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Examining the role of nuclear and renewable energy in reducing carbon footprint: Does the role of technological innovation really create some difference?



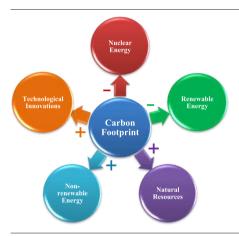
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HIGHLIGHTS

- Significant cross-sectional dependency exists within the data set.
- We applied novel panel data methods such as AMG, and CCEMG estimators.
- Nuclear and renewable energy significantly protect environmental quality.
- Technological innovations, natural resources and use of non-renewable energy degrade the environment.
- Bidirectional causality exists between technological innovations, renewable, and non-renewable energy with carbon footprint.

GRAPHICAL ABSTRACT



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ABSTRACT

The deployment of energy sources is considered the compassion of several United Nations Sustainable Development Goals (SDGs). Countries should keep balance with the three major proportions of the global energy trilemma: energy security, affordability, energy access, and ecological balance to construct a solid basis for competitiveness and prosperity. In this regard, this study examines the influence of nuclear energy, technological innovations, renewable energy, non-renewable energy, and natural resources on carbon footprint in the highest nuclear energy-producing countries from 1990 to 2019. To do this, we developed an inclusive and comprehensive empirical investigation and applied modern econometric approaches. Panel second-generation long-run cointegration advocates long-run associations among the series. The findings reveal that nuclear and renewable energy consumption extensively improve environmental excellence. Conversely, technological innovations and non-renewable energy significantly reduce environmental sustainability. Moreover, natural resources play an adverse role in long-run. The findings of the panel causality test discovered unidirectional causality is running from carbon footprint to nuclear energy. Additionally, bidirectional causality test discovered unidirectional causality innovations, renewables, non-renewables, and natural resources with carbon footprint. This recommends that these nations should integrate energy policy activities and develop energy strategy consistency by harmonizing the vital global nuclear energy aspects to assist a well-calibrated energy structure.

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1. Introduction

The environmental variation concern and its intimidation to creature health remain the major policy concerns and the central point for the universal agenda. For this purpose, the concept of sustainable development depends on the three crucial pillars as societal, economic, and sustainability of environmental quality, which have gained immense significance for humanity to be proficient in survival. The extreme weather events are responsible for the commotion of the ecosystem variations, water supply, infrastructure descent, disruption of food production, and higher morbidity and mortality rate (Usman et al., 2022a). While sustainable development has also been based on three pillars, the sustainable environment has developed into more important in this course due to instant environmental variations dispersion with stumpy ecological situations (Balsalobre-Lorente et al., 2021). Meanwhile, the ecological footprint especially carbon footprint is considered an important measure of sustainable development; a widespread indicator of environmental deficit specifically environmental sustainability (Usman and Makhdum, 2021). Nevertheless, the literature has explored the ecological footprint as a measure of environmental damage from mixed angles. It enforced scholars to inspect the ecological dynamics due to economic, geographical, human, and social activities.

Nuclear energy being a less polluted technology makes sure an unspoiled environment, thus improving human wellbeing. Nuclear energy is providing and evolving more efficiency and flexibility. It offers access to cheap, steadfast, trustworthy, and carbon-neutral power for developed as well as developing countries. Over the previous 50 years, nuclear energy evaded carbon emissions by 60 gigatons (IEA, 2019). This type of energy does not emit much pollution while in commission and has extremely little pollution during its operational existence conveying a huge volume of energy (IAEA, 2018). Nuclear power plants are cost-effective and supply secure energy support and supply economic stability and being protected from climate change makes the country climate-resilient. The power plants have elevated preliminary capital costs whereas their operating costs are decreased. Consequently, nuclear energy prices have remained steady and predictable for decades as variations in nuclear power are less apparent because of the nuclear plant's cost structure. However, the electricity production from nuclear power plants raised from 2563 to 2657 tetra watt hours (TWh) from 2018 to 2019 (WNP, 2020). Nuclear energy has also the ability to reinstate non-renewable energy in a reliable, safe, protected, and sustainable economic way; as a result, the nuclear energy role will be leading in the energy transition (Menyah and Wolde-Rufael, 2010; Knapp and Pevec, 2018).

The nuclear energy payback resulted in enlarged significance in investigating the impact of nuclear energy consumption on the environment. After the Paris Agreement (PA) declaration, nuclear energy utilization has achieved substantial concentration. In this pursuit, several researchers and scientists (Lee et al., 2017; Ozturk, 2017) recommended that the deployment of nuclear energy sources has the ability to determine the problems of energy security and ecological deprivation, on the other side, nuclear power units entail substantial infrastructural development (Mahmood et al., 2020) and elevated capital expenses which are insufficient in emerging economies (Goldenberg, 2009). Although the direct pollution from nuclear energy units is unimportant, nevertheless, the small infrastructure footprints amenities are better than their reimbursement for environmental quality. Nuclear power is also a facade with many confronts such as radioactive waste, radiation disclosure, the off-site impact of nuclear catastrophes (IAEA, 2018), and explosions (Budnitz, 2016). In addition, it is observed that the foreign dependency and consumption of conventional energy do have not much ability to reduce environmental pollution through the deployment of nuclear energy resources (Gralla et al., 2017). Fig. 1 shows the graphical appearance of top nuclear energyproducing (Gigawatt) countries.

The influences of technological innovations on the development of the association between environmental damages and economic growth have been elucidated by the endogenous growth theory, which believes that production procedures are enhanced by escalating the substitute of emitting/

dirty resources capacity with other resources that are further emissionfree and eco-friendly (Fernandez et al., 2018). Such functions are based on inhabitants' steadfastness to the atmosphere, which could spend more assets and their resources for defense as their real income enhances. If environmental pollution reduces as real economic growth increases, technological innovations will play a significant role and the reason for the decrease in pollution level would be the "induced innovation" in the wisdom of Hicks. One more difficulty that happens in this scenario from the perspective of ecological strategy is whether a total patent application can be taken as a determinant of eco-friendly economic development. Recently, the wide-ranging agreements reached about the change in technological development being the corridor to attaining sustainable economic and environmental expansion has caused immense attention to improvement/innovations and its encouragement, linking most economic mediators. In this circumstance, the problem to inquire is what are the influences of technological improvement in diminishing environmental pollution? There were several scholars that accomplished in the energy sector, both at worldwide, national, and sectoral levels. According to (Usman and Hammar, 2021), technological innovations are the chief driver of economic growth but their final influence on the environment is still unclear. On one side, a higher economic activity level would direct to elevated energy utilization levels and, perhaps, environmental pollution. On another side, an innovative progression has the ability to consume fewer energy resources and consequently protect environmental quality. The question would be to distinguish the absolute mesh upshot. Above and beyond, all these procedures occur in every single sector, not only in the power sector, as energy deceit in every one of them.

The call for energy has been offered from diverse sources to date. Conventional energy sources, for instance, natural gas, oil, and coal are the major non-renewables shaped millions of times (Usman et al., 2022a). Nevertheless, non-renewables have been swiftly exhausted consequently to the escalating economic expansions, and world population, and are expected to come to an end in the vicinity of the future. Besides, non-renewable causes considerable damage to the atmosphere, making it predictable to come back to cleaner energy sources (Usman et al., 2022b). Renewable and alternative energy sources like solar energy, geothermal energy, biomass energy, hydropower, and wind energy (Baloch et al., 2019) are considered the most important energy resource that has the ability to be utilized without making any transformation as they arrive from the environment (Huang et al., 2022). Even though the non-renewable energy resources are limited, and the steps can be taken about non-renewable resources are also restricted, cleaner energy resources can be efficiently used since they are both hypothetically unconstrained and susceptible to the atmosphere. Moreover, renewable and alternative energy utilization is considered one of the supreme sources for dealing with energy enhancement concerns. High renewable energy growth is attained in the course of augmented solar and wind energy competitiveness (BP, 2018). The cleaner and alternative energy sector prolongs to be one of the main energetic, quickly transforming, and changing sectors of the worldwide country. The technological expansions, the turndown in expenses, and the massive influence of novel financing organizations have made the segment the pouring strength of economic development all over the world. Especially, there is a worldwide agreement on how to contract with the climate variation intimidation throughout the deployment of renewable energy modern equipment worldwide.

Alongside this backdrop, this study contributes to the current literature in the following manners. Many researchers have scrutinized the relationship between technological innovations, energy utilization, and environmental degradation using diverse approaches, modeling methods, and results/outcomes. Nevertheless, none of them have inspected the associations between nuclear energy, technological innovations, renewable and non-renewable energy, natural resources, and carbon footprint, particularly for the top nuclear energy-producing countries. In the previous literature, investigating the technological advancement contribution to this association is overlooked. In view of the fact that technological development may fetch cleaner and alternative energy fabrication as atmospheric

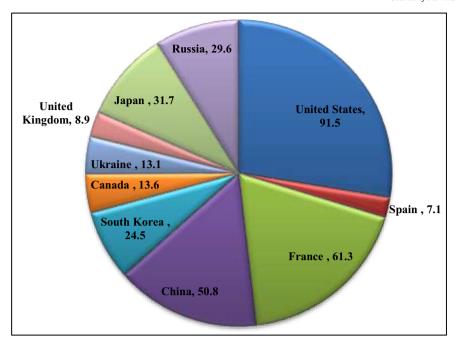


Fig. 1. Graphical appearance of top nuclear energy (gigawatt) producing countries. Source: Global Data (2021).

contamination risk is condensed, the technological development parameter is worthy of to be evaluating in nuclear energy utilization-carbon footprint nexus. Moreover, by selecting the top nuclear energy-producing economies for the empirical investigation, it will be more reasonable and rational to investigate the dynamic association between the selected series as these nations are the highly developed ones that have a high investment in nuclear energy projects, the highest economic growth, and the elevated amount of research and development (R&D) expenses on technological development. Therefore, this study's focus is to fulfill this literature gap by answering the subsequent questions: What is superior between renewable and nuclear energy for reducing carbon footprint in top nuclear energyproducing countries? The association between nuclear power and renewable energy in diminishing carbon footprint is substitutional or complementary? In order to respond to these questions, various estimation approaches are applied with the aim of discovering the long-run and causal relationships. In addition, in view of the cross-sectional dependence (CSD) that may prevail across countries, the evaluation approaches applied in the present research takes the CSD issue into the description, which has the ability to offer a more robust and reliable investigation of the relationship between the carbon footprint, nuclear energy, technological innovations, renewable and non-renewable energy, and natural resources. Moreover, the estimated empirical findings will assist development practitioners, environmentalists, and energy experts in redesigning and executing practical implications that are emission-free/eco-friendly and can make sure a sustainable environment protects the environment in the long-run. Furthermore, the present research will be useful for governments, economies, and central authorities, prioritizing investment in nuclear energy sector.

