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Research article

Forecasting synergistic pathways between rare earth elements, renewable energy, and product and economic complexities in achieving a low-carbon future

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ABSTRACT

Recent decades have witnessed an unprecedented transformation in the global energy landscape, driven by environmental concerns and the quest for sustainable economic growth. As the world grapples with the urgent need for decarbonization, the utilization of renewable energy technologies with the instrumental role of rare earth elements (REEs) has come to the forefront. However, empirical investigations into their synergistic pathways for product and economic complexities concerning achieving a low-carbon future remain scarce. Therefore, we forecast synergistic pathways between the REE supply, renewable energy, economic and product complexities, and GDP growth using a panel dataset of 11 REE-producing countries from 1990 to 2023. We used Common Correlated Effects and Temporal Causal Models as primary methods to estimate panel long-run elasticities and subsequently forecast mutual causal synergies between the variables. The results indicated that REE supply led to renewable energy and economic growth that further elevated the countries' product and economic complexities rankings. GDP growth increased REE production, economic complexity, and renewable energy directly, and consequently, product complexity and REE production through them. This underscores the positive role of REE production coupled with renewable energy technologies in achieving a low-carbon future based on economic diversification, enhanced industrial capabilities, and technological sophistication.

List of abbreviations

REEs	Rare Earth Elements
PCI	Product Complexity Index
ECI	Economic Complexity Index
GDP	Gross Domestic Product
TCM	Temporal Causal Modelling
CCE	Common Correlated Effects
IEA	International Energy Agency
SDG	Sustainable Development Goals
USGS	United States Geological Survey

1. Introduction

Over the past two decades, there has been a remarkable shift in the global energy landscape, driven by escalating environmental concerns, climate change, energy security imperatives, and the pursuit of sustainable economic growth. This transition has been particularly evident in the increasing deployment of renewable energy technologies, such as solar photovoltaics, wind power, and energy storage systems, as viable alternatives to traditional fossil fuels. These technologies have witnessed unprecedented growth and adoption worldwide, owing to advancements in technology, declining costs, and supportive policy frameworks

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aimed at mitigating climate change and reducing carbon emissions (Elshkaki, 2021). Concurrently, global production of rare earth elements (REEs) has reached historic highs in the last two decades, fuelled by their indispensable role in the aforementioned clean energy technologies, aiming at efficiency, design, cost reduction, storage, integration, and trade (Czerwinski, 2022; Zhang et al., 2022). For instance, advancements in solar photovoltaic technology have resulted in increased efficiency and affordability, making solar energy increasingly competitive with conventional energy sources (Badhoutiya, 2023). Similarly, developments in wind turbine design and engineering have led to larger, more efficient turbines capable of harnessing wind energy in diverse geographical locations (Škvorc and Kozmar, 2021). Additionally, breakthroughs in energy storage technologies, such as lithium-ion batteries and pumped hydro storage, have addressed the intermittency challenges associated with renewable energy sources, enhancing their reliability and grid integration (Verma et al., 2022; Imholte et al., 2018).

This widespread adoption of renewable energy technologies offers significant environmental and economic benefits, contributing to climate change mitigation, energy security, and economic development. The renewable energy sector has emerged as a key driver of economic growth, job creation, and investment, fostering innovation, technological development, and industrial competitiveness (Hille and Oelker, 2023; European Commission, 2023; IRENA & ILO, 2021). The reason is that the commercial and household consumption of non-renewable energy has predisposed detrimental impacts on human health, the environment, and biodiversity, in conjunction with climate change due to rampant CO_2 emissions. This unsustainable nexus is motivating stakeholders to go for energy transitions by focusing more on the adoption of green energy technologies, which utilize rare earth elements, including solar power, wind energy, electric/hybrid vehicles, and fuel batteries and cells, to subsequently neutralize carbon emissions (Wadia et al., 2009). Besides, REEs are the enablers of complex, diversified, and sophisticated technological products and various high-tech applications, and are consensually considered catalysts to achieve sustainable techno-economic growth in the 21st century (Bradley S., 2014). For that reason, the momentum towards renewable energy adoption has been bolstered by international agreements and commitments aimed at addressing climate change and promoting sustainable development. The Paris Agreement, signed by nearly 200 countries, sets out ambitious targets for limiting global warming to well below 2 °C above pre-industrial levels and pursuing efforts to limit it to 1.5 °C (UNFCCC, 2015). Similarly, the United Nations Sustainable Development Goals (SDGs) include targets related to affordable and clean energy (SDG 7) and climate action (SDG 13), underscoring the importance of renewable energy in achieving sustainable development objectives (UNDP, 2015).

