological footprint of 25 countries in 1970–2016 by quantile regression and found that economic complexity positively affected the ecological footprint in quantiles 10 and 15 but not in quantiles 75 and 90. Similarly, in OECD countries from 1990 to 2019, Hassan et al. (2023) examined the relationship between the economic complexity index, nuclear energy and globalization with ecological footprints. They found that the economic complexity enlarges the pressure on the ecological footprints in these countries.

Assumed that human development could be defined as the process of increasing people's welfare and expanding their freedoms and opportunities (Akbar et al., 2021). The Human Development Index (HDI) is a combination of indicators including life expectancy, education and per capita income. A country's index score nearing 1, which ranges from 0 to 1, denotes an improvement in per capita income, life expectancy, and educational attainment. Shah (2016) claims that the Human Development Index is a comprehensive tool created by the UN to evaluate the level of social and economic development of various nations and to provide a ranking to them.

Human development became evident with the debates on the relationship between ecological footprint and development that started to take root in the late 80 s, and by the 90 s, it was accepted as both a target and an indicator of development (Yunani et al., 2020). It is stated that since the early 1990 s, the perspective on the ratio of CO2 emissions to GDP has evolved, and the development debate has been addressed on the grounds that go beyond GDP (Mrabet & Alsamara, 2017). In this context, the ecological footprint concept, which emerged as a new perspective aiming to explain the link between human activities and resources, offers an inclusive perspective on environmental sustainability and sustainable development (Kassouri & Altıntaş, 2020).

Defining the relationship between human well-being and environmental quality is an important factor in understanding sustainable development (Kassouri & Altıntaş, 2020). According to Lin et al. (2018), combining the Ecological Footprint with the Human Development Index determines the distance of countries to global sustainable development. Human development provides individuals with more space for movement in their lives, which affects their ecological footprint. Long (2020), who states that human welfare improves as the Human Development index increases, also draw attention to the fact that natural capital consumption decreases with the decrease in the ecological footprint. In this context, the author states that reducing the footprint and increasing the human development index points to ideal sustainable development. In parallel, it is pointed out that the ecological footprint alone cannot be comprehensive enough to measure sustainable development. However, when defined together with human development, it will form a valuable basis for outlining the outlines of achieving sustainable development (Bostan et al., 2017: Lin et al., 2018).

As a result, it is suggested to evaluate human development and ecological footprint together as the main way to evaluate sustainable development from an ecological perspective (Zhang et al., 2017). In the literature, studies on ecological footprint and human development generally point to similar results. Wang et al. (2019) examined the impact of HDI, globalization and financial development on carbon dioxide by grouping OECD countries for the period 1990–2015. The results show that both the human development index and financial development promote environmental improvement. Kassouri and Altıntaş (2020) studied the relationship between human development and ecological footprint using panel data for 13 MENA countries from 1990 to 2016. In the study, in which the countries of the region are divided into two subgroups, oil exporters and non-exporters, it is reported that ecological footprint has a positive impact on human development for both sample groups. Yunani et al. (2020) aimed to determine how the quality of life (per capita income, happiness and human development) affects the ecological footprint in ASEAN countries over 30 years and found that per capita income, happiness, and human development have a significant effect on ecological footprint. For the top 10 nations with the most significant ecological footprints, Pata et al. (2021) sought to examine the effects of globalization, renewable energy use, an abundance of natural resources, and the human development index on environmental deterioration. The analysis' findings show that the increased use of renewable energy and human development have a detrimental and statistically significant impact on ecological footprint. Mrabet et al. (2021) examined the causality of environmental quality and human development and the effects of political stability on this relationship in MENA countries from 1990 to 2016. The study found that the high level of the Human Development Index reduces the ecological footprint.

As urbanization, industrialization and population increase, global energy consumption also increases (Ibrahiem, 2020), and the increasing resource demand reduces environmental quality. Innovation is considered one of the main methods to eliminate the contradictory situation between the economy and the environment (Ke et al., 2022a, 2022b). Innovation can be defined as applying a modern and significantly better product, process or organizational technique in business activities or environmental relations (Usman & Hammar, 2020). According to Ke et al. (2021), improving innovation is the main force to make society and the development of ecology sustainable.

It is emphasized that it is important to grow and improve the quality of the environment with green technologies, which are seen as a practical and realistic tool to face global warming and environmental problems (Töbelmann & Wendler, 2020), and that using technology and innovation efficiently has an influential role in this direction (Usman & Hammar, 2020). It is stated that innovation achieved through Research and Development (R&D) investments will positively affect energy efficiency and may reduce energy consumption (Wang et al. 2019). According to Yang et al. (2021), an economy that grows through environmentally friendly technologies will grow fast and contribute to environmental quality by improving energy efficiency.

Nowadays, where environmentally friendly growth is prominent, it is emphasized that especially developing economies should aim to accelerate their economic growth and reduce their ecological footprint simultaneously (Jahanger et al., 2022a, 2022b). From the perspective of endogenous growth theory, it is stated that technological progress resulting from R&D investments can lead to greater efficiency in the production and use of natural resources and energy (Churchill et al., 2019). In this context, the theory suggests that technological innovation can have a long-term improvement effect on environmental issues (Sherif et al., 2022). It is also emphasized that improving innovation in an environment pressured by environmental degradation and resource constraints will encourage countries to continuously optimize their economic and industrial structures to ensure the efficient use of natural energy (Ke et al., 2021; Jahanger et al., 2022a, 2022b). Therefore, it is recommended to use innovation systematically and as a catalyst for transformation to face environmental problems (Töbelmann & Wendler, 2020).

Innovation can have various effects on environmental quality, following Sherif et al. (2022). Innovation drives efficiency boosts labour and capital productivity and promotes green technologies. In this context, environmental quality can be achieved through technological innovation investments that enable access to clean energy sources. Therefore, it is possible to argue that R&D investments in innovation are significant in reducing the ecological footprint and ensuring environmental welfare.

In the literature, it has been observed that studies on the innovation process and the environment point to different findings based on region, measurement criteria and methodology. Usman & Hammar (2020) reported that technological innovation reduced pressure on environmental quality in Asia Pacific Economic Cooperation (APEC) countries in the period 1990–2017. Chen & Lee (2020) investigated the impact of technological innovation on the environment in a panel of 96 countries in the period 1996–2018 and reported that technological innovation did not have a significant reduction effect on CO2 emissions globally. Töbelmann and Wendler (2020) analyzed the effects of environmental innovation on CO2 emissions in EU-27 countries between 1992 and 2014 and found that environmental innovation contributed to reducing CO2 emissions, while general innovation activity did not cause a decrease in emissions.

In addition, there are many findings that innovative technologies that provide resource efficiency improve environmental quality. Ibrahiem (2020) investigated the relationship between CO2 emissions, technological innovation, alternative energy sources, economic growth and financial development in Egypt from 1971 to 2014 and reported that technological innovation and alternative energy sources improve environmental quality. Ke et al. (2021) explored the impact of innovation efficiency on the ecological footprint in 280 cities in China from 2012 to 2018. They showed that promoting innovation efficiency significantly inhibits ecological footprint. In another study, Ke et al. (2022a, 2022b) aimed to analyze the threshold effect of innovation efficiency on ecological footprint at different levels of economic development in provinces of China from 2003 to 2013. They found that the effect of regional innovation efficiency on ecological footprint is negative.

Similarly, Jahanger et al. (2022a, 2022b) concluded that natural resource consumption increases ecological footprint and deteriorates ecological welfare, but technological innovation reduced ecological footprint levels in 73 developing countries from 1990 to 2016. Additionally, it has been demonstrated that technology innovation has a regulatory impact on lowering harmful environmental impacts. Sherif et al. (2022)'s research sought to shed light on the possible role of technological innovation and clean power in lowering the ecological footprint in the N-11 countries between 1992 and 2015. They reported that environmental degradation leads to a shift towards technological innovation and clean energy in the long run. Sahoo & Sethi (2022) investigated how Newly Industrialized Countries (NICs)' ecological footprint and air quality changed between 1990 and 2017 due to urbanization, economic structure, technological innovation, and population density. The study found that technological innovation improves environmental quality by reducing the ecological footprint. Ahmad et al. (2020) state that natural resources and economic growth expand the ecological footprint, while technological innovations help to reduce the resulting environmental degradation in 22 developing economies in the period 1984–2016. The study by Yang et al. (2021) indicated that technological innovation is a key driver in lowering the ecological footprint, while remittance inflows and financial development considerably impair the BICS economies. Islam et al. (2022) found a negative relationship between technological innovation and ecological footprint in Bangladesh over the period 1972–2017.

The economic growth patterns of nations can explain the relationship between renewable energy and ecological footprint. When economic growth reaches a particular level, environmental awareness of environmental damage increases, policymakers and industries prioritize renewable energy sources, and the economy's growth pattern results in less environmental degradation (Destek & Sinha, 2020). Renewable energy consumption provides an additional source of energy that should be promoted for sustainable development. Renewable energy sources require a smaller ecological footprint than fossil fuel sources and are therefore expected to reduce the ecological footprint (Ahmed et al. 2022a, 2022b). Given the diversity of countries' economic structures, the relationship between renewable energy and ecological footprint is still under debate. When related studies are examined, Alola et al. (2019) examined the factors for reducing environmental pollution for 16 European Union member countries in the period 1997–2014 and found that renewable energy consumption improves environmental sustainability. Similarly, Destek & Sinha (2020) validated the EKC for 24 selected OECD countries from 1980 to 2104 and revealed that increased renewable energy consumption reduces ecological footprint.

Sharif et al. (2020) analyzed the impact of renewable energy on the ecological footprint of Turkey in the period 1965Q1-2017Q4, Usman et al. (2020) examined the impact of renewable energy consumption on the ecological footprint of the United States in the period 1985Q1-2014Q4 and found that renewable energy reduces ecological footprint. Similarly, Danish et al. (2020) examined the relationship between renewable energy, real income, natural resource rent, urbanization and ecological footprint in BRICS economies over 1992–2016 and found that renewable energy reduces ecological footprint. On the contrary, Nathaniel & Khan (2020) found that non-renewable energy contributed significantly to environmental degradation, while no significant relationship was found between renewable energy and the ecological footprint of ASEAN countries for the period 1990–2016. Similarly, Nathaniel et al. (2020) found that renewable energy did not contribute significantly to environmental quality in the period 1990–2016 for MENA countries.