The remaining sections of the research are set as follows. Section 2 reviews the previous literature on nuclear energy, technological innovations, renewable and nonrenewable energy, natural resources, and carbon footprint. Section 3 analyzes the data sources, model specification, and methodological strategy. Section 4 confers empirical findings and their interpretations. Finally, the concluding annotations and policy suggestions are expressed in Section 5.

2. Literature review

The empirical nexus between nuclear energy, technological innovation, renewable energy, non-renewable energy, natural resources, and

environmental deficit has been documented in various existing studies. Nevertheless, the literature has been alienated into pairwise connected based on previous projected results among the variables that have been precise under the following parts.

2.1. The nuclear energy-environment nexus

In recent times, many studies have paid attention to how the deployment of nuclear energy influences atmospheric quality in diverse aspects. Along with this, several research articles have enclosed the link between nuclear energy utilization and environmental degradation (Baek, 2015; Ozturk, 2017; Saidi and Omri, 2020). On the other hand, due to the significance of uncontaminated energy, various research scholars have examined the coverage to which environmental degradation and economic growth level might be associated by enchanting nuclear energy into their description (Baek and Pride, 2014; Menyah and Wolde-Rufael, 2010). In excessive scenarios of clean and green energy, nuclear energy has more ability to play a vital role in the mitigation of environmental degradation as compared to other deployment of renewable energy sources (Saidi and Mbarek, 2016; Dong et al., 2018; Usman et al., 2022b). In contrast, Hassan et al. (2020) found an opposite link between nuclear energy and environmental deprivation in the context of the BRICS region. Moreover, Ozcan and Ulucak (2021) bridged the environmental Kuznets Curve (EKC) hypothesis with the IPAT hypothesis and observed that the utilization of nuclear energy is favorable for the mitigation of environmental pollution and climate change. Furthermore, Mahmood et al. (2020) linked the economic growth, nuclear energy, and carbon emissions in Pakistan over the span from 1973 to 2017. The ARDL findings summarize that nuclear energy has an adverse impact on carbon emissions. Moreover, causality analysis explored that bidirectional causality exists between carbon dioxide (CO2) emissions and nuclear energy. In very recent, Sadiq et al. (2022) explored the influence of nuclear energy, financial globalization, and external debt in protecting environmental quality and supporting human development concurrently in BRICS countries period from 1990 to 2019. The results reveal bidirectional causality between carbon emissions, human development, and nuclear energy. Moreover, the findings show that external debt diminishes human development, while nuclear energy and financial globalization add to increase the level of human development. Likewise, external debt and nuclear energy significantly protect the ecological eminence, but financial globalization boosts the pollution level in the region. Similarly, Khan et al. (2022) also studied the linear influence of nuclear and alternative energy in the 3 highest carbon emitter nations from 1981 to 2016 in the EKC framework. The results reveal that nuclear and renewable energy significantly protects the environment. However, income growth and general government final expenditure worsen the environmental quality. Moreover, this study found the evidence of EKC hypothesis in these countries. Baek, (2015) discovered the nexus between nuclear energy and the environment in the 12 highest nuclear energy-producing economies. The findings demonstrate that nuclear energy leads to overcoming environmental pollution in the region. However, this research found insufficient evidence of the EKC hypothesis in long run.

2.2. The technological innovations-environment nexus

It is hard to disregard how technology and science have malformed individual's economic and financial verdicts. Nevertheless, this revolution has also increased distresses connected to ecological sustainability in the worldwide regions with widespread technological innovations penetration. In this regard, one part of the existing literature has scrutinized the dynamic association between technological innovation and ecological excellence by applying the time-series, cross-sectional, and panel data. For example, Zhang and Liu (2015) examined the linkage between technological innovations and environmental pollution by applying a Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model over the period from 2000 to 2010 by utilizing regional data for China. The dynamic results of the panel approach reveal that technological innovations have facilitated a decrease in pollution levels in China. On the other hand, an inverted U-shaped association between technological innovation and ecological contamination has been explored by Anon et al. (2017). This research applied the data from underdeveloped and developed nations to test the asymmetric link between technological innovations and environmental pollution. Considering technological development as the threshold variable, Zhao et al. (2021) scrutinized the association between the capital allocation efficiency of new energy vehicle enterprises and CO2 emissions. The findings reveal that there is a double threshold effect between vehicle CO2 emissions and capital allocation efficiency. Further, when R&D investment, and personnel input intensity or patent number ratio to R&D personnel is near the ground level, the development of capital allocation competence will considerably augment vehicle CO2 emissions. Finally, technological modernization has a positive accumulation effect. Moreover, Sohag et al. (2015) demonstrate that technological improvement diminishes the deployment of energy use, which, sequentially, overcomes the pressure on the environment in Malaysia. Furthermore, Abid (2016) inspects the indicator influencing environmental pollution by applying panel data for 25 SSA nations from 1996 to 2010. His results verify the significance of the control indicators in diminishing ecological deprivation. In contrast, Usman and Hammar (2021) discovered a positive link between technological innovations and ecological footprint in the APEC region. This depicts that the existing technology in this region is not cleaner. However, Bai et al. (2018) applied a stochastic frontier method to compute the determinant of atmospheric quality in 39 different industrial sectors of china from 2005 to 2011. Their outcomes show that the integration of elevated technology in the manufacturing procedure is an aspect of ecological development. For a similar state, Zhang et al. (2016) relate a Malmquist approach to examine the outcome of technological modernism on carbon emissions in 38 industrial segments of the Chinese economy. This research observed that technological advancement increases environmental performance. Xiang et al. (2017) also utilized the interprovincial longitudinal data from 1998 to 2014 to establish that the association between modernism capability and natural atmosphere is influenced by threshold indicators for example industrial structure and economic level, and found the nonlinear association between them. He et al. (2021) investigated the mechanism and influence from the market perspective of renewable energy-based technological development on the total factor carbon recital index based on the data from 25 China's provinces over the period

from 2002 to 2015. The empirical evidence shows that renewable energybased technological innovation improves the total factor carbon recital index, and this effect has a significant single threshold influence in terms of market potential and segmentation. Furthermore, it is observed that there is an inverted "U-shaped" link exists between the total factor carbon recital index and market segmentation. Following the 4th industrial revolution within the EKC framework, Bilgili et al. (2021) observed the disaggregated energy R&D effect on CO₂ emissions in 13 high-income economies spanning from 2003 to 2018. The results explored that energy efficiency R&D expenses are more useful in reducing ${\rm CO}_2$ emissions as compared to renewable energy R&D and fossil fuels. Furthermore, this study verifies the EKC hypothesis. By applying the two-regime threshold autoregressive method, Kassouri et al. (2022) empirically analyzed the convergence of the energy technology research, demonstration, and development budgets from 1985 to 2017 across OECD economies. The findings explore that only a few developed nations (e.g., Japan, Canada, and the U.S.) pursue an asymmetric procedure and demonstrate partial convergence in the budgets of energy technology research, demonstration, and development with Japan as a transition economy. Fascinatingly, the outcomes also offer obvious support for the worldwide energy technology research, demonstration, and development budgets convergence formerly accounting for two regimes mutually.

2.3. The renewable and non-renewable energy consumption-environment nexus

Several empirical research articles in the existing literature have observed that deployment of non-renewable energy reduces ecological performance, while, renewable energy use protects the environmental condition. This prospect is endorsed by many empirical researchers, for instance, Usman and Makhdum (2021) for the BRICS-T countries, Usman et al. (2022b) for Pakistan, and Balsalobre-Lorente et al. (2021) for the PIIGS countries. In addition, Belaïd and Youssef (2017) presented a confirmation that cleaner energy sources are helpful for the atmosphere; while fossil fuel-based energy sources have an adverse blow on the environment in the case of Algeria. Using the vector error correction model (VECM), Bekhet and Othman (2018), suggested that alternative and renewable energy significantly offer a good solution to overcome the pollution level in the case of Malaysia over the span from 1971 to 2015. In South Africa, Sarkodie and Adams (2018) also verified that alternative energy sources significantly lower environmental deprivation; in contrast, non-renewable (fossil fuel) energy utilization boosts contamination levels. Moreover, Pao and Tsai (2011) investigate the long-run relationship as well as causal interaction between economic growth, renewable energy utilization, and CO2 emissions in the case of Brazil during the period from 1980 to 2007. Using Grey prediction and vector error correction model (VECM) causality approaches, this study affirms that a strong bidirectional causality relationship exists between economic growth, energy utilization, and CO2 emissions.