However, it has also raised serious concerns regarding the long-term availability or supply of required REEs (Kleijn et al., 2011), as their demand is rapidly increasing every year because as the world transitions towards renewable energy sources, the demand for REEs has grown significantly due to their use in renewable energy technologies and more (USGS, 2017). Besides, the world's growing population will also increase the demand for raw materials tremendously as they not only need food and drinking water but also rare earth elements, which are widely used in high-tech applications and complex sophisticated products. The REE industry produced 7.06 billion dollars in 2021 and is predicted to grow to over 15 billion dollars by 2030 (GIS, 2022). With the instrumental role of reliable REE supply, the expansion of the renewable energy sector can have significant impacts on product and economic complexities, and GDP growth, with both positive economic potential and potential negative environmental and geopolitical consequences. Achieving sustainable development requires careful resource management, technological innovation, and international cooperation to ensure that economic growth is balanced with environmental and social considerations.

Therefore, the study of renewable energy adoption and its implications for sustainable development requires an interdisciplinary approach, drawing on insights from various fields, including energy economics, environmental science, engineering, and policy studies. This interdisciplinary perspective is essential for understanding the complex interactions between technological innovation, policy frameworks, market dynamics, and societal preferences that shape the deployment and diffusion of renewable energy technologies (Sovacool et al., 2018). By integrating diverse perspectives and methodologies, researchers can gain a more comprehensive understanding of the opportunities and challenges associated with renewable energy adoption and inform evidence-based policymaking and decision-making processes (Markard et al., 2012). In this context, despite the growing importance of renewable energy technologies and REEs, empirical studies exploring the synergistic pathways between REE production, renewable energy utilization, the product complexity index (PCI), the economic complexity index (ECI), and economic growth, remain scarce.

Therefore, filling this research gap is crucial for a deeper understanding of sustainable economic development and technological advancement, particularly in the context of achieving a low-carbon future and mitigating climate change. This novel study aims to comprehensively investigate the intricate interrelationships between renewable energy consumption, REE production, PCI, ECI, and GDP growth. Specifically, we intend to discuss their mutual causal dynamics and their implications for sustainable economic growth. We hypothesize that there exists a mutual causal relationship between renewable energy consumption, REE production, GDP growth, and economic and product complexities. For this purpose, we employ dynamic Common Correlated Effects (CCE) to estimate panel long-run elasticities by analysing data of the top providers of REEs from 1990 to 2023, such as China, the USA, Myanmar, Malaysia, Brazil, Australia, Thailand, India, Russia, Madagascar, Sri Lanka, and Vietnam. Their selection is based on data availability and their prominence of being the primary global REE producers and exporters during the specified period. Then, temporal causal modelling (TCM), an extension of Granger causality, is used to suggest proper causal inference. TCM in SPSS Statistics v.26 is a specially designed technique to unravel synergistic mutual causal associations between the variables by processing them both as input and target variables. It uniquely synthesizes the influences of renewable energy usage coupled with REE production on both PCI and ECI, shedding light on their combined effects on a country's economic diversification, industrial sophistication, and overall economic growth.

This study holds significance in that it contributes to the existing literature by offering empirical insights into the synergistic pathways between REE production and renewable energy utilization, GDP growth, product complexity, and economic complexity, advancing our understanding of tracking present synergies from the perspective