Ansari et al. (2021) found a negative relationship between renewable energy consumption and ecological footprint in the top renewable energy-consuming countries from 1991 to 2016. Similarly, Ullah et al. (2021) showed that there is a negative relationship between renewable energy consumption and ecological footprint for the 15 largest renewable energy-consuming economies in the world for the period 1996–2018. In addition, Sharma et al. (2021) demonstrated that the rise of renewable energy considerably decreased the ecological footprint in eight developing countries of South and Southeast Asia from 1990 to 2015. Caglar et al. (2021) found that renewable energy consumption reduces environmental degradation in the ten most pollutive countries. Similarly, Miao et al. (2022) examined the impact of renewable energy consumption on the ecological footprint for a sample of newly industrialized countries for the period 1990–2018, Abid et al. (2022) for Saudi Arabia for the period 1990–2017, and Li et al. (2022) for a sample of 120 countries for the period 1995–2014 and argued that renewable energy consumption decreases the ecological footprint and thus contributes to environmental quality. On the contrary, Raghutla et al. (2022) found that renewable energy consumption has a significant role in increasing the ecological footprint of N-11 countries over the period 1990–2018.

It is observed that the findings on the relationship between economic complexity, human development, innovation process, renewable energy consumption, energy innovation and ecological footprint in the literature do not exhibit a consistent structure. Otherwise, this study examines the moderating role of human development and innovation process variables on ecological footprint. Based on the above discussions, we formulate the following hypothesis:

H1. U-inverted EKC is valid for the relationship between economic complexity and ecological footprint.

H2. Human development contributes to controlling the ecological footprint.

H3. The interaction between economic complexity and human development accelerates the stage of sustainable development where compositional and technical effects exceed scale effects.

H4. Energy innovation reduces the ecological footprint.

H5. The damper effect of energy innovation on economic complexity accelerates the raising of sustainable development where compositional and technical effects exceed scale effects.

H6. Renewable energy consumption reduces the ecological footprint.

3. Data and empirical model

3.1. Data

To investigate the moderating effect of human development (HDI) and high innovation processes (RDD) on the relationship between ecological footprint (EF) and economic complexity (ECI), the data used in the econometric analyses were obtained from databases published by the Global Footprint Network (GFN), The Observatory of Economic Complexity (OEC), the Organization for Economic Co-operation and Development (OECD), Our World in Data (OWID) and the World Bank (WB). The authors used data from the G-7 countries (Canada, Germany, France, Italy, Japan, United States and the United Kingdom) between 1991 and 2018. Ecological footprint data was published in the GFN database until 2018. Therefore, the data set of the study is limited to the year 2018. The variables selected for the study are ecological footprint, economic complexity, high innovation processes, human development and renewable energy consumption. In particular, we also consider the interaction of human development and economic complexity (LnECI*LnHDI) and energy innovation and economic complexity (LnECI*LnRDD) to better understand it as an innovation. The ecological footprint is measured in hectares (gha), while the economic complexity index is based on the diversity and breadth of products a country exports. High innovation processes are measured by total RD&D in Million USD, while the HDI index measures human development. Renewable energy consumption is calculated as a percentage of total energy consumption. Table 1 provides more detailed information on the data sources for each variable. The ecological footprint per capita in G-7 countries in 2018 was calculated as 8.1 gha for Canada, Germany 4.7 gha, France 4.4 gha, Italy 4.3 gha, Japan 4.6 gha, UK 4.2 gha, and USA 8.1 gha. The world average is 2.77 gha, and the average of G-7 countries is 5.48 gha (GFN, 2022). In 2018, the ECI average for Canada was 0.608, Germany 2.126, France 1.357, Italy 1.459, Japan 2.480, UK 1.481, USA 1.552, and the G-7 average was 1.580.

3.2. Empirical models

In the current study, the explained variable is EF, and the explanatory variables are ECI, HDI, RDD and RNW. This study also investigates the validity of the EKC hypothesis. In the current study, the explained variable is EF, and the explanatory variables are ECI, HD, RDD and RNW. This study also investigates the validity of the EKC hypothesis and analyzes the inverted U-shaped relationship between ecological footprint and economic complexity with the variables ECI and the square of ECI. This study analyzes the interaction of human development and high innovation processes in the effect of economic complexity on ecological footprint with HD*ECI and RDD*ECI explanatory variables. The econometric function of this study is reported in Eqs. (1)–(3).

$$\mathrm{EF_{it}} = \mathrm{f_1}\left(\mathrm{ECI_{it}}, \mathrm{ECI^2_{it}}, \mathrm{RDD_{it}}, \mathrm{RNW_{it}}, \mathrm{HDI_{it}}\right) \tag{1}$$

$$\mathrm{EF_{it}} = \mathrm{f_2}\left(\mathrm{ECI_{it}}, \mathrm{ECI^2_{it}}, \mathrm{RDD_{it}}, \mathrm{RNW_{it}}, \mathrm{HDI_{it}}, \mathrm{HDI_{it}} \times \mathrm{ECI_{it}}\right) \tag{2}$$

$$\mathrm{EF_{it}} = \mathrm{f_3}\left(\mathrm{ECI_{it}}, \mathrm{ECI^2_{it}}, \mathrm{RDD_{it}}, \mathrm{RNW_{it}}, \mathrm{HDI_{it}}, \mathrm{RDD_{it}} \times \mathrm{ECI_{it}}\right) \tag{3}$$

Natural logarithmic transformations of all variables are made to avoid the possibility of multicollinearity in the model and to provide a more precise assessment. The empirical EF function is developed as in Eq. (4).

Table 1
Variables Definition and data sources.

Variables	Acronym	Definition	Sources	Literature
Ecological footprint	EF	A metric of environmental sustainability based on consumption, the ecological footprint is expressed in global hectares (gha). People's need for biological resources and the availability of nature are taken into consideration by the ecological footprint.	GFN	Sherif vd. (2022), Rafique et al. (2022a, 2022b), Baz et al. (2020).
Economic complexity	ECI	Combining data on the various commodities that a country exports gives an overall picture of its productive composition appearance.	OEC	Doğan vd. (2021), Neagu and Teodoru (2019)
Human Development Index	HDI	A long and healthy life, a good education, and a fair level of living are the three main aspects of human development that the Human Development Index (HDI) measures in summary form.	OWID	Khan vd. (2018), Hussain ve Dey (2021), Djordjevic vd. (2023)
High innovation processes	RDD	Total RD&D in Million USD (2020 prices and exch. rates)	OECD	Kim and Brown (2019), Consoli vd. (2023), Ding et al. (2020)
Renewable energy consumption	RNW	The percentage of renewable energy in total final energy consumption is known as renewable energy consumption.	WB	Saint Akadiri et al. (2019), Rahman and Velayutham (2020), Alola et al. (2019)

$$\ln(\mathrm{EF_{it}}) = \beta_0 + \beta_1 \ln(\mathrm{ECI_{it}}) + \beta_2 \ln\left(\mathrm{ECI^2}_{\mathrm{it}}\right) + \beta_3 \ln(\mathrm{HDI_{it}}) + \beta_4 \ln(\mathrm{RDD_{it-1}}) + \beta_5 \ln(\mathrm{RNW_{it}}) + \mu_{\mathrm{it}} \tag{4}$$

A review of the empirical literature reveals that studies analyzing the relationship between economic complexity and ecological footprint are limited. In this study, we extend the model by adding the moderating effects of human development and renewable energy consumption on the effect of economic complexity on ecological footprint, as reported in Eqs. (5) and (6).

$$\ln(\mathrm{EF_{it}}) = \beta_0 + \beta_1 \ln(\mathrm{ECI_{it}}) + \beta_2 \ln\left(\mathrm{ECI^2_{it}}\right) + \beta_3 \ln(\mathrm{HDI_{it}}) + \beta_4 \ln(\mathrm{RDD_{it-1}}) + \beta_5 \ln(\mathrm{RNW_{it}}) + \beta_6 \ln(\mathrm{HDI_{it}} \times \mathrm{ECI_{it}}) + \mu_{\mathrm{it}} \tag{5}$$

$$\ln(\mathrm{EF_{it}}) = \beta_0 + \beta_1 \ln(\mathrm{ECI_{it}}) + \beta_2 \ln\left(\mathrm{ECI^2_{it}}\right) + \beta_3 \ln(\mathrm{HDI_{it}}) + \beta_4 \ln(\mathrm{RDD_{it-1}}) + \beta_5 \ln(\mathrm{RNW_{it}}) + \beta_6 \ln(\mathrm{RDD_{it-1}} \times \mathrm{ECI_{it}}) + \mu_{\mathrm{it}} \tag{6}$$

In the models, i, t ve μ_{it} denote cross-sections (G-7 countries), time dimension and the stochastic error term. β_0 is the constant term and $\beta_1 - \beta_6$ are the elasticity coefficients to be estimated. In the model, EF represents ecological footprint, ECI economic complexity index and economic development, RDD Total RD&D and high innovation processes, HDI Human Development Index and RNW total final energy consumption and renewable energy consumption. For the EKC hypothesis to be valid, the pre-estimated or expected sign of the coefficient of ECI in the equations should be statistically significant and positive, and the coefficient of ECI2 should be significant and negative. This shows that the relationship between EF and ECI is inverted U-shaped. Renewable energy sources require a smaller ecological footprint compared to fossil fuel sources, so RNW is expected to have a reducing effect on EF (Ahmed et al., 2022a, 2022b). HDI will support sustainable development by providing equal opportunities for each individual and will have a reduced impact on the ecological footprint (Baloch et al., 2019). RDD High innovation processes are expected to reduce the EF in line with supporting sustainability. The interactions between economic complexity and energy innovation and human development are predicted to reduce EF by accelerating the stage of sustainable development with the combination and technical effects exceeding the scale effect. The coefficients β_2-β_6 are expected to be negative, except for those between EF and β_1. The study aims to investigate the validity of the EKC hypothesis and the relationship between economic and environmental objectives. How improve environmental quality is important for achieving sustainable development.