Conversely, notwithstanding an immense majority that endorses the negative consequence of renewable and alternative energy sources on carbon emissions in the existing literature, a few studies offered incongruous results as compared to the above-mentioned studies. Such as, some authors investigate that non-renewable energy and renewable energy use significantly boost environmental pollution (Farhani and Shahbaz, 2014; Bulut, 2017; Bölük and Mert, 2014). Besides, Al-Mulali et al. (2015) originated an insignificant association between environmental pollution and renewable energy. Besides, chasing a different perception that an augmentation in real economic development and carbon emissions can influence the extra investment in the consumption of renewable energy resources, Lu (2017) established the constructive influence of environmental pollution on renewable and alternative energy use for a panel of 24 Asian countries, while found insignificant and adverse relation with carbon emissions for some countries that depict renewable and cleaner energy sources reduces/boosts as environmental degradation boots/reduce in the associated economies.

2.4. The natural resources rent-environment nexus

The exploit, and then the superfluous exploitation, deployment, and depletion of natural resources, emissions, and global warming construct an extensive field of investigation in the existing literature relating to the environment and economic development. Consequently, in the current decade, natural resources and environmental degradation have attained more concentration from scholars, policymakers, and environmentalists. Particularly, Usman et al. (2022a) analyzed the link between natural resources, financial development, globalization, renewable, and non-renewable energy on income growth and the environment for 8 Arctic economies from 1990 to 2017. The results showed that renewable energy and a strong financial system considerably reduce emission levels, whereas globalization, non-renewables, and economic growth add to boost pollution levels. Furthermore, all study variables enhance economic growth. Similarly, Khan et al. (2020) observed the negative effect of natural resource utilization on carbon emissions for the BRICS region by taking into account the function of technological improvement. In the case of China, Ahmed et al. (2020) scrutinized the role of natural resources in ecological footprint and found that an enhancement in natural resources consumption escorts to growing pollution levels in the long run. In addition, Dong et al. (2017) examine the nexus between carbon emissions, natural gas, GDP growth, and renewable energy use within the EKC framework in a group of BRICS economies from 1985 to 2016. The results show that renewable energy and natural gas combustion diminishes pollution levels, which designates that, a 1 % enhancement in renewable energy and natural gas will reduce carbon emissions by 0.2601 %, and 0.1641 %, respectively. In addition, Jahanger et al. (2022) inspected the association between technological innovations, economic growth, globalization, natural resource, financial development, human capital, and ecological footprint in 73 emerging countries from 1990 to 2016. Their findings reveal that natural resource increases pollution level whereas; technological modernisms assist to slow down them. Ulucak et al. (2020) showed the disaggregated energy and natural resource impact on ecological performance in the OECD region from 1980 to 2016. This study's result specifies that renewable energy use help to reduce emission level, while non-renewable energy increases the atmosphere in terms of ecological, and carbon footprint. Furthermore, the extraction of natural resource rents donates to boost carbon emissions in the long run.

All the same, to the best of the author's information, none of the single empirical work has investigated to examine the long-run and causal association between carbon footprint, technological innovations, nuclear energy, renewable and non-renewable energy, and natural resources employing the modern and robust econometric approaches for the case of top nuclear energy-producing countries. Furthermore, the significance of nuclear energy consumption as a potential resource of carbon footprint alleviation requires more research that inspects the long-run and causal relationship among carbon footprint, nuclear energy consumption, technological innovations, renewable and non-renewable energy, and natural resources in top renewable energy-producing countries. Moreover, it is imperative to note that a renewable energy elucidation that can fetch a sustainable environment by diminishing the intensity of CO₂ emissions in the environment. The present study advocated for the consumption of nuclear and alternative energy in the decarbonization agenda, in conjunction with technological developments and natural resources, which would have constructive ecological effects and would be advantageous for a long-term sustainable environment. For this reason, there is a dire requirement for further empirical investigation exploring a valuable role for the atmosphere by employing the deployment of nuclear energy sources in social, economic, and other sectors of the economy.

3. Data, model development and methodological framework

3.1. Data and descriptive statistics

The current research aims to scrutinize the association between nuclear energy, technological innovations, and carbon footprint, taking renewable

energy, non-renewable energy, and natural resources as additional carbon footprint determinants. The list of top nuclear energy-producing countries includes Canada, China, France, Japan, South Korea, Russian Federation, Spain, the United Kingdom, and the United States (the US). Because of missing data for Ukraine, we eliminate this country from the panel. The assortment of time span varies over the spanning from 1990 to 2019 for each country based on the availability of data. The carbon footprint (CFP) is measured in global hectares per person, and nuclear energy consumption (NUCE) is presented in terms of Terawatt hours (TWh). Technological innovations (TECH) are applied as a measure of the number of total patent applications. Patent applications are global applications mediated and filed by the Patent Cooperation Treaty (PCT) process or a national patent office. Renewable energy use (RE) is collected in % of total final energy consumption, non-renewable energy use is in term of the kilogram in oil equivalent per capita, and natural resources rents (NR) is measured as the percentage GDP. The data on CFP is gathered from the global footprint network (GFPN, 2020), and data on NUCE is obtained from the World Energy British Petroleum Statistical Review (BP, 2020). All remaining series (TECH, RE, NRE, and NR) data are obtained from the World Development Indicators (WDI, 2020) developed by the World Bank. This data set encloses the balanced panel with $N^*T = 270$ observations (N = 9 and T = 30). The variables description, measurement unit, and data sources of this study are reported in Table 1.

Table 2 illustrates the descriptive statistics of the analyzed variables. The findings explore that the nominal highest mean value is 112,581.5 for technological innovations, which falls between 1288 and 1,393,815, followed by carbon footprint with the minimum (0.050393) and maximum (7.674969), nuclear energy consumption with the minimum (0.010152) and maximum, then renewable energy consumption minimum (0.441574) and maximum (34.08361), non-renewable energy consumption with minimum (43.49082) and maximum (97.07511), and natural resources with minimum (0.010885) and maximum (22.01136). Furthermore, the findings of standard deviation explored that carbon footprint is more reliable and consistent, followed by nuclear energy, technological innovations, renewable energy, non-renewable energy, and natural resources. Fig. 2 shows the trend analysis of analyzed variables for top nuclear energy-producing countries.

The bivariate correlations between the study interest variables, namely, nuclear energy, technological innovations, renewable and non-renewable energy, natural resources, and carbon footprint are listed in Table 3. The first inspection is the positive bivariate correlation between all study variables (NUCE, TECH, RE, NRE, and NR), and carbon footprint. Moreover, nuclear energy is positively correlated with technological innovations (0.230477) and adversely correlated with renewable energy (0.211027), non-renewable energy (0.204963), and natural resources (0.197354). Furthermore, it is observed that technological innovations are adversely correlated with renewable energy (0.121880), natural resources (0.128907), and are also positively correlated with non-renewable energy use (0.265076). Moreover, renewable energy is adversely correlated with non-renewable energy (0.391666) and natural resources (0.433192). Finally, there is a positive correlation between non-renewable energy and natural resources (0.340882) in these countries.

3.2. Econometric specification

According to the earlier study by Saidi and Omri (2020) and Usman and Balsalobre-Lorente (2022), the econometric specification of this study is expressed in Eq. (1) as follows:

$$CFP_{it} = f(NUCE_{it}, TECH_{it}, RE_{it}, NRE_{it}, NR_{it})$$
(1)

All these selected variables are transformed into the form of their natural logarithmic in order to generate immobility in the variance-covariance matrix and reduce the chances of data sharpness and heteroscedasticity

Table 1 Variables description, measurement unit and data sources.

Variables	Acronym	Measurement unit	Sources
Carbon footprint	CFP	Global hectares per person	(GFPN, 2020)
Nuclear energy consumption	NUCE	Terawatt hours (TWh)	(BP, 2020)
Technological innovations	TECH	The number of total patent applications	(WDI, 2020)
Renewable energy consumption	RE	% of total final energy use	(WDI, 2020)
Non-renewable energy consumption	NRE	Kilogram in oil equivalent per capita	(WDI, 2020)
Natural resources rents	NR	% of GDP	(WDI, 2020)

Note: GFPN stands for Global Footprint Network, BP stands for World Energy British Petroleum Statistical Review, and WDI stands for World Development Indicators.

Table 2Descriptive statistics.

Variable		Mean	Std. dev.	Minimum	Maximum	Observations
CPF	Overall	3.381632	1.896761	0.050393	7.674969	N = 270
	Between		1.946651	0.057427	6.835013	n = 9
	Within		0.465601	2.148684	4.715762	T = 30
NUCE	Overall	2.095532	2.215513	0.010152	8.117302	N = 270
	Between		2.274309	0.559109	7.487206	n = 9
	Within		0.541891	0.087204	4.486133	T = 30
TECH	Overall	112,581.5	199,574.9	1288	1,393,815	N = 270
	Between		136,123.2	2637.167	330,902.5	n = 9
	Within		152,637.6	-2,124,891	1,175,494	T = 30
RE	Overall	9.487377	8.056908	0.441574	34.08361	N = 270
	Between		7.693903	1.341083	21.93883	n = 9
	Within		3.478413	-0.56705	22.17836	T = 30
NRE	Overall	79.87101	11.71207	43.49082	97.07511	N = 270
	Between		11.80261	51.25483	91.47626	n = 9
	Within		3.590065	69.49492	91.16044	T = 30
NR	Overall	2.362669	4.404875	0.010885	22.01136	N = 270
	Between		4.269908	0.022744	13.19674	n = 9
	Within		1.770976	-6.424251	11.17723	T = 30

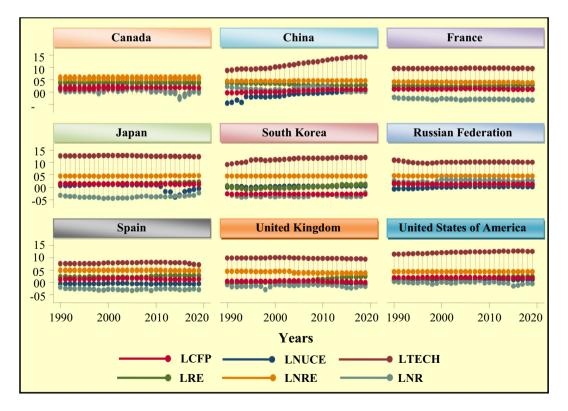


Fig. 2. Trend analysis of analyzed variables for top nuclear energy producing countries.

Table 3
Correlation matrix.

	CFP	NUCE	TECH	RE	NRE	NR
CFP	1.000000					
	0.559081	1.000000				
NUCE	[11.0389]	_				
	(0.0000)	_				
	0.529058	0.230477	1.000000			
TECH	[9.47597]	[3.87745]	-			
	(0.0000)	(0.0001)	-			
	0.530653	-0.211027	-0.121880	1.000000		
RE	[10.5025]	[-3.53425]	[-2.01024]	_		
	(0.0000)	(0.0005)	(0.0454)	_		
	0.696151	-0.204963	0.265076	-0.391666	1.000000	
NRE	[12.1347]	[-3.42817]	[4.50047]	[-6.96858]	_	
	(0.0000)	(0.0007)	(0.0000)	(0.0000)	_	
	0.651548	-0.197354	-0.128907	-0.433192	0.340882	1.000000
NR	[11.0095]	[-3.29563]	[-2.12805]	[-6.54367]	[5.93607]	-
	(0.0000)	(0.0011)	(0.0342)	(0.0000)	(0.0000)	-

Note: the *t*-statistics are in [], and probability values are in parentheses ().

(Huang et al., 2022). To do this, Eq. (1) can be articulated in Eq. (2) as follows:

$$\begin{array}{l} ln\;(CFP_{it}) = \beta_0 + \beta_1\;ln\;(NUCE_{it}) + \beta_2\;ln\;(TECH_{it}) + \beta_3\;ln\;(RE_{it}) \\ + \beta_4\;ln\;(NRE_{it}) + \beta_5\;ln\;(NR_{it}) + \mu_{it} \end{array} \tag{2} \label{eq:2}$$

where *i* depicts the cross-section (top nuclear energy-producing countries), t specifies the selected time span (1990–2019) for this study; β_0 denotes the constant term of the selected model; $\beta_1 - \beta_5$ depict the coefficient parameters of the selected series; the random error term is signified as μ_{it} . The authors suppose that an adverse association will prevail between NUCE and CFP such as $\left(\beta_1 = \frac{d(\textit{CFP})}{d(\textit{NUCE})} < 0\right)$. It has been also explored in the earlier studies that technological improvement and renewable energy release some stress on the atmosphere. In other words, the influence of technological development and renewable energy on carbon footprint is negative. In this sense, the coefficient sign are expected to be negative like $\left(\beta_2 = \frac{d(\mathit{CFP})}{d(\mathit{TECH})} < 0\right)$, and $\left(\beta_3 = \frac{d(\mathit{CFP})}{d(\mathit{RE})} < 0\right)$. In contrast, it is evident that non-renewable energy puts forth huge pressure on the environment. This depicts that a significant positive correlation exists between nonrenewable energy and carbon footprint such as $\left(\beta_4 = \frac{d(CFP)}{d(NRE)} > 0\right)$. Finally, for the relationship between natural resources and carbon footprint, we expect a positive association based on the ground reality. This suggests that the coefficient sign is positive like $\left(\beta_5 = \frac{d(CFP)}{d(NR)} > 0\right)$.

3.3. Estimation strategy

3.3.1. Cross-sectional dependence tests

The implication of the cross-sectional dependence (CSD) test is very crucial for capturing the interdependency among cross-sections in the longitudinal data. Owing to the rising tendency in economic, social, and financial cointegration, and globalization process, among cross-sections, there may a more chances of CSD. For that reason, examination of the CSD tests is very important before moving further to stationarity, long-run cointegration, and long-run estimation of parameters for selected variables. However, ignoring the problem of CSD in the process of longitudinal data estimation will lead to biased, inconsistent, and misleading outcomes (Huang et al., 2022). Therefore, in order to check the occurrence of possible CSD among selected series, the current research applied three different CSD tests proposed by Friedman (1937) (Eq. (3)), Frees (1995) (Eq. (4)), and Pesaran (2004) (Eq. (5)).

Friedman =
$$(j-1)$$
 $\left[\frac{2}{n} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \pi_{ij} \right] \chi^2(j-1)$ (3)

Frees =
$$\frac{(j-1)\left[\frac{2}{n}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\pi_{ij} + \frac{1}{j}\right]}{SE(O)} N(0,1)i,j$$
 (4)

$$Pesaran = \sqrt{\frac{2T}{N(N-1)}} \binom{N-1}{\sum\limits_{i=1}^{N}\sum\limits_{j=i+1}^{N}\widehat{\rho}_{ij}} \sim N(0,1)$$
 (5)

3.3.2. Panel unit root tests

After testing the possible CSD, the very next step of econometric analysis is to test the unit root property of the selected series. In this pursuit, this investigation provides second-generation panel unit root tests (Cross-section Im, Pesaran and Shin (CIPS), and Cross-section Augmented Dickey-Fuller (CADF)) developed by Pesaran (2007) which have the ability to tackle the CSD issue in a specific dataset. The functional presentation of the CADF unit root test is articulated in Eq. (6) as follows:

$$\Delta Z_{it} = \xi_i + \eta_i z_{i,t-1} + \Psi_i \overline{z}_{t-1} + \gamma_i \Delta \overline{z}_t + \varepsilon_{it}$$
(6)

Incorporating a single lag value (t-1) in the finding of Eq. (6), the following Eq. (7) is presented as follows:

$$\Delta Z_{it} = \xi_i + \eta_i z_{i,t-1} + \Psi_i \overline{z}_{t-1} + \sum_{j=0}^p \gamma_{ij} \Delta \overline{z}_{t-j} + \sum_{j=1}^p \pi_{ij} \Delta z_{i,t-j} + \varepsilon_{it}$$
 (7)

where \overline{z}_{t-j} and $\Delta z_{i,\ t-j}$ show the mean value of the lag level for each nuclear energy-producing nation and the operator of the first difference I(1). Moreover, the CIPS unit root test is also presented in Eq. (8) as follows:

$$CIPS = N^{-1} \sum_{i=1}^{N} \eta_i(N, T)$$
(8)

where, the coefficient $\eta_i(N, T)$ denotes the CADF stationary test statistics that can reinstate by the term shown in Eq. (9) as follows:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_i$$
 (9)

3.3.3. Panel cointegration test

After discovering the CSD, and unit root of the selected series, the next footstep is to examine the detection of long-run association by using the panel long-run cointegration approaches. In this regard, we applied three different cointegration tests for instance Pedroni, Kao, and Westerlund. Pedroni and Kao's cointegration tests ignore the problem of CSD, while the Westerlund test addresses this issue. Subsequent to the validation of CSD linking the selected variables; the current research applies a consistent and robust cointegration method developed by Westerlund (2007). This

method assists in approximating the statistical values that establish the long-run cointegrated association of the data. Eq. (10) is applied for this reason as follows:

$$\Delta Z_{i,t} = \alpha_i' \Psi_t + \gamma_i (Z_{i,t-1} - \eta_i' X_{i,t-1}) + \sum_{i=1}^q \gamma_{i,j} \Delta Z_{i,t-j} + \sum_{i=0}^q \eta_{i,j} \Delta X_{i,t-j} + \varepsilon_{i,t}$$
 (10)

The empirical findings will be a stable and constant trend if $\Psi_t=1$, and in a condition where there is no constant trend, that case, it will be $\Psi_t=0$. On the other hand, if this is equivalent to (1,t), afterward it can be constant and trend.

$$\mu_{i,t} = \gamma_i \Psi_t + \varepsilon_{i,t} \tag{11}$$

In addition, in order to approximate of mean, CSD offers the substitutes for (Ft) which is the factor metric in Eq. (11). These substitutes are predictable to be consistent and efficient for the well-organized executive of the CSD findings. The null hypothesis of the Westerlund test shows the absence of the long-run relationship between variables, and the alternative is vice versa.