4. Methodological construction

4.1. Cross-section dependency tests

Several factors, such as standard shocks, country-specific latent indicators, externalities, geographical effects, and financial and economic assimilation that may occur in the cross-sections that make up the panel data may create dependence between cross-sections. Estimations without taking cross-sectional dependence (CSD) into account may produce inconsistent and erroneous parameters. Therefore, it is vital to control for CSD to proceed to the next stage of panel data analysis. For this reason, four different tests are used in the present study to detect the CSD problem. These tests are Breusch and Pagan's (1980) LM, Pesaran CSD and Scaled LM (2004), and Pesaran et al. (2008) Bias-Corrected Scaled LM test. The mathematical expression of the CSD test is shown in Eqs. (7)–(9).

$$\mathrm{CSDLM_1} = \mathrm{T}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\mathrm{p}}_{ij}^2 \tag{7}$$

$$CSDLM_2 = \sqrt{\frac{1}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\hat{p}_{ij}^2 - 1\right)\right) \tag{8}$$

$$\mathrm{CSD} = \sqrt{\frac{2\mathrm{T}}{\mathrm{N(N-1)}}}\left(\sum_{\mathrm{i=1}}^{\mathrm{N-1}}\sum_{\mathrm{j=i+1}}^{\mathrm{N}}\hat{\mathrm{p}}\mathrm{ij}\right)\mathrm{N(0,1)i,j} \tag{9}$$

$$\mathrm{CSD} = (1, 2, 3 \cdots\cdots..50 \cdots\cdots\cdots \mathrm{N})$$

In the present study, the findings of the Bias-Corrected Scaled LM test are considered. This test eliminates the LM test's bias and the Pesaran CD test's potential for the correlation sum to be 0 when the time dimension exceeds the cross-sectional dimension. The Bias-Corrected Scaled LM test is presented in Eq. (10).

$$LM_{adj} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\Psi}ij\right)\left[\frac{(T-K)\hat{\Psi}_{ij}^2 - (T-K)\hat{\Psi}_{ij}^2}{Var(T-K)\hat{\Psi}_{ij}^2}\right] \tag{10}$$

The test statistic obtained with Eq. (10) shows an asymptotically standard normal distribution in the formula μTij is the mean, vTij is the variance, and *K* is the regressor.

4.2. Slope heterogeneity findings

In order to decide on the tests to be used in cointegration and causality analyses and to evaluate the findings correctly, the homogeneity of panel data models should be investigated. The first study on the homogeneity of slope coefficients in the panel cointegration equation started with Swamy (1970). Later, Pesaran and Yamagata (2008) improved the Swamy (1970) model. Pesaran and Yamagata (2008) introduced two types of test statistics to test the hypotheses depending on the sample size (Pesaran and Yamagata, 2008). Eqs. (11) and (12):

$$\text{Big Data}: \tilde{\Delta}_{adj} = \sqrt{N}\frac{N^{-1}\ \hat{S} - E(\check{Z}_{it})}{\sqrt{Var}(\check{Z}_{it})} \tag{11}$$

$$\text{Small Data}: \tilde{\Delta}_{adj} = \sqrt{N}\frac{N^{-1}\ \hat{S} - E(\check{Z}_{it})}{\sqrt{Var}(\check{Z}_{it})}N(0,1) \tag{12}$$

In the test statistics, N reflects the number of cross-sections, S reflects the Swamy test statistic, $E(\check{Z}_{it})$ reflects the number of explanatory variables, and Var(t,k) reflects the standard error.

4.3. Panel stationary tests

The next step after examining cross-sectional dependence is to check the stationarity properties of the variables. Due to economic, political and social globalization, countries' economies have become interdependent. Therefore, first-generation stationarity tests are not valuable because they do not consider CSD effects, slope heterogeneity and dimensionality. For such problems, second-generation unit root tests are used. Pesaran (2007) proposes the cross-sectional Im, Pesaran and Shin (CIPS) and Cross-sectional Augmented Dickey-Fuller (CADF) tests that solve the CSD problems and take heterogeneity into account. Eq. (13) reports the CADF test statistics.

$$\Delta X_{it} = \beta_i + \pi_i x_{i,t-1} + \lambda_i \bar{x}_{t-1} + \delta_i \Delta \bar{x}_t + \varepsilon_{it} \tag{13}$$

When a lagged value (t-1) is added to Eq. (6), Eq. (7) is obtained.

$$\Delta X_{it} = \beta_i + \pi_i x_{i,t-1} + \lambda_i \bar{x}_{t-1} + \sum_{j=0}^{p} \delta_i \Delta \bar{x}_{t-j} + \sum_{j=1}^{p} \phi_{ij} \Delta x_{i,t-j} + \varepsilon_{it} \tag{14}$$

Where $\bar{x}_{t-1}$ ve $\Delta x_{i,t-j}$ are the average of the lagged value of each cross-section, and the first order difference operator. The CIPS test is reported as in Eq. (15).

$$CIPS = N^{-1}\sum_{i=1}^{N} \pi_i(N,T) \tag{15}$$

The term π_i (N,T) is replaced by the panel CADF unit root test statistics as in Eq. (16).

$$CIPS = N^{-1}\sum_{i=1}^{N} CADF_i \tag{16}$$

Another alternative in the unit root testing process is the approach where the null hypothesis is based on stationarity. Hadri and Kurozumi (2012) follow Pesaran (2007) in the second-generation unit root test, which takes into account cross-sectional dependence through unobserved common factors in the error term in the KPSS testing process and tests the stationarity of the null hypothesis with asymptotically normally distributed Z_A^{SPC} and Z_A^{LA} statistical values are shown in Eqs. (17) and (18).

$$Z_A^{SPC} = \frac{1}{\hat{P}_{iSPC}^2 T^2}\sum_{t=1}^{T}\left(S_{t=1}^{w}\right)^2 \tag{17}$$

$$Z_A^{LA} = \frac{1}{\hat{P}_{iLA}^2 T^2}\sum_{t=1}^{T}\left(S_{t=1}^{w}\right)^2 \tag{18}$$

4.4. Panel cointegration test

Panel cointegration study looks at the long-term linkages between non-stationary series after checking the trend components and level of integration of all chosen series. In this study, the Westerlund-Durbin-Hausman (2008) WDH test is used to examine the long-term correlations between variables. The WDH test provides reliable results in the presence of CSD, is based on common factors and bases the cointegration relationship on two different test statistics, namely the Durbin-H panel and the Durbin-H group. The Durbin-H group (DHg) test statistic allows the autoregressive parameter to be heterogeneous, while the Durbin-H (DHp) panel test statistic allows the autoregressive parameter to be homogeneous. The DHg and DHp test statistics are expressed in Eqs. (19) and (20).

$$DH_g = \sum_{i=1}^{n} \hat{S}_i \left(\tilde{\phi}_i - \tilde{\phi}_i\right)^2 \sum_{t=2}^{T} \hat{e}_{it}^2 - 1 \tag{19}$$

$$DH_g = \hat{S}_n \left(\tilde{\phi} - \tilde{\phi}\right)^2 \sum_{i=1}^{n} \sum\nolimits_{t=2}^{T} \hat{e}_{it-1}^2 \tag{20}$$

In the equations, S_i is the variance term, ϕ is the cointegration parameters, and e is the error term.

4.5. Panel Long-Run estimates

In this study, the continuously updated fully modified estimator (Cup-FM) developed by Bai et al. (2009) is used to investigate the long-run effect of the regressors affecting the ecological footprint. This estimator provides efficient and consistent results in multifactor models with different degrees of integration of variables in the presence of CSD and heterogeneous panels. Continuously Updated Fully Modified OLS (Cup-FMOLS) is expressed in Eqs. (21)–(24).

$$E_{jt} = \gamma Y_{jt}^2 + \beta Y_{jt} + \varepsilon_{jt} \rightarrow \ x_{jt} + \varepsilon_{jt} \tag{21}$$

where,

$$\varepsilon_{jt} = \lambda_j' F_t + u_{jt} \tag{22}$$

$$x_{jt}' = x_{jt-1}' + \varepsilon_{jt} \tag{23}$$

$$F_t = F_{t-1} + \eta_{jt} \tag{24}$$

The Cup-FMOLS long-run coefficient estimator corrects and improves the biases in traditional panel data models with two-equation iterations.