3.3.4. Panel long-run estimation tests

After testing the long-run relationship between selected variables, the next econometric analysis step is to approximate the long-run elasticity of the series. In this regard, the current research employed an unbiased, consistent, robust, and reliable estimation method that can solve the issue of CSD. To do this, Eberhardt and Bond (2009) developed a second-generation panel estimation method named the augmented mean group (AMG) estimator that relied on different two-stages of estimation. The first empirical stage of the AMG estimator is measured to comprise the time spanning with latent common dynamics as presented in the OLS at the first difference (Δ) equation while this approach (first-stage) can be functionally presented in Eq. (12) as follows:

First stage of AMG:

$$\Delta X_{it} = \xi_i + \Psi_i \Delta Z_{it} + \phi_i f_t + \sum_{k=2}^{T} \beta_i \Delta D_t + \mu_{it} \tag{12} \label{eq:deltaXit}$$

where Δ denotes the first difference I(1) operator; the time dimension coefficient is linked to β_i . The second AMG of method incorporates the estimator of all parameters and after doing so, it unites all coefficients. The second stage can be listed in Eq. (13) as follows:

Second stage of AMG:

$$\widehat{\beta}_{AMG} = N^{-1} \sum_{i=1}^{N} \widehat{\beta}_{i}$$
 (13)

However, for robustness checks, this study also employs one more second-generation cointegration test that has the ability to address the dilemma of CSD. This test is named the common correlated effect mean group (CCEMG) estimator proposed by Pesaran (2006). This method combines the latent common factors in the company of the cross-sectional mean value of regressors and dependent series that provide detail to confirm the consistency in the CSD presence. The mathematical expression of the CCEMG test can be listed in Eq. (14) as follows:

$$A_{it} = \theta_{1i} + \Psi_i B_{it} + \Phi_i \overline{b}_{it} + \delta_i \overline{c}_{it} + \eta_i \delta_{it} + \epsilon_{it}$$
 (14)

where, the term Ψ_i shows the slope parameter of each cross-section. Despite the fact that the term, δ_i shows the latent common constant value including θ_{1i} heterogeneously and μ_{it} shows the stochastic error term. This mathematical form of CCEMG estimator is also represented in Eq. (15) as follows:

$$CCEMG = N^{-1} \sum_{i=1}^{N} \widehat{\beta}_i$$
 (15)

3.3.5. Panel Dumitrescu and Hurlin causality test

To discover the causal link among selected series, the present study employs the panel heterogeneous causality tests as developed by Dumitrescu and Hurlin (2012). This method is a customized adaptation of Granger causality and modified to a mixed longitudinal data-set. Furthermore, the performance of Monte Carlo simulations denotes that Dumitrescu and Hurlin's method provides unbiased, consistent, and efficient findings under the umbrella of possible CSD. This method can be presented in Eq. (16) as follows:

$$Z_{it} = \xi_i + \sum_{\kappa=1}^{K} \Psi_i^{\kappa} Z_{i(t-k)} + \sum_{\kappa=1}^{K} \eta_i^{\kappa} Y_{i(t-\kappa)} + \varepsilon_{it}$$
 (16)

In addition, Dumitrescu and Hurlin, (2012) test describes the mean statistic $W_{N,T}^{HINC}$ linked with the null hypothesis of homogeneous non-causality (HNC) can be explored in Eq. (17) as follows:

$$W_{N,T}^{HNC} = N^{-1} \sum_{i=1}^{N} W_{i,T}$$
 (17)

wherever $W_{N,T}^{HNC}$ test statistic is acquired with a mean value of each Wald test statistics for all cross-sections i and $W_{i,T}$ illustrates the single Wald test statistics for each country i_{th} subsequent to the individual test statistics H_0 : $\Psi_i = 0$. At this time, the average value of $W_{N,T}^{HNC}$ test statistics successively congregates in allocation presented in Eq. (18) as follows:

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2R}} \Big(W_{N,T}^{HNC} - R \Big)$$
 (18)

Fig. 3 presents the econometric modeling strategy applied in this study.

4. Results and discussion

4.1. Cross-sectional dependency findings

This study tests the CSD for the analyzed model by using the Friedman, Frees, Pesaran, and Breusch & Pagan CSD tests. The empirical outcomes of the CSD tests are illustrated in Table 4. This study's results explore that all the variables have the significant CSD issue in the series. The implication of this possible CSD issue stalks from the fact that nuclear energy-producing countries are interconnected in the globally interrelated atmosphere. This depicts that any distraction in one nation's primary variables may increase in other countries. The series is cross-sectionally dependent as a result of the spillover effects.

4.2. Unit root findings

The next step further reports the findings of panel unit root tests. To do this, we applied two different panel unit root tests to check the integration order of the series before estimation of cointegration association and panel long-run elasticity estimates to identify whether these analyzed variables are following the stationary property or not. For this reason, this study applied CADF and CIPS tests of panel stationery for both at levels I(0) and at the first difference I(1) for the analyzed variables. The findings of CADF and CIPS unit root tests are provided in Table 5. All the panel unit root tests reject the null (H_0) hypothesis of the presence of unit root which decrees that all the variables have no unit root at first difference. The findings of these two-panel stationary tests confirm that the unit root cannot be rejected at level except for technological innovation in the CADF unit root test but the null hypothesis can be rejected at the first differences for all series. This validates that we can further precede our analysis of long-run cointegration and elasticity estimation.

4.3. Long run cointegration findings

The findings of unit root tests make it possible to establish the long-run association between the study variables. For this, the authors employ three cointegration tests, (e.g., Pedroni, Kao, and Westerlund). The first two are

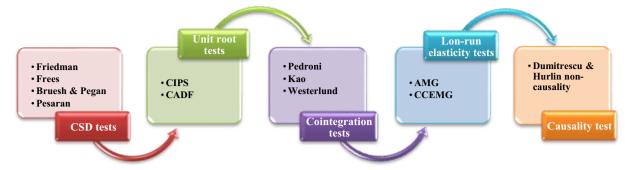


Fig. 3. Econometric modeling strategy.

Table 4Cross-sectional dependence results.

Tests	Freidman	Frees	Pesaran	Breusch & Pagan LM
	CSD	CSD (Q)	CSD	Chi ²
FE model	31.856*	2.784*	2.921*	213.296*
<i>p</i> -Value	0.0000	0.0000	0.0000	0.0000
RE model	39.667*	2.961*	-3.236*	273.779*
<i>p</i> -Value	0.0000	0.0000	0.0000	0.0000

^{*} p < 0.01.

residual-based Pedroni and Kao test that confirms the presence of a longrun correlation between study variables. First-strand (A) of Table 6 exhibits that all six test statistics of the Pedroni cointegration test recommend rejecting the null hypothesis of no long-run cointegration among variables at a 1 % significance level. Similarly, the second strand (B) also confirms the cointegration among variables at a 1 % significance level. Moreover, The third strand (C) of Table 6 shows the findings of the Westerlund cointegration test, among groups (Gt and Ga) test findings, reveal that there is a high significance (e.g., 1 % and 5 %) of cointegration, while between panels (Pt and Pa) test findings maintain that panel long-run cointegrated relationship exists at the 10 % significance level. For that reason, there is a group and panel indication of a long-run association among the series across 9 nuclear energy-producing countries. Since the panel long-run cointegrated test's findings advocate the existence of a long-run association among variables, we can carry on with the approximation of the long-run elasticity/coefficients using panel second-generation approaches.

4.4. Empirical results analysis and discussion

First strand (A) of Table 7 presents the empirical findings of long-run elasticity estimates. It seems that nuclear power consumption comes into view to have an adverse influence on carbon footprint, other things remaining the same; for instance, a 1 % increase in nuclear energy deployment will lessen the carbon footprint by 0.2628 % in the top nuclear energy-producing countries for the long-run. This result offers empirical facts of

Table 5Unit root evidence.

Series	CADF		CIPS		
	Level	First difference	Level	First difference	
LCFP	-1.662	-3.528*	-1.770	-4.936*	
LNUCE	-1.479	-3.530*	-1.765	-5.048*	
LTECH	-2.210***	-3.185*	-2.011	-4.162*	
LRE	-1.587	-3.851*	-1.977	-5.356*	
LNRE	-1.052	-3.622*	-1.004	-5.003*	
LNR	-1.446	-3.785*	-1.916	-5.099*	

Note: *p < 0.01, **p < 0.05 and ***p < 0.10. The critical values of CIPS test for 1 %, 5 %, and 10 % at level are -2.51, -2.25, -2.12, and for first difference are -2.44, -2.22, and -2.1 respectively.

conclusions and declarations from an extensive series of research that, in view of the fact that nuclear energy is approximately free of carbon emissions, reinstating traditional non-renewable energy-based power units with nuclear power units could assist diminish ecological humiliation to a large extent because of nuclear energy consumption activities (Nian et al., 2014); such as, carbon emissions generating from nuclear power units are expected to be two-degree orders lesser than those of non-renewable power plants. These results are in line with the conclusions of (Dong et al., 2018; Hassan et al., 2020; Saidi and Omri, 2020; Mahmood et al., 2020). The possible motive behind this negative relationship could be the negative externalities originating from the installed nuclear energy plants, nuclear plant capacity, and industrial effectiveness of using nuclear energy. However, It is imperative to observe that, while nuclear energy plays a significant role in plummeting carbon emissions, organizing nuclear power units constantly engages a few jeopardizes; these are largely reliant on broad cross-country differences in political, economical, and social factors (Baek, 2015; Sadiq et al., 2022). These hazards in consequence should be appraised and reduced when conferring the health and environmental influences of nuclear and other energy consumption and production systems (e.g., renewables, non-renewable energy sources). Nevertheless, it is obligatory to remember that nuclear power consumption/generation necessitates protection and managing costs in order to evade any disaster that could potentially spoil human beings and the environment. Consequently, when dealing with policy verdicts regarding nuclear power, an assessment ought to be accomplished carefully not only from its gain/advantage in the reduction of carbon footprint but also from several other characteristics, for instance, its latent risks. Moreover, the electricity production from nuclear sources significantly involves an immense concentration treaty regarding safety measures. The installation and management of radioactive waste in the nuclear power plants require to be cautiously treated to avoid undesired disasters with health and environmental impacts (Ozturk, 2017). Another advantage of nuclear energy is that it has an exceptional marketplace potential, and it is also lucrative (Usman et al., 2022b). The nuclear energy expansion makes sure to encourage economic growth and energy security. In this pursuit, the estimated evidence recommends that policy supporting the adoption and promotion of nuclear energy utilization together with the development of renewable energy deployment in the energy mix could help this region to accomplish the intended nationally determined contributions commitment by 2030 and realize the objectives of energy security of this region as a complement of sustainable development goals (SDG-7 and SDG-13) in company with offering a significant movement in the way of eliminating power poverty problems connected with this region.