4.6. Panel causality test

Once the CSD, stationarity and cointegration processes are verified, the next step in the econometric analysis is to analyze the panel causality relationships between variables (Jahanger et al., 2022a, 2022b). In this study, causality relationships between variables are investigated with the Bootstrap panel causality test presented by Konya (2006). It is based on the Seemingly Unrelated Regressions (SUR) estimator developed by Zellner (1962) and is implemented based on cross-sectional bootstrap critical values and the Wald test. In addition, it is a non-stationary method that considers country-specific heterogeneity and CSD. The Konya (2006) Bootstrap panel causality test can be reported as in Eqs. (25) and (26).

$$y_{1,t} = \alpha_{1,1} + \sum\nolimits_{l=1}^{mly_1} \beta_{1,1,l} \gamma_{1,t-1} + \sum\nolimits_{l=1}^{mlx_1} \gamma_{1,1,l} x_{1,t-1} + \varepsilon_{1,1,t} \tag{25}$$

$$y_{2,t} = \alpha_{1,2} + \sum\nolimits_{l=1}^{mly_1} \beta_{1,2,l} \gamma_{2,t-1} + \sum\nolimits_{l=1}^{mlx_1} \gamma_{1,2,l} x_{2,t-1} + \varepsilon_{1,2,t} \tag{26}$$

$$y_{N,t} = \alpha_{1,N} + \sum\nolimits_{l=1}^{mly_1} \beta_{1,N,l} \gamma_{N,t-1} + \sum\nolimits_{l=1}^{mlx_1} \gamma_{1,N,l} x_{N,t-1} + \varepsilon_{1,N,t} \tag{27}$$

and

$$x_{1,t} = \alpha_{2,1} + \sum\nolimits_{l=1}^{mly_2} \beta_{2,1,l} \gamma_{1,t-1} + \sum\nolimits_{l=1}^{mlx_2} \gamma_{2,1,l} x_{1,t-1} + \varepsilon_{2,1,t} \tag{28}$$

$$x_{2,t} = \alpha_{2,2} + \sum\nolimits_{l=1}^{mly_2} \beta_{2,2,l} \gamma_{2,t-1} + \sum\nolimits_{l=1}^{mlx_2} \gamma_{2,2,l} x_{2,t-1} + \varepsilon_{2,2,t} \tag{29}$$

$$x_{N,t} = \alpha_{2,N} + \sum\nolimits_{l=1}^{mly_2} \beta_{2,N,l} \gamma_{N,t-1} + \sum\nolimits_{l=1}^{mlx_2} \gamma_{2,N,l} x_{N,t-1} + \varepsilon_{2,N,t} \tag{30}$$

The variables in the equations are y and x; N represents the panel's cross-sections I = 1, 2,…, N), t is the period (t = 1, 2,…, T), and l is the lag length. The lag lengths for y and × are mly and mlx, respectively. ε reflects the error term. In the first stage, out of five Konya (2006) Bootstrap panel causality test, Eqs. (25)–(27) are estimated, and the error terms are obtained under H0, where there is no causality relationship from X to Y. In the second stage, the error terms are resampled using Eqs. (28)–(30). In the third stage, a bootstrap sample is generated under the assumption that X is not the cause of Y based on the equation given in Eq. (31).

$$y^*_{i,t} = \widehat{\alpha}_{1,i} + \sum\nolimits_{l=1}^{mly_1} \widehat{\beta}_{1,i,l} y^*_{i,t-1} + \varepsilon^*_{H0,i,t} \tag{31}$$

In the fourth stage, $y_{1,i}$ in Eqs. (25)–(27) is replaced by $y^*_{1,i}$ without any parameter restrictions and the null hypothesis of no causality for each cross-section is tested using the Wald test. The distribution of the Wald test statistics is created in the fifth and final stage by repeatedly performing stages 2, 3, and 4. after choosing the correct percentile in the sample distribution, bootstrap critical values are calculated.

4.7. Panel vector autoregressive (PVAR) impulse response function and variance decompositions

The PVAR model, developed by Love and Zicchino (2006), increases the reliability and robustness of the estimation results in the fixed effects model by representing unobserved singular heterogeneity in the data set. The PVAR approach can analyze changes in macroeconomic factors, does not distinguish between endogenous and exogenous variables in the model and treats all variables as endogenous. PVAR is based on the current developments of a series, and it is unbiased concerning a particular hypothesis or economic theory. Every PVAR variable depends on its previous values and many circumstances and synchronizes these elements' actions. In the PVAR model, all variables must be stationary, i.e. do not contain unit roots. The general PVAR model is stated as follows:

$$y_{it} = \beta_{0it} + \sum_{k=1}^{p} \alpha_{it} y_{it-k} + u_{it} \tag{32}$$

In the equation, y_{it} represents the vector of K endogenous variables for each cross-section, $i = 1;\ldots$ N cross-sections $t = 1\ldots$ T time dimension and β_{0it} represents the deterministic components.

The PVAR model is also used to determine the response of a given variable to shocks in another variable and the variance of the variable in response to the shock. Impulse-response functions (IRFs) are used to determine the response of one variable to changes in another variable, assuming all other shocks are equal to zero. In order to estimate the IRF, it is necessary to estimate the confidence intervals of the IRF because IRFs are derived from the estimated VAR parameters and their standard deviations. The IRF functions are expressed in VAR matrix form in Eqs. (33) and (34).

$$\begin{bmatrix} y_{it} \\ z_{it} \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{bmatrix} y_{i,t-1} \\ z_{i,t-1} \end{bmatrix} + \begin{bmatrix} e_{1it} \\ e_{2it} \end{bmatrix} \tag{33}$$

In terms of moving average (ε_{yt}) and (ε_{zt}) series,

$$\begin{bmatrix} y_{it} \\ z_{it} \end{bmatrix} = \begin{bmatrix} \bar{y} \\ \bar{z} \end{bmatrix} + \sum_{I,t=0}^{\infty} \begin{pmatrix} \Phi_{11(i,t)} & \Phi_{12(i,t)} \\ \Phi_{21(i,t)} & \Phi_{22}(i,t) \end{pmatrix} \begin{bmatrix} \varepsilon_{yit-1} \\ \varepsilon_{zit-1} \end{bmatrix} \tag{34}$$

The moving average representation in the equations is an important tool for identifying the interaction between the y_{it} and z_{it} series. The coefficients of ϕi can be used to identify the effects of (ε_{yit}) and (ε_{zit}) shocks on the entire time path of the y_{it} and z_{it} series.

In variance decomposition analysis, shocks are orthogonalized by defining the P matrix to isolate the contribution of each variable to the forecast error variance. In this context, the contribution of the variable m at step h to the prediction error variance is calculated as in Eqs. (35) and (36), where s denotes the column of $'i_s$ I_k (Abrigo & Love, 2015).

$$\sum\nolimits_{i=0}^{h-1} \theta^2_{mn} = \sum\nolimits_{i=1}^{h-1} \left(i'_n P \varnothing i_m\right)^2 \tag{35}$$

$$\sum\nolimits_{i=0}^{h-1} \theta^2_{.n} = \sum\nolimits_{i=1}^{h-1} i'_n \varnothing'_i \sum \varnothing_i i_n \tag{36}$$

When using the variance decomposition analysis, the shocks affecting all variables are subdivided by taking into account each variable's variance. In other words, the change in the variable itself in the analysis. In this direction, the effect of variables on each other in percentage terms has been revealed.

5. Results and discussion

In this study, a panel cointegration test has been conducted to reveal the long-run relationships between variables. After revealing the existence of long-run relationships, long-run estimators have been used to determine the coefficients and direction of these relationships. After coefficient estimation, causality analysis determines whether the relationships are reciprocal. After analyzing the long-run relationships, the effects of short-run shocks are investigated with the PVAR model.

5.1. Descriptive statistics and correlation matrix (multicollinearity-endogeneity)

The descriptive information of the variables analyzed for G-7 countries is given in Table 2. According to the descriptive information statistics, LnEF has the highest mean value (20.00171), while LnHDI has the lowest mean value (0.125065). LnEF has the highest median value (19.63558), and the lowest median value (0.119910) is associated with LnHDI. LnRDD has the highest volatility, while LnHDI is the least volatile. All variables except LnEF are negatively skewed. According to the J-B values, the null hypothesis of a normal distribution is rejected for all variables except LnRDD. Fig. 3 explores the box plot for each variable and the trend analysis for 1991–2018.

Table 3 presents the multicollinearity results. If there are higher than 90% correlations between the explanatory variables in the model, a multicollinearity problem arises, which may make the model estimation results inconsistent and inaccurate (Tabachnick & Fidell, 2001). According to the information in Table 2, the variables are not normally distributed, and therefore Spearman test is used for the correlation matrix. Accordingly, while LnEF has a positive correlation with LnECI and LnRDD, it has a negative corre-

Table 2
Descriptive statistics.

Stats.	LnEF	LnECI	LnHDI	LnRDD	LnRNW
Mean	20.00171	0.455875	−0.125065	4.624575	1.913578
Median	19.63558	0.525783	−0.119910	4.599225	1.980993
Maximum	21.82699	0.965012	−0.056570	7.840069	3.121924
Minimum	19.23705	−0.888282	−0.244623	0.062035	−0.497146
Std. Dev.	0.756394	0.365157	0.039324	1.484252	0.854690
Skewness	1.524306	−1.250252	−0.724509	−0.412425	−0.653814
Kurtosis	3.962411	4.666280	3.172418	3.107033	3.095712
Jarque-Bera	83.46555	73.73689	17.38992	5.649982	14.03892
Probability	0.000000	0.000000	0.000167	0.059309	0.000894
Sum	3920.336	89.35152	−24.51273	906.4166	375.0613
Sum Sq. Dev.	111.5658	26.00120	0.301547	429.5859	142.4466
Observations	196	196	196	196	196

Note: LnEF, LnECI, LnHDI, LnRDD, and LnRNW denote the ecological footprint, economic complexity index, human development, research, development, and demonstration and renewable energy consumption in logarithmic form.

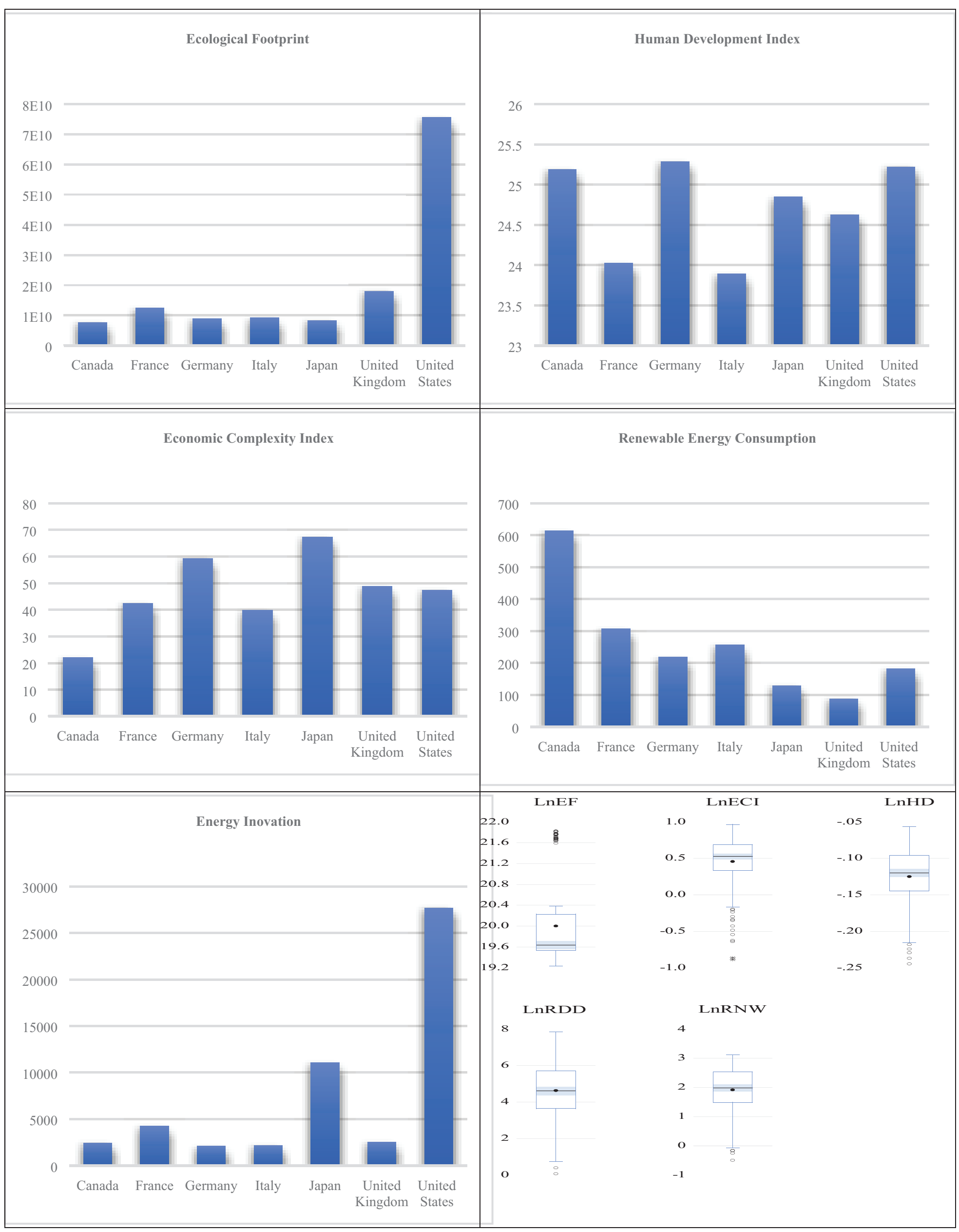

Fig. 3. Box chart and trend analysis of selected variables.

Table 3
Spearman correlation matrix for multicollinearity.

Series	LnEF	LnECI	LnHDI	LnRDD	LnRNW
LnEF	1.0000				
LnECI	0.1075	1.0000			
	[1.507]				
LnHDI	−0.0779	−0.0923	1.0000		
	-[1.089]	[-1.291]			
LnRDD	0.2249***	0.0494	0.4926***	1.0000	
	[3.215]	[0.689]	[7.885]		
LnRNW	−0.4037***	−0.7434***	0.3805***	0.0839	1.0000
	[-6.146]	[-15.481]	[5.732]	[1.173]	

Note: *, ** & *** denote the significance 10%, 5% and 1% levels, respectively. The t-statistics are presented in [ ].

lation with LnHDI and LnRNW. The highest correlation between the variables (0.7434) is between LnRNW and LnECI. The lowest correlation is between LnHDI and LnEF. According to these results, there is no multicollinearity problem among the explanatory variables in the model.

High-level correlations between the model's error term estimated through OLS and the explanatory variables cause endogeneity problems. According to the endogeneity results in Table 4, the highest correlation coefficient (0.1153) is between the error term and LnRDD, and there is no endogeneity problem in the model.

5.2. Cross-sectional dependence (CDS) findings

In the present study, the empirical analysis starts by checking the cross-sectional dependence of the panel. Ignoring the CSD problem may lead to biased and inconsistent stationarity and long-run coefficient estimates (Chudik and Pesaran, 2013). The findings are reported in Table 5. In the globalizing world, countries and economies are in a relationship with each other through trade agreements and financial integration. These countries are connected economically, financially and socially.

Consequently, this leads us to examine the CSD. The authors observe that all series and models are most significant at the 1% level. This indicates that there is CSD in the series. Consequently, the authors reject H0 and accept H1. The evidence of all CSD tests suggests significant cross-sectional dependence in the variables and models in the panel. The CSD findings have identified tests that should be used in other analysis processes in panel data.

5.3. Slope heterogeneity findings

Since slope coefficients are expected to vary across cross-sectional units after CSD, it would be appropriate to check slope heterogeneity. Ignoring slope heterogeneity issues may produce biased and inconsistent estimates. In this study, although G-7 countries are interconnected in various respects, there are significant differences in macroeconomic aggregates, such as income levels, energy consumption, renewable energy structures, etc., between them. In this respect, slope heterogeneity concerns cannot be denied. For this reason, the Pesaran and Yamagata (2008) slope heterogeneity test was applied in this study. This method involves estimating two test statistics ($\widetilde{\Delta}$ and $\widetilde{\Delta}_{adj}$) under the null hypothesis of slope homogeneity across cross-sectional units. The Pesaran and Yamagata (2008) test results for variables and models are reported in Table 6. According to $\widetilde{\Delta}$ and $\widetilde{\Delta}_{adj}$ test statistics, the null hypothesis is rejected for all variables and models, and slope heterogeneity is confirmed. Considering the CSD and slope heterogeneity issues, the most appropriate unit root, cointegration, long-run coefficient estimation and causality methods are selected.

5.4. Panel unit root findings

After testing for CSD and slope heterogeneity in the data set, it is necessary to check the stationarity of all variables (second generation) to estimate reliable and consistent coefficients and avoid spurious regression. Since the CSD test results in Table 5 show cross-sectional dependence for all variables and all variables in Table 6 have slope heterogeneity, CIPS and HK second-generation unit root tests are applied. These tests can be used under CSD and slope heterogeneity. Table 7 shows the results of the CIPS and HK tests on the data set. The H_0 of these tests is that there is a unit root in the series, i.e. the series is non-stationary. It shows that all variables are non-stationary at I(0) level in constant, constant and trend, and they are I(1) stationary when they are first-order differences. This means that there is no unit root problem among the variables.

5.5. Panel cointegration findings

Table 8 reports the results of the Westerlund-Durbin-Hausman cointegration test. This test is a cointegration test that can be used under CSD and slope heterogeneity. According to the WDH test results, the DHg and DHp test statistics are below the 5% significance level in all models and confirm a strong cointegration rela-

Table 4
Spearman correlation matrix for endogeneity.

Series	Error Term	LnECI	LnHDI	LnRDD	LnRNW
Error Term	1.0000				
LnECI	−0.0014	1.0000			
	[-0.019]				
LnHDI	0.0146	−0.0923	1.0000		
	[0.203]	[-1.291]			
LnRDD	−0.1153	0.0494	0.4926***	1.0000	
	[-1.617]	[0.689]	[7.885]		
LnRNW	0.0423	−0.7434***	0.3805***	0.0839	1.0000
	[0.589]	[-15.481]	[5.732]	[1.173]	

Note: *, ** & *** denote the significance 10%, 5% and 1% levels, respectively. The t-statistics are presented in [ ].

Table 5
Cross-sectional dependence tests.

Variables	Breusch-Pagan LM		Pesaran scal. LM		Bias-corrected scal. LM		Pesaran CD	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
LnEF	172.7511***	0.0000	23.4157***	0.0000	23.2860***	0.0000	7.4780***	0.0000
LnECI	275.6118***	0.0000	39.2874***	0.0000	39.1578***	0.0000	15.3907***	0.0000
LnECI^2	285.3640***	0.0000	40.7922***	0.0000	40.6626***	0.0000	9.9086***	0.0000
LnHDI	562.8031***	0.0000	83.6020***	0.0000	83.4724***	0.0000	23.7204***	0.0000
LnRDD	177.7619***	0.0000	24.1888***	0.0000	24.0592***	0.0000	11.2603***	0.0000
LnRNW	366.1065***	0.0000	53.2510***	0.0000	53.1214***	0.0000	18.8222***	0.0000
Model A	45.707***	0.0010	3.812***	0.0000	6.663***	0.0000	3.525***	0.0000
Model B	48.470***	0.0010	4.239***	0.0000	1.980**	0.0240	3.525***	0.0000
Model C	34.554**	0.0320	2.092**	0.0180	4.226***	0.0000	3.220***	0.0010

Note: *, ** & *** denote the significance 10%, 5% and 1% level respectively.

Table 6
Slope homogeneity tests.

Variables	$\tilde{\Delta}$	P-value	$\tilde{\Delta}_{adj}$	P-value
LnEF	1.775**	0.038	1.878**	0.030
LnECI	1.400*	0.081	1.481*	0.069
LnECI^2	2.498***	0.006	2.644***	0.004
LnHDI	8.973***	0.000	9.692***	0.000
LnRDD	9.805***	0.000	10.818***	0.000
LnRNW	9.398***	0.000	10.602***	0.000
Model A	9.234***	0.000	10.602***	0.000
Model B	7.607***	0.000	8.939***	0.000
Model C	8.229 ***	0.000	9.670***	0.000

Note: *, ** & *** denote the significance 10%, 5% and 1% level respectively.

Table 7
Second generation panel unit root tests.