An applicable finding of technological innovations is that a 1 % increase in technological innovations would cause to increase the carbon footprint by 0.1591 % in the long run. This outcome is aligned with Sinha et al. (2020) for Asia Pacific nations. In this research, the display of technological innovation is that calculates the digit/amount of patent applications in current US dollars which is more practical than arises in countries with superior capability for technological absorption and higher industrial capacity. This higher industrial capacity and the human capital accretion that engenders further technological innovations can be connected with the product

Table 6
Long-run cointegration results (Pedroni, Kao, and Westerlund).

A) Pedroni cointegration test							
Alternative hypothesis: common AR coefs. (within-dimension)							
	Statistic	Prob.	Statistic	Prob.			
Panel v-statistic	-1.203995	0.8857	-2.349627	0.9906			
Panel rho-statistic	1.080559	0.8601	1.273196	0.8985			
Panel PP-statistic	-2.496891*	0.0063	-2.087113**	0.0184			
Panel ADF-statistic	-2.655240*	0.0040	-2.212699**	0.0135			
Alternative hypothesis: individu	al AR coefs. (between-dimension)						
Group rho-statistic	2.273728	0.9885					
Group PP-statistic	-4.364630*	0.0000					
Group ADF-statistic	-2.425200*	0.0076					
B) Kao cointegration test							
ADF		-4.630157*		0.0000			
Residual variance		0.0001861					
HAC variance		0.02072					
C) Westerlund cointegration tes	t						
Statistic	Value	Z-value	<i>p</i> -Value	Robust p-Value			
Gt	-2.881*	-2.012	0.022	0.000			
Ga	-10.828**	0.350	0.637	0.010			
Pt	-6.433***	-0.645	0.260	0.090			
Pa	-9.487***	-0.772	0.232	0.070			

^{*} *p* < 0.01.

increment; as a result, the long-run association between carbon footprint and technological progress is positive. The top nuclear energy-producing countries have been occurrence very highly developed countries having high-income growth, and this development is an effect of the quick industrialization in these countries. Therefore, it can be supposed that the technological improvements and ecological policies in top nuclear energy-producing countries are chiefly embattled at attaining industrial development, which is accomplished even at environmental cost by producing ambient environmental pollution. The real income growth and environmental worsening both are being influenced by the technical modernism started in these countries, and this is predictable to have cost on the sustainable development. In this pursuit, the current strategies in these countries require to be reorganized for internalizing the adverse externalities influenced by the real growth trajectory and guaranteeing sustainable environmental development.

Furthermore, renewable energy, which plays a positive role in the environment and is also a crucial source of cleaner and green energy sources, is adversely linked with a carbon footprint. Particularly, a 1 % change in renewable energy will lead to reducing carbon footprint by 0.1910 % in the long run. This entails that the constant utilization of alternative and renewable energy resources is proficient in plummeting the carbon footprint level in the highly nuclear energy-generating countries and as a result, protecting the natural environmental quality. These results are related to those of earlier study (Usman and Balsalobre-Lorente, 2022). Alternative and renewable energy usage by its character encompasses emission-free appearances, therefore, its adverse influences on carbon footprint in the atmosphere. This also elucidates the clean function of alternative and renewable energy use in diminishing carbon footprint which depicts that these highly nuclear energy-producing countries are on the right pathway toward achieving sustainable development goals through the addition and progression of clean energy technologies. Further, these results reveal that these countries shifting from non-renewable energy sources to alternative and renewable/cleaner energy sources that have more power to curtail carbon footprint. These countries require installing cleaner technologies

Table 7Long-run elasticity estimates (AMG and CCEMG).

Regressors	Coeff.	Std. Err.	z	P > z	[95 % Conf. Interval]	
A) Augmented mea	A) Augmented mean group estimator (Eberhardt and Bond, 2009)					
LNUCE	-0.262841*	0.0709653	-3.32	0.008	-0.1619304	0.1162484
LTECH	0.1590686**	0.0606882	2.97	0.030	-0.0598781	0.1780153
LRE	-0.191081*	0.1131243	-4.69	0.000	-0.4128003	0.0306388
LNRE	0.877392***	0.4938034	1.78	0.076	-0.090444	1.8452321
LNR	0.1234022**	0.0205196	2.14	0.024	-0.0636199	0.0168155
Cons.	-3.344865***	0.9047997	-1.76	0.079	-7.078202	0.388472
RMSE	0.0287					
B) Common correla	ted effects mean group estimator	(Pesaran, 2006)				
LNUCE	-0.35155*	0.0310851	-3.66	0.007	-0.1124798	0.0093715
LTECH	0.130642*	0.0658931	7.47	0.000	-0.0985062	0.1597902
LRE	-0.10246*	0.0196104	-6.86	0.002	-0.3368961	0.1319683
LNRE	1.00122**	0.0126277	2.43	0.015	0.1924842	1.8099554
LNR	0.01099***	0.0193716	1.99	0.070	-0.0489611	0.0269742
Cons.	-0.0674**	0.0262891	-2.80	0.011	-8.2766271	8.2901221
RMSE	0.0315					

Note: *p < 0.01, **p < 0.05 and ***p < 0.10. RMSE denotes Root Mean Squared Error (sigma).

^{**} p < 0.05.

^{***} p < 0.10.

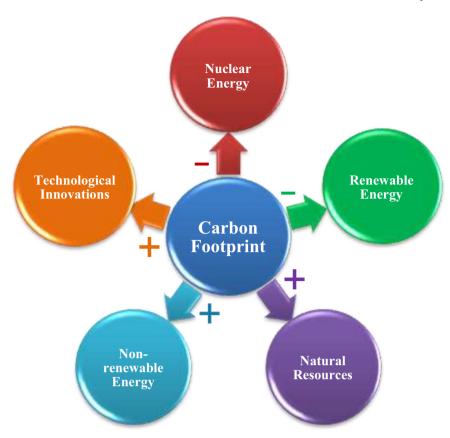


Fig. 4. Long-run influence of regressors on the carbon footprint.

 Table 8

 Pairwise Dumitrescu Hurlin Panel Causality test results.

Null hypothesis: W-Stat. Zbar-Stat. Prob. Causality direction LNUCE \Rightarrow LCFP 6.18518* 4.97257 0.0000 Unidirectional LCFP \Rightarrow LNUCE 2.87905 0.85712 0.3914 LTECH \Rightarrow LCFP 5.39347* 3.98705 0.0000 Bidirectional LCFP \Rightarrow LTECH 4.97374* 3.46457 0.0005 Bidirectional LCFP \Rightarrow LRE 4.36045* 2.70116 0.0069 0.0069 LNRE \Rightarrow LCFP 4.14893** 2.43787 0.0148 Bidirectional LCFP \Rightarrow LNRE 6.64439* 5.54418 0.0000 LNR \Rightarrow LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 Unidirectional LNUCE \Rightarrow LRE 5.0016* 3.49747 0.0005					
LCFP \Rightarrow LNUCE 2.87905 0.85712 0.3914 LTECH \Rightarrow LCFP 5.39347* 3.98705 0.0000 Bidirectional LCFP \Rightarrow LTECH 4.97374* 3.46457 0.0005 LRE \Rightarrow LCFP 8.64756* 8.03770 0.0000 Bidirectional LCFP \Rightarrow LRE 4.36045* 2.70116 0.0069 LNRE \Rightarrow LCFP 4.14893** 2.43787 0.0148 Bidirectional LCFP \Rightarrow LNRE 6.64439* 5.54418 0.0000 LNR \Rightarrow LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	Null hypothesis:	W-Stat.	Zbar-Stat.	Prob.	Causality direction
LTECH ⇒ LCFP 5.39347* 3.98705 0.0000 Bidirectional LCFP ⇒ LTECH 4.97374* 3.46457 0.0005 LRE ⇒ LCFP 8.64756* 8.03770 0.0000 Bidirectional LCFP ⇒ LRE 4.36045* 2.70116 0.0069 LNRE ⇒ LCFP 4.14893** 2.43787 0.0148 Bidirectional LCFP ⇒ LNRE 6.64439* 5.54418 0.0000 LNR ⇒ LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP ⇒ LNR 4.25553** 2.57055 0.0102 LTECH ⇒ LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE ⇒ LTECH 5.95277* 4.68326 0.0000 LRE ⇒ LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE ⇒ LRE 5.00016* 3.49747 0.0005 LNRE ⇒ LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE ⇒ LNRE 10.1506* 9.90863 0.0000 LNR ⇒ LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE ⇒ LNR 2.06870 −0.15158 0.8795	LNUCE ⇒ LCFP	6.18518*	4.97257	0.0000	Unidirectional
LCFP \Rightarrow LTECH 4.97374* 3.46457 0.0005 LRE \Rightarrow LCFP 8.64756* 8.03770 0.0000 Bidirectional LCFP \Rightarrow LRE 4.36045* 2.70116 0.0069 LNRE \Rightarrow LCFP 4.14893** 2.43787 0.0148 Bidirectional LCFP \Rightarrow LNRE 6.64439* 5.54418 0.0000 LNR \Rightarrow LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LCFP \Rightarrow LNUCE$	2.87905	0.85712	0.3914	
LRE \Rightarrow LCFP 8.64756* 8.03770 0.0000 Bidirectional LCFP \Rightarrow LRE 4.36045* 2.70116 0.0069 LNRE \Rightarrow LCFP 4.14893** 2.43787 0.0148 Bidirectional LCFP \Rightarrow LNRE 6.64439* 5.54418 0.0000 LNR \Rightarrow LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNUCE 10.1506* 9.99863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LTECH \Rightarrow LCFP$	5.39347*	3.98705	0.0000	Bidirectional
LCFP \Rightarrow LRE 4.36045* 2.70116 0.0069 LNRE \Rightarrow LCFP 4.14893** 2.43787 0.0148 Bidirectional LCFP \Rightarrow LNRE 6.64439* 5.54418 0.0000 LNR \Rightarrow LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNR 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LCFP \Rightarrow LTECH$	4.97374*	3.46457	0.0005	
LNRE \Rightarrow LCFP 4.14893** 2.43787 0.0148 Bidirectional LCFP \Rightarrow LNRE 6.64439* 5.54418 0.0000 LNR \Rightarrow LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNUCE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LRE \Rightarrow LCFP$	8.64756*	8.03770	0.0000	Bidirectional
LCFP \Rightarrow LNRE 6.64439* 5.54418 0.0000 LNR \Rightarrow LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 Unidirectional LNUCE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LCFP \Rightarrow LRE$	4.36045*	2.70116	0.0069	
LNR \neq LCFP 4.61494* 3.01794 0.0025 Bidirectional LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRCE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRCE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LNRE \Rightarrow LCFP$	4.14893**	2.43787	0.0148	Bidirectional
LCFP \Rightarrow LNR 4.25553** 2.57055 0.0102 LTECH \Rightarrow LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LCFP \Rightarrow LNRE$	6.64439*	5.54418	0.0000	
LTECH ⇒ LNUCE 6.48461* 5.34529 0.0000 Bidirectional LNUCE ⇒ LTECH 5.95277* 4.68326 0.0000 LRE ⇒ LNUCE 2.18117 -0.01159 0.9908 Unidirectional LNUCE ⇒ LRE 5.00016* 3.49747 0.0005 0.0005 LNRE ⇒ LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE ⇒ LNRE 10.1506* 9.90863 0.0000 LNR ⇒ LNUCE 1.47354 -0.89243 0.3722 Nocausality LNUCE ⇒ LNR 2.06870 -0.15158 0.8795	$LNR \Rightarrow LCFP$	4.61494*	3.01794	0.0025	Bidirectional
LNUCE \Rightarrow LTECH 5.95277* 4.68326 0.0000 LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LCFP \Rightarrow LNR$	4.25553**	2.57055	0.0102	
LRE \Rightarrow LNUCE 2.18117 −0.01159 0.9908 Unidirectional LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	LTECH ⇒ LNUCE	6.48461*	5.34529	0.0000	Bidirectional
LNUCE \Rightarrow LRE 5.00016* 3.49747 0.0005 LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	LNUCE \Rightarrow LTECH	5.95277*	4.68326	0.0000	
LNRE \Rightarrow LNUCE 4.51268* 2.89066 0.0038 Bidirectional LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LRE \Rightarrow LNUCE$	2.18117	-0.01159	0.9908	Unidirectional
LNUCE \Rightarrow LNRE 10.1506* 9.90863 0.0000 LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	$LNUCE \Rightarrow LRE$	5.00016*	3.49747	0.0005	
LNR \Rightarrow LNUCE 1.47354 −0.89243 0.3722 Nocausality LNUCE \Rightarrow LNR 2.06870 −0.15158 0.8795	LNRE \Rightarrow LNUCE	4.51268*	2.89066	0.0038	Bidirectional
LNUCE ⇒ LNR 2.06870 -0.15158 0.8795	$LNUCE \Rightarrow LNRE$	10.1506*	9.90863	0.0000	
	$LNR \Rightarrow LNUCE$	1.47354	-0.89243	0.3722	Nocausality
LRE LTECH 3 54278*** 1 68333 0 0923 Bidirectional	$LNUCE \Rightarrow LNR$	2.06870	-0.15158	0.8795	
EACH // ETECT CIC /E/C Troccoc Cic /EC Entroccional	$LRE \Rightarrow LTECH$	3.54278***	1.68333	0.0923	Bidirectional
LTECH ⇒ LRE 5.84946* 4.55466 0.0000	$LTECH \Rightarrow LRE$	5.84946*	4.55466	0.0000	
LNRE ⇒ LTECH 5.13170* 3.66121 0.0003 Bidirectional	LNRE \Rightarrow LTECH	5.13170*	3.66121	0.0003	Bidirectional
LTECH ⇒ LNRE 5.07835* 3.59479 0.0003	$LTECH \Rightarrow LNRE$	5.07835*	3.59479	0.0003	
LNR ⇒ LTECH 2.57334 0.47658 0.6337 Nocausality	$LNR \Rightarrow LTECH$	2.57334	0.47658	0.6337	Nocausality
LTECH \Rightarrow LNR 1.72020 -0.58539 0.5583	$LTECH \Rightarrow LNR$	1.72020	-0.58539	0.5583	
LNRE \Rightarrow LRE 4.30621* 2.63365 0.0084 Bidirectional	$LNRE \Rightarrow LRE$	4.30621*	2.63365	0.0084	Bidirectional
LRE \Rightarrow LNRE 5.87910* 4.59156 0.0000	$LRE \Rightarrow LNRE$	5.87910*	4.59156	0.0000	
$LNR \Rightarrow LRE$ 2.20464 0.01763 0.9859 Unidirectional	$LNR \Rightarrow LRE$	2.20464	0.01763	0.9859	Unidirectional
LRE \Rightarrow LNR 4.84197* 3.30055 0.0010	$LRE \Rightarrow LNR$	4.84197*	3.30055	0.0010	
$LNR \Rightarrow LNRE$ 1.06780 -1.39749 0.1623 Unidirectional	$LNR \Rightarrow LNRE$	1.06780	-1.39749	0.1623	Unidirectional
LNRE \Rightarrow LNR 5.13112* 3.66048 0.0003	$LNRE \not\Rightarrow LNR$	5.13112*	3.66048	0.0003	

Note: \Rightarrow shows 'does not Granger cause'. *p < 0.01, **p < 0.05 and ***p < 0.10.

and releasing monetary funds for sophisticated technology to enhance the consumption of renewable energy for a sustainable atmosphere. The highly nuclear energy-producing countries are before now spotlighting on accomplishing the cleaner energy targets by dipping the outlay of lowering taxes, financing, and raising the financial support for cleaner energy ventures.

As expected, non-renewable energy leads to increase the carbon footprint level in highly nuclear energy-producing countries. Predominantly, a 1 % augmentation in non-renewable energy will escort to an augmentation in carbon footprint between 0.8773 % and 1.0012 %, as explored in the AMG and CCEMG estimators. The sources of non-renewable energy, for example, coal, petroleum, jet fuel, and various others, have been recognized in the earlier published literature as the chief polluter of carbon and other GHGs to the atmosphere. The fossil fuel and non-renewable energy sources are indefensible and finite, and their intensive deployment increases climate change and global warming through growing GHGs emissions, while on the other side, renewables are sustainable and profuse and also diminish environmental degradation. Bearing in mind the energyintensive circumstances of highly nuclear energy-producing countries, another optional policy is to augment energy competence in curbing carbon emissions by encouraging the usage of energy-saving technologies that are one of most the crucial green growth inputs for the countries (Danish et al., 2020). The persistent deployment of these fossil fuel energy sources could constrain more ecological dilapidation in the course of carbon emissions, as maintained in the work of Dogan and Ozturk (2017) for the USA, Danish et al. (2020) for BRICS countries, Usman and Balsalobre-Lorente (2022) for newly industrialized countries, and Usman and Makhdum (2021) for BRICS-T countries. It is observed that there is the high positive magnitude of non-renewable energy utilization than the negative magnitude of renewable and nuclear energy deployment with respect to carbon footprint across the region. This evidence reveals that the deployment of non-renewable energy consumption reduces the environmental quality. In this regard, the central authorities and policymakers should

espouse various instruments for a sustainable environment, for instance, safe and healthy long-term growth, pollution-free technologies, and renewable and nuclear energy sources that help to reduce the consumption of non-renewable energy, in due course it would reduce the carbon footprint and amplify the nuclear, renewable, and alternative energy utilization that advances the agenda of sustainable policy across the region.

Lastly, the deployment of natural resources is found to have a statistically significant and positive impact on the carbon footprint. This depicts that, the extraction of natural resources leads to environmental damages in the case of highly nuclear energy-producing countries. It also depicts that an influence of a 1 % increase in natural resources would also boost carbon footprint by 0.1234 % in the long run. This is useful for the motive that the mining of natural resources would directly increase economic growth and in that way increases environmental pollution. Baloch et al. (2019) and Bekun et al. (2019) also established analogous findings for the BRICS group and 16 European Union countries. As per the recent study by Baloch et al. (2019), the industrialization process escorts to the excessive deployment of natural resources that considerably enhances pollution levels in the region. Furthermore, extra augmentation in extractive activity has the ability to bring several remunerations for fiscal growth; however, they also have an adverse influence on the atmosphere. This study finding recommends that natural gas, oil, mineral mining, and coal may be the offender in the wake of biodiversity loss, environmental discrepancy, deforestation, and soil erosion in these countries. As a result, strategies to enlarge the competence of natural resource extraction and decrease the adverse effect of this utilization on the atmosphere are essential. Moreover, Fig. 4 reported the long-run impact of selected independent variables on the carbon footprint in these countries during the given span.

Second strand of Table 7 also reports the empirical findings of the series by the common correlated effect mean group (CCEMG) estimator. As observed previously (see first strand of Table 7), the long-run findings of the augmented mean group (AMG) approach are in line with the results of the CCEMG estimator developed by Pesaran (2006), as the coefficient signs for all series are indistinguishable (see second strand (B) of Table 7). The empirical results acquired from this alternative method, therefore, sustain the earlier findings offered to employ the AMG method and permit us to evaluate the long-run findings' robustness using another measurement approach.