Variables	Intercept					
	Pesaran CIPS		Hadri & Kurozumi HK			
	CIPS t-stat.	p-value	Z_A^{SPC}	p-value	Z_A^{LA}	p-value
LNEF	−1.9769	≥0.10	1.4734*	0.0703	6.6623***	0.0000
Δ LNEF	−3.0483***	<0.01	−0.9365	0.8255	−0.7062	0.7600
LNECI	−1.8569	≥0.10	1.4103*	0.0792	416.9390***	0.0000
Δ LNECI	−3.2702***	<0.01	−0.1844	0.5732	−0.4938	0.6893
LnHDI	−1.2184	≥0.10	16.2187***	0.0000	14.6585***	0.0000
Δ LnHDI	−3.4606***	<0.01	0.1388	0.4448	−0.0579	0.5231
LnRDD	−1.8452	≥0.10	49.4878***	0.0000	15.9459***	0.0000
Δ LnRDD	−5.4780***	<0.01	0.2012	0.4203	0.7069	0.2398
LnRNW	−1.3355	≥0.10	10.0301***	0.0000	52.2360***	0.0000
Δ LnRNW	−4.3804***	<0.01	0.6886	0.2455	1.1330	0.1286
Critical Values	1%	5%	10%			
	−2.58	−2.33	−2.21			
Variables	Intercept and Trend					
	Pesaran CIPS		Hadri & Kurozumi HK			
	CIPS t-stat.	p-value	Z_A^{SPC}	p-value	Z_A^{LA}	p-value
LnEF	−1.6659	≥0.10	10.3063***	0.0000	4.6962***	0.0000
Δ LnEF	−3.0496**	<0.05	1.2731	0.1015	1.8929**	0.0292
LnECI	−1.9150	≥0.10	22.7117***	0.0000	18.1735***	0.0000
Δ LnECI	−3.0570**	<0.05	1.5823*	0.0568	1.4790*	0.0696
LnHDI	−2.8184	<0.10	2.9785***	0.0014	3.8274***	0.0001
Δ LnHDI	−3.7803***	<0.01	0.7292	0.2329	1.0818	0.1397
LnRDD	−1.6025	≥0.10	2.5356***	0.0056	2.2403**	0.0125
Δ LnRDD	−5.0986***	<0.01	1.6336*	0.0512	1.5429*	0.0614
LnRNW	−2.0976	≥0.10	13.2687***	0.0000	14.6195***	0.0000
Δ LnRNW	−2.9531**	<0.05	0.4763	0.3169	1.1885	0.1173
Critical Values	1%	5%	10%			
	−3.12	−2.87	−2.73			

Note: *, ** & *** denote the significance 10%, 5% and 1% levels, respectively.

tionship between LnEF and LnECI, LnHDI, LnRDD, LnRNW and interaction variables. This finding rejects the null hypothesis of no cointegration H_0 and accepts H_1. After confirming the long-run cointegration relationships, it is necessary to determine the direction of the relationships with panel data estimators and panel causality analyses.

Table 8
Westerlund Durbin-Hausman cointegration test.

Statistic	Model A		Model B		Model C	
	Value	p-value	Value	p-value	Value	p-value
DH_g	−2.015 **	0.022	−2.071**	0.019	−2.158**	0.015
DH_p	−1.927**	0.027	−1.588*	0.056	−1.655**	0.049

Note: *, ** & *** denote the significance 10%, 5% and 1% levels, respectively.

5.6. Panel long-run elasticity estimates

Once the long-run cointegration relationship between the variables is confirmed, it is essential to estimate the long-run coefficient. In Table 9, the relationship between economic complexity, human development, high innovation processes, renewable energy consumption and ecological footprint is investigated using Cup-FMOLS. The empirical findings reveal that all regressors are statistically significant. When Model A is analyzed to test the existence of a second-order inverted U-shaped EKC relationship, the coefficient of LnECI is significant and positive in the long run. The positive elasticity implies that a 1% increase in economic complexity, in the long run, will lead to a 5.101% increase in the ecological footprint in G7 countries. However, after economic complexity reaches a certain point, the coefficient of LnECI^2 is statistically significant and negative. Specifically, it shows that a 1% increase in LnECI^2 leads to a 0.271% decrease in the ecological footprint in the long run. This indicates the existence of an inverted U-shaped EKC relationship for the ecological footprint in G7 countries.

Similarly, Model B and Model C validate the inverted U-shaped EKC hypothesis for the G7 countries. As previously proved by Pata (2021) for the US, Ahmad et al. (2021) for developing countries, Bilgili et al. (2021) for countries with high carbon emissions, Ahmed et al. (2022a, 2022b)) for G7 countries, and Nguyen and Doytch (2022) for medium–low countries, it has been proven that in the initial stage of economic development, increased economic development leads to high levels of environmental degradation. After reaching a certain economic level where the ecological footprint tends to decrease, increasing economic complexity reduces environmental degradation. This process confirms the scale effect of compositional and technical effects.

Growth models can explain the linkage between LnRNW and LnEF. When economic development reaches a certain level, increasing environmental awareness encourages policymakers and industries to emphasize renewable energy sources and reduces environmental degradation (Destek and Sinha, 2020). In Model A, Model B and Model C for G7 countries, a significant and negative relationship was found between LnRNW and LnEF. Specifically, it shows that a 1% increase in Ln LnRNW will lead to a 0.068% decrease in the ecological footprint (Model A) in the long run. This indicates that renewable energy sources require a smaller ecological footprint and provide an additional energy source that should be promoted for sustainable development (Ahmed et al., 2022a, 2022b). These findings are in line with previous studies conducted by Alola et al. (2019) for EU member countries, Destek and Sinha (2020) for Organization for Economic Cooperation and Development countries, Sharif et al. (2020) for Turkey, Usman et al. (2020) for USA, Danish et al. (2020) for BRICS countries, Miao et al. (2022) for newly industrialized countries, Abid et al. (2022) for Saudi Arabia. Raghutla et al. (2022) for N-11 countries, Nathaniel et al. (2020) for MENA countries and Nathaniel and Khan (2020) for ASEAN countries. Evaluating ecological footprint and human development together is the main way to evaluate sustainable development from an ecological perspective (Zhang et al., 2017). Ideally, for sustainable urban development, the ecological footprint should be reduced, and human development should be increased (Long et al., 2020a, 2020b). The HDI is a statistic that combines data on life expectancy, education, and per capita income to rank nations based on four levels of human development (Shah, 2016). The study found a significant and negative relationship between LnHDI and LnEF in Model A, Model B and Model C for G7 countries. Specifically, it shows that a 1% increase in Ln LnHDI will lead to a 0.059% decrease in the ecological footprint (Model A) in the long run. This evidence suggests sustainable development can be realized by improving the social and income dimensions. These findings are similar to the study conducted by Pata et al. (2021) for ten countries with a high ecological footprint and different from the studies conducted by Yunani et al. (2020) and Marbet et al. (2021) for MENA countries. Our study also aims to explain further the impact of economic complexity and human development index on ecological footprint with the interaction variable (LnHDI*LnECI). In Model B, where we reveal the interaction of economic complexity and human development index, a significant and negative relationship was found between LnHDI*LnECI and LnEF. As a result, the interaction between economic complexity and human development reduces the ecological footprint and accelerates sustainable development.

The relationship between LnRDD and LnEF can be explained by endogenous growth theory. According to this theory, locally generated technological innovation through investment in the research

Table 9
Cointegrating factors of the model.

Cup-FMOLS						
	Model A		Model B		Model C	
Regressors	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
LnECI	5.101***	3.267	5.073**	1.916	5.314**	1.674
LnECI^2	−0.271*	0.602	−0.347*	0.525	−0.103	0.770
LnHDI	−0.059**	1.191	−1.198**	1.870	−0.493*	0.551
LnRDD	−0.097**	1.388	−0.375*	0.520	−0.045**	1.843
LnRNW	−0.068*	0.946	−2.555**	1.837	−0.275*	0.771
LnHDI*LnECI			−0.434*	0.493		
LnRDD*LnECI					−0.476*	0.570
EKC	U-shaped		U-shaped		U-shaped	

Note: *, ** & *** denote the significance 10%, 5% and 1% levels, respectively.

and development sector helps countries to achieve economic and environmental prosperity. In the energy sector, technological innovation is regarded as a tipping point for the transition from unclean energy sources to cleaner energy sources (Jahanger et al., 2022a, 2022b). Thus, technological innovation will reduce the growth in the ecological footprint. In the study, a significant and negative relationship was found between LnRDD and LnEF in Model A, Model B and Model C for G7 countries. Specifically, it shows that a 1% increase in Ln LnHDI will lead to a 0.097% decrease in the ecological footprint (Model A) in the long run. These findings are similar to those of Ke et al. (2021, 2022a, 2022b) for China, Jahanger et al. (2022a, 2022b) for developing countries, and Sherif et al. (2022) for N-11 countries, but differ from Cheng et al. (2019) for OECD countries. Our study aimed to explain the impact of economic complexity and high innovation process on ecological footprint with the interaction variable (LnRDD*LnECI). In Model C, where we reveal the interaction of economic complexity and high innovation process, a significant and negative relationship was found between LnRDD*LnECI and LnEF. The connection between economic complexity and ecological footprint is more significant in Model B than it was in Model A. As a consequence, an enhance in the high innovation process leads to a decrease in the level of ecological footprint and accelerates the stage of sustainable development. According to the findings obtained in all models, it can be said that the U-shaped EKC relationship is valid for G7 countries and that explanatory and interaction variables accelerate sustainable development by reducing the ecological footprint (see Fig. 4).

5.7. Panel causality findings

After revealing the long-run cointegration relationship and long-run dynamics between the variables, it is necessary to prove the causality relationships between the variables. The Kónya (2006) Bootstrap panel causality test reveals the causality relationships between the series. The Konya test is used in the panel under CSD and slope heterogeneity. The findings from Konya causality (unidirectional, bidirectional and no causality) are reported in Table 10. According to the causality test results, unidirectional causality is found from LnHDI to LnEF, from LnECI to LnEF, from LnECI to LnRNW, and from LnHDI to LnRDD. These findings are in line with Yilanci and Pata (2020) for China, Nathaniel (2021) for Asian countries, Pata (2021) for the US, Castro et al. (2022) for G-7 countries, Can and Ahmed (2022) for European Union countries and Martins et al. (2021) for the top 7 countries in the economic complexity index. In addition, bidirectional causal relationships between LnEF and LnRNW, between LnHDI and LnRNW, and between LnRDD and LnRNW were also discovered. These findings are in line with Ahmed et al. (2022a, 2022b) for G-7 countries, Sharif et al. (2020) for Turkey, Miao et al. (2022) for newly industrialized countries, Raghutla et al. (2022) for N11 countries, Usman et al. (2022) for European countries, Wang et al. (2022) for seven developing countries and Hashemizadeh et al. (2022) for G-7 countries (see Fig. 5).