4.5. Panel Dumitrescu and Hurlin (D-H) non-causality finding

Though the long-run dynamic impact of the underlying series has been explored through the AMG, and CCEMG estimators, however, the causal associations between these analyzed series are still in question. In this regard, we employed the panel heterogeneous non-causality test proposed by Dumitrescu and Hurlin (2012). Therefore, we discover the causal

linkages between ecological footprint, nuclear energy, technological innovations, renewable and non-renewable energy, and natural resources. The Dumitrescu and Hurlin causality test findings are presented in Table 8 and Fig. 5. Fascinatingly, the empirical results only discover a unidirectional causality association running from nuclear energy consumption to carbon footprint. This depicts that a small variation in nuclear energy consumption will lead to modifying the carbon footprint. This estimated result is also consistent with the findings of long-run estimation which is more important for governing and policymaking authorities. This outcome is analogous to the econometric findings of Menyah and Wolde-Rufael (2010) for the United States, Lee et al. (2017) for 30 different economies, and Saidi and Omri (2020) for 15 OECD countries. From the policy-making perspective, governing and policymaking authorities of these countries can diminish environmental pollution by managing nuclear energy extraction in an efficient way. Additionally, there are also found unidirectional causality linkages from nuclear energy consumption to renewable energy use, renewable and non-renewable energy usage to natural resources.

Moreover, there is observed bidirectional causality between technological innovations, non-renewable and renewable energy, and natural resources with ecological footprint. These outcomes are in line with the previous conclusion of Bekun et al. (2019) for 16 European Union economies, Usman and Hammar (2021) for APEC countries, and Danish et al. (2020) for the BRICS region. This shows that there is a validation of the feedback hypothesis between these variables with the ecological footprint. For this reason, extra deployment of technology, energy, and natural resources has a lot of potentials to influence the carbon footprint and vice-versa. In this pursuit, for technological innovations, this significant causality association recommends that any action to increase the spending on technological innovations in order to transfer from fossil fuel energy resources to cleaner, alternative and renewable energy use will drive carbon footprint in the region, as both renewable and non-renewable energy variables significantly granger cause carbon footprint.

5. Conclusion and practical implication

Environmental pollution has turned out to be one of the most well-known subjects of discussion all over the world. Accordingly, almost all nations across the world are challenged to implement and establish new environmental laws that will permit them to accomplish a sustainable environment without affecting their economic growth. Plummeting pollution levels is very crucial for emerging and developed economies, as all of these economies are expected to add significantly to global production and, consequently, are predictable to provide for the high mass of worldwide environmental pollution. The all parties Paris Agreement conference (COP-26) and the Kyoto Protocol are international agreements that connect world countries to reduce global environmental pollution and maintain

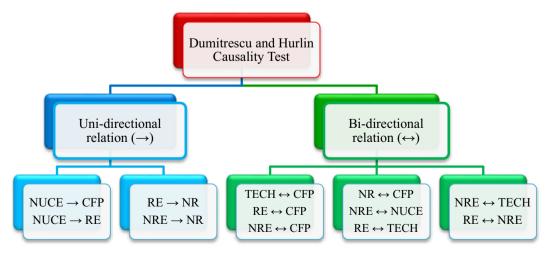


Fig. 5. Causality relationship schema.

average temperatures lower than 1.5 Celsius grade in the course of a mixture of sustainable policy tools. Greener strategies that assist to reduce environmental exposure are based on the expansion of clean technologies, green energy infrastructure, and carbon pricing. Adjacent to these conditions, this research scrutinizes the impact of nuclear energy, technological innovations, non-renewable and renewable energy consumption, and natural resources on carbon footprint in the highly nuclear energy-producing economies by utilizing longitudinal data over the span from 1990 to 2019. The present research employed a second-generation estimation procedure due to the existence of possible cross-sectional dependency. The cointegration outcomes explored a long-run association between the series. In addition, the long-run findings from both AMG and CCEMG explored that nuclear energy and renewable energy usage significantly diminish the carbon footprint by 0.2628 %, and 0.1911 % respectively. However, technological innovations, natural resources, and non-renewable energy significantly boost the carbon footprint in the region. Specifically, a 1 % increase in technological innovations, natural resources, and non-renewable energy consumption will increase the carbon footprint by 0.1591 %, 0.1234 %, and 0.8773 %, respectively. Finally, the Dumitrescu and Hurlin causality findings disclosed that a one-way causality is running from nuclear energy to carbon footprint. In contrast, two-way causality is discovered between technological innovations, renewable and non-renewable energy, and natural resources with carbon footprint. These results predict that these indicators significantly influence the carbon footprint in top nuclear energy-producing countries. These estimates recommend that nuclear and alternative energy sources and carbon pricing would be liable to pursue the decarbonization agenda. Conversely, insufficient access to green technology and clean fuel and the limited share of cleaner energy sources in the traditional energy-mix would likely enlarge the carbon reimbursement. Therefore, policy directions toward all these explanatory indicators will have a noteworthy influence on the carbon footprint.

Considering the empirical analysis of this study, several policy-level proposals can be advocated for these countries to concurrently achieve environmental and economic interests. First, concerning the significant role of nuclear energy, this study's findings support the argument that nuclear energy consumption can be applied as an imperative source of energy in long-run environmental policies and energy development that convene the increasing demands for world energy. Significant efforts should be made to promote industry and government to augment their investments in the supply of nuclear energy sources and to reduce the limitations of evaluating the nuclear energy consumption without affecting their growth trajectory. Developments in the production of nuclear energy infrastructure should be also commenced at the initial. Additionally, the domestic private shareholder and investors could be capable to hold more vigorously in the wide range of alternative energy movements by promoting more initiatives related to Public-Private Partnership (PPPs) and recognizing obstacles to rising investments in cleaner and alternative energy sources. Private investors show their apprehension about governancerelated jeopardizes, which could exaggerate the stress of revolutionizing on central authorities and policymakers. Moreover, we observed that the situation in every nuclear energy-producing country is dissimilar; consequently, the choice of nuclear energy should be potted open under the Paris Agreement (PA) for gathering that desire to include it and therefore advance the cost-effectiveness of their proceedings for reducing environmental pollution reduction. Furthermore, nuclear power production entails precise safety and security measures since its ruthless irrevocable results to the environment and human beings.

On the other hand, it is essential to remember that nuclear power production needs protection and safety managing costs in order to evade any disaster that may significantly harm the environment and damage human beings. For that reason, when dealing with policy choices regarding nuclear energy, an assessment should be cautiously accomplished not only from its benefit in the reduction of environmental pollution but also from several characteristics for instance its possible risks.

Second, public policies must embrace financial support for different projects of technological innovation, specifically for related technologies

expansion that can guarantee complimentary between less pollution and high economic growth. The credit directing system toward the manufacturing sector in encouraging enhanced nuclear resolutions should also believe the technological modernism for determining energy efficiency. It is also vital to expand eco-friendly equipment in order to overcome the adverse (negative externalities) ecological consequences of natural resource rent in these countries. While literature might have accounted for a direct dynamic nexus between environmental damages and natural resource rent, the authors are of the view that both variables (natural resources and nuclear energy) with technological development offered attractive results. Furthermore, policymakers and governing bodies of these countries must encourage private enterprise projects for determining better nuclear energy resolutions and consequently the protection of the environment. This proposal will assist these countries to take a primary step toward achieving the objectives of SDGs 7 (affordable and clean energy), SDGs 8 (decent work and economic growth), SDGs 9 (industry, innovations, and infrastructure), and SDGs 13 (climate action).

Third, governments and policymaking authorities should execute restrictive strategies, promote investment levels in alternative energy resources, and boost energy modernization to decrease environmental pollution. Cleaner energy usage upsurges people's welfare. Extra energy from economic expansion should be malformed into cleaner energy sources and technical evolution is mandatory, which is a useful measure to counterbalance carbon footprint. Policymakers and governing authorities of these countries should execute timely and efficient energy strategies to curtail environmental concerns. This could be made by implementing lowcarbon-intensive, clean, and less nonrenewable consumption within these countries. In addition, to preserve energy, it is suggested that the deployment of renewable and alternative energy to diminish the dependence on feeble energy structures and make sure energy safety in definite bulky energy deployment regions. This should embrace segments such as industrial, residential, transport, etc. Also, policymakers should publicize rules on charges or cleaner and renewable energy costs to facilitate businesses and individuals to replacement of fossil fuel energy with renewable and alternative energy promptly.

Fourth, governmental authorities of these countries need to deliberate instantly on taking full advantage of the environmental influence of technological innovations in order to encourage the natural atmosphere. Thus, policymakers should compose a considerable endeavor to endorse environmental improvements and technology schemes to promote green policies. Technology policies and green innovations must guarantee that social and environmental concerns can be addressed while endorsing sustainable economic and environmental development. It is also imperative to put standards to decide on green and clean standards for expertise that has the ability to protect environmental excellence. Technological innovation constructs a market podium that permits firms to split inventive technologies and recompense while developing insightful synergies. Furthermore, the reward of sustainable economic development will also support ecological consciousness and administration policies for education.

In this study, the empirical analyses are at an aggregated level. This can be revealed as the main study limitation. Another limitation of the current study only lies in limited sample countries (only 9), data (1990–2019), and econometric methods. Upcoming research can be performed on different samples and may comprise several other factors with nuclear energy to intensely examine this relationship. Upcoming research can also include poverty, income inequality, institutional quality, human capital, environmental-related technologies, governance, financial development indicators, and corruption in this relationship, as these indicators make policies that have the ability to strengthen other sectors related to protect environmental quality and boost economic development.

CRediT authorship contribution statement

Muhammad Usman: Conceptualization, Introduction, Literature review, Visualization, Data curation, Methodology, Software, Formal

analysis, Results and discussion, Revised draft, Project administration, Supervision, Writing – original draft and Writing – review & editing.

Magdalena Radulescu: Formal analysis, Validation, and 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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