In addition to the empirical findings of the long-run forecasting regressions, the causality findings of this study confirm the impact of economic complexity, renewable energy consumption and human development on the ecological footprint in the long run for G-7 countries. This shows that the productive structure of a country is related to the environment and that renewable energy sources should be promoted for sustainable development, and that sustainable development is possible not only through the economic dimension but also by improving human welfare.

5.8. Impulse response functions

Fig. 2 shows the response functions of all endogenous variables of the PVAR model to shocks for G-7 countries. The response of ecological footprint to economic complexity index shocks is positive and statistically significant. It reveals that LnEF responds positively to a one standard deviation shock in LnECI for the first three

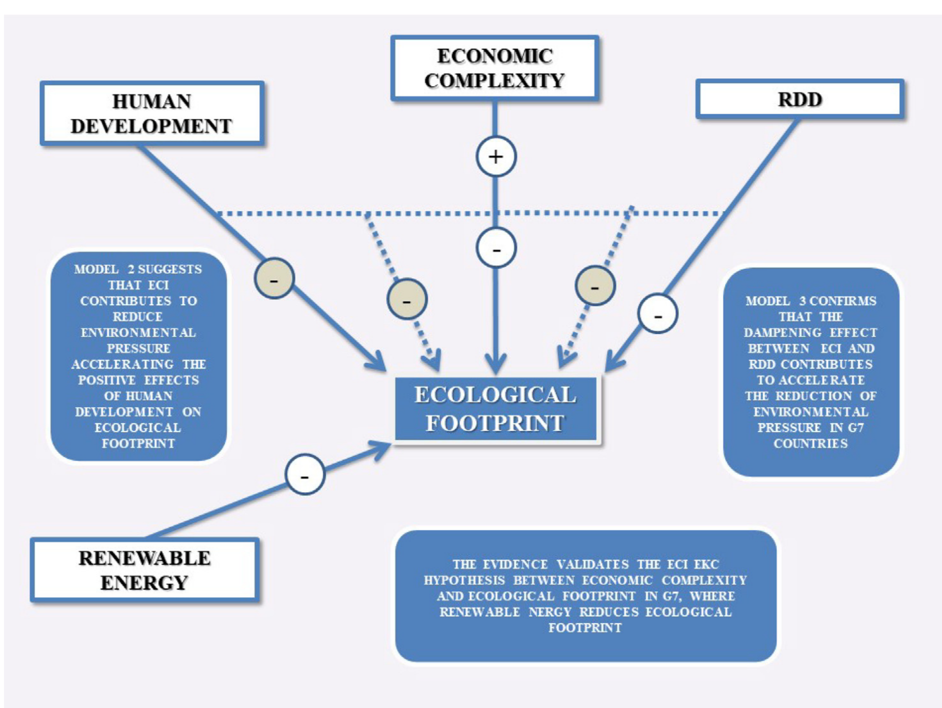

Fig. 4. Graphical summary of results.

Table 10
Konya panel causality test.

Explained					
	LnEF	LnECI	LnHDI	LnRDD	LnRNW
LnEF		13.136 [0.516]	20.273 [0.122]	17.806 [0.216]	25.425** [0.031]
LnECI	24.653** [0.038]		13.736 [0.470]	8.220 [0.878]	23.798** [0.048]
LnHDI	22.352* [0.072]	13.287 [0.504]		25.965** [0.026]	34.828*** [0.002]
LnRDD	9.739 [0.781]	15.197 [0.365]	14.328 [0.426]		47.294*** [0.000]
LnRNW	22.282* [0.073]	6.450 [0.954]	26.802** [0.020]	25.547** [0.030]	

Note: p-values are presented in [ ] respectively. *, ** & *** denote the significance 10%, 5% and 1% level respectively.

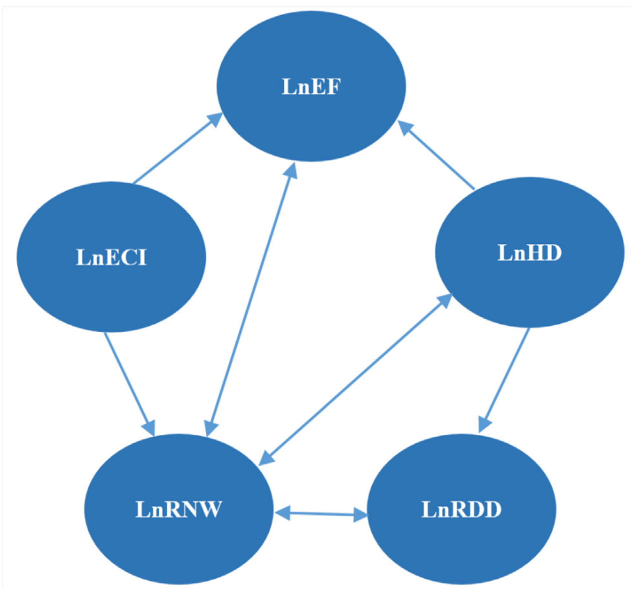

Fig. 5. Konya causality relation flow.

years and then rebalances between the 4th and 5th years. The response of the ecological footprint to shocks of the economic complexity index squared is negative and statistically significant. It reveals that LnEF responds negatively to a one standard deviation shock in LnECI2 for the first three years and then rebalances between years 4 and 5. These findings confirm the validity of the inverted U-shape EKC hypothesis for the ecological footprint in G-7 countries and are consistent with our other findings. The response of ecological footprint to a one standard deviation shock in HDI (human development index) is negative and significant. LnEF responds negatively to the shock in LnHDI for the first three years and returns to equilibrium in the 8th year. Ecological footprint responds negatively and significantly to the shock in high innovation processes in the 5th year, and this response seems to stabilize in the 9th year. Ecological footprint responds negatively and significantly to the shock in renewable energy consumption. This response is negative for the first four years and stabilizes in the 5th year. The response of LnEF to the shock in the interaction variable LnRDD*LnECI is negative for the first two years and stabilizes in year 5. LnEF reacts negatively to a shock in the other interaction variable LnHDI*LnECI for the first six years and stabilizes after one year. The impulse-response findings reveal that LnEF responds negatively and statistically significantly to shocks in all explanatory variables except LnECI. These findings are in line with other findings (see Fig. 6).

5.9. Variance decomposition findings

Table 11 shows the variance decompositions of all endogenous variables of the PVAR model for G-7 countries in response to shocks. In Model A, it is observed that the total change in LnEF in the first year is caused by its shocks, but the effect of its shock decreases over the years. LnECI causes about a 3% change in LnEF over the years, while LnECI^2 causes a 1.88% change in year-2 and a 4% change in year-3 and subsequent years. LnHDI, LnRDD and LnRNW variables cause less than a 1% change in LnEF. The cause of changes in LnEF in the other models shows similar results (see Fig. 7). Human development is responsible for more changes in the ecological footprint than other variables. This result implies that the impact of human development on sustainable development in G-7 countries is higher than other explanatory variables. In addition, in Models B and C, the interaction variables LnHDI*LnECI and LnRDD*LnECI cause more changes in ecological footprint in the following years. The findings obtained in variance decomposition support the other findings.

6. Conclusions and policy implications

The current study examines the relationship between economic complexity, human development, high innovation processes, renewable energy consumption, the interaction between economic complexity and human development, the interaction between economic complexity and high innovation processes, and ecological footprint. This study uses panel data for G7 countries from 1991 to 2018. Breusch and Pagan (1980) LM, Pesaran CSD and Scaled LM (2004), Pesaran et al. (2008) Bias-Corrected Scaled LM tests, Pesaran and Yamagata (2008) delta test for slope heterogeneity, CSD effects for unit root, Pesaran and Shin (CIPS) and Hadri and Kurozumi (2012) KPSS tests, which are second generation unit root tests that take slope heterogeneity into account.

The WDH test results confirm a strong cointegration relationship between LnEF and LnECI, LnHDI, LnRDD, LnRNW and interaction variables in all models. Then, the long-run coefficient between the variables is investigated using Cup-FMOLS. The estimation results reveal that all regressors are statistically significant. The estimated Cup-FMOLS findings explain an inverted-U-shaped relationship between second-order LnECI and LnEF for G7 countries from 1991 to 2018 and confirm the EKC hypothesis. Moreover, human development, high innovation processes, renewable energy consumption, the interaction between economic complexity and human development, and the interaction between economic complexity and high innovation processes reduce the ecological footprint in the long run. These findings suggest that renewable energy sources, technological innovation and human welfare will reduce the ecological footprint and accelerate the stage of sustain-

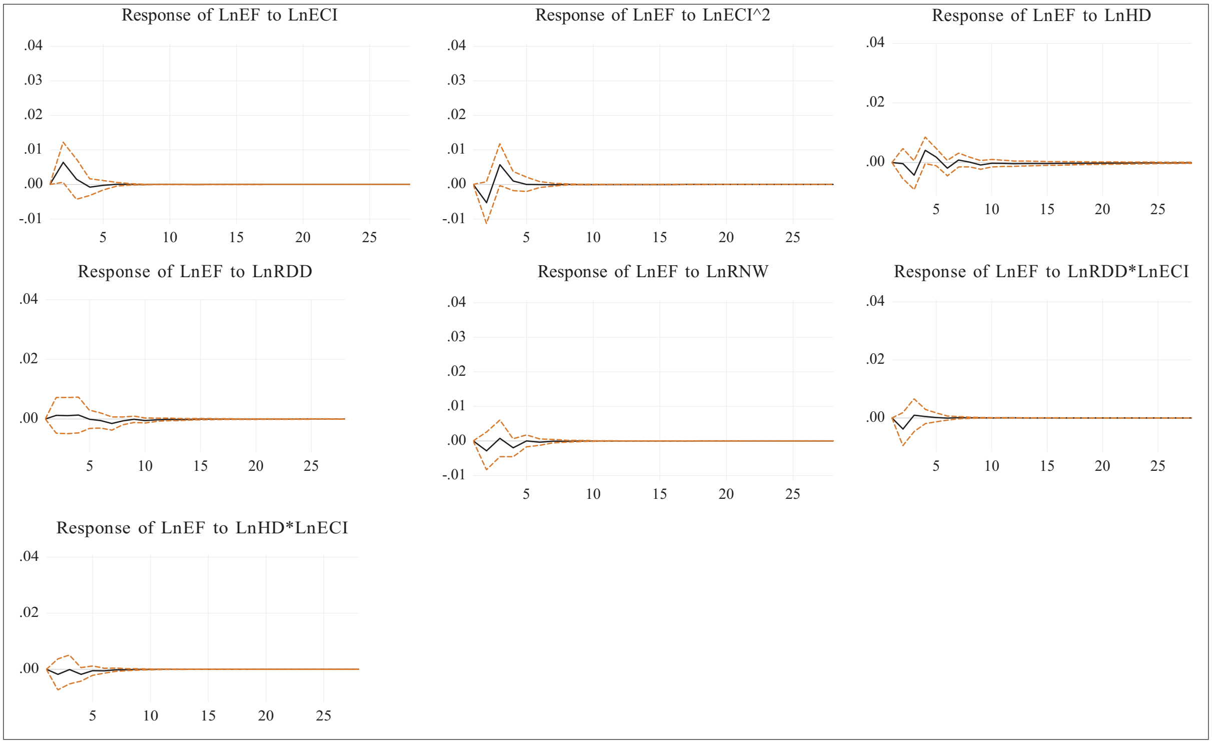

Fig. 6. Graphs of impulse response functions.

Table 11
Panel variance decomposition (PVD_Monte Carlo).

Model A								
Period	S.E.	LnEF	LnECI	LnECI^2	LnHDI	LnRDD	LnRNW	
1	0.036714	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	
2	0.038180	93.85447	2.832982	1.887038	0.763559	0.103366	0.558584	
3	0.038785	90.95830	2.899286	4.027984	0.839880	0.695623	0.578924	
4	0.038861	90.63099	2.926510	4.080055	0.836662	0.693497	0.832290	
5	0.038862	90.62708	2.929731	4.079850	0.836817	0.694178	0.832347	
6	0.038864	90.61679	2.929702	4.079410	0.839603	0.694099	0.840394	
7	0.038864	90.61587	2.929724	4.079676	0.839913	0.694098	0.840717	
8	0.038865	90.61509	2.929712	4.079642	0.840265	0.694107	0.841187	
9	0.038865	90.61496	2.929708	4.079637	0.840350	0.694106	0.841235	
10	0.038865	90.61488	2.929705	4.079641	0.840392	0.694106	0.841277	
Model B								
Period	S.E.	LnEF	LnECI	LnECI^2	LnHDI	LnRDD	LnRNW	LnHDI*LnECI
1	0.036879	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.038431	93.54738	2.744852	1.975456	0.862488	0.099705	0.551253	0.218861
3	0.039005	90.82578	2.783388	3.984813	0.909640	0.706797	0.576809	0.212773
4	0.039107	90.37437	2.812116	3.995325	0.905080	0.706124	0.834648	0.372338
5	0.039113	90.34533	2.815117	3.994746	0.905359	0.707470	0.835085	0.396889
6	0.039122	90.30511	2.814472	3.996688	0.917107	0.707566	0.843836	0.415222
7	0.039124	90.29562	2.814394	3.997691	0.921720	0.707641	0.843800	0.419138
8	0.039125	90.28986	2.814221	3.997961	0.924892	0.707759	0.844206	0.421103
9	0.039125	90.28813	2.814165	3.998032	0.926097	0.707773	0.844193	0.421612
10	0.039126	90.28727	2.814138	3.998148	0.926629	0.707778	0.844213	0.421819
Model C								
Period	S.E.	LnEF	LnECI	LnECI^2	LnHDI	LnRDD	LnRNW	LnRDD*LnECI
1	0.036675	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.036675
2	0.038398	92.51196	2.838521	1.899662	0.747815	0.101627	0.573953	0.038398
3	0.039007	89.65517	2.867537	4.081102	0.838099	0.650470	0.597994	0.039007
4	0.039102	89.22098	2.915655	4.179613	0.834226	0.655437	0.889649	0.039102
5	0.039104	89.21286	2.922169	4.179310	0.835057	0.655759	0.889919	0.039104
6	0.039108	89.19720	2.922054	4.180378	0.837301	0.655701	0.902476	0.039108
7	0.039108	89.19634	2.922150	4.180412	0.837952	0.655704	0.902554	0.039108
8	0.039108	89.19509	2.922148	4.180359	0.838439	0.655729	0.903360	0.039108
9	0.039109	89.19496	2.922143	4.180361	0.838535	0.655729	0.903393	0.039109
10	0.039109	89.19485	2.922140	4.180368	0.838588	0.655728	0.903453	0.039109

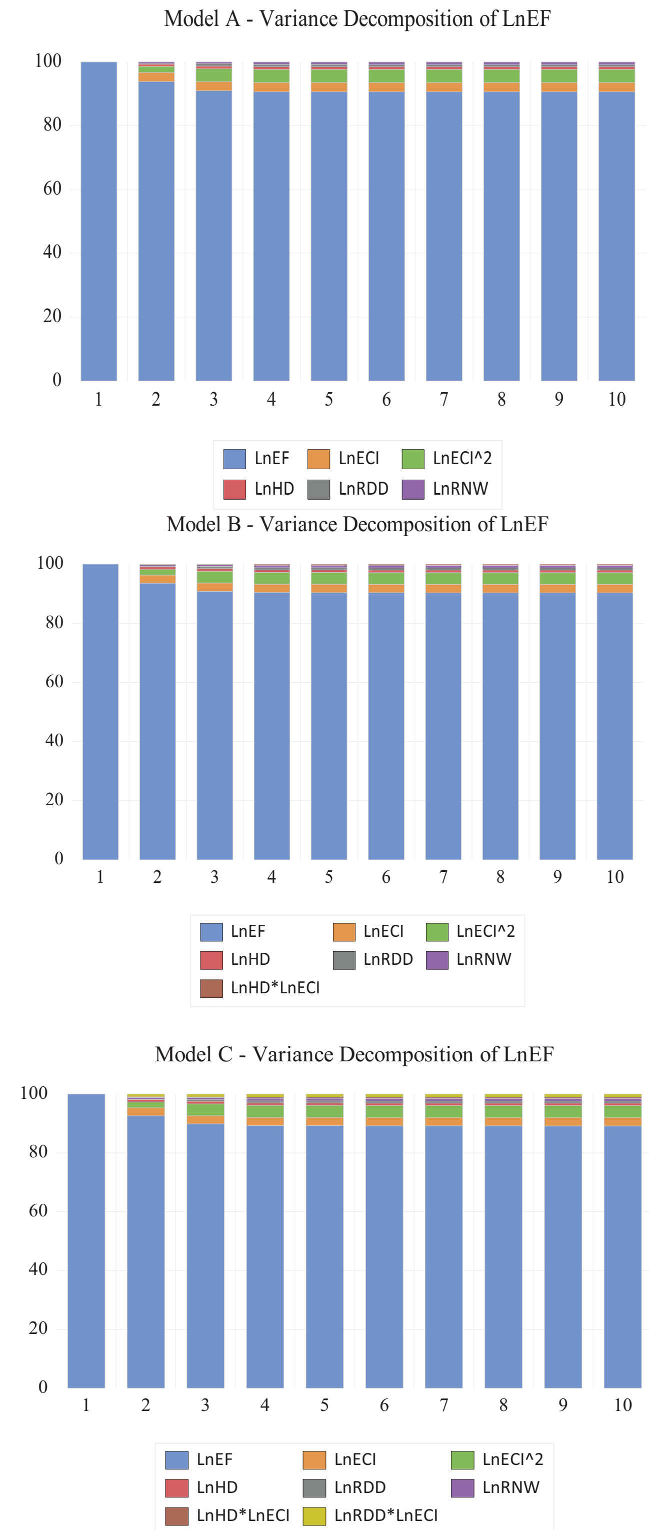

Fig. 7. Graphs of panel variance decompositions.

able development where compositional and technical effects exceed the scale effect.

After revealing the long-run cointegration relationship and long-run dynamics between the variables, the causality relationships between the variables are revealed by the Konya Bootstrap panel causality test. According to the causality test results, it is found that there is a unidirectional causality relationship from LnHDI to LnEF, from LnECI to LnEF, from LnECI to LnRNW, and from LnHDI to LnRDD. These findings confirm the impact of economic complexity, renewable energy consumption and human development on the ecological footprint in the long run for G-7 countries. In addition, the response functions of all endogenous variables of the PVAR model for G-7 countries support the validity of the inverted U shape EKC hypothesis for an ecological footprint in G-7 countries and reveal that LnEF responds negatively and statistically significantly to shocks in all explanatory variables except LnECI. According to the variance decompositions of all endogenous variables of the PVAR model in the face of shocks, it is found that the impact of human development on sustainable development in G-7 countries is higher than other explanatory variables.

For G-7 countries, where economic complexity is higher than in other countries, it can be said that sustainable development can be accelerated by improving economic complexity, renewable energy resources, R&D investments and social dimension. In order to achieve sustainable development, which is an indicator of the relationship between economic and environmental goals, it is important to how environmental quality can be improved. For sustainable development, increasing the Human Development Index and reducing the ecological footprint by meeting demands with green technologies can be set as targets. The impact of technology is significant in creating environmental awareness for environmental protection in developed countries. Countries should develop strategies that promote green energy technologies and renewable energy sources. In addition, technological innovations, especially patent applications and grants, should be encouraged, and R&D activities for a modern and green economy should be financially supported.

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CRediT authorship contribution statement

Daniel Balsalobre-Lorente: Supervision, Writing – review & editing. **Tugba Nur:** Data curation, Resources, Validation, Writing – review & editing. **Emre E. Topaloglu:** Data curation, Software, Formal analysis, Methodology, Writing – review & editing. **Ceren Evcimen:** Resources, Writing – review & editing.

Declaration of Competing Interest

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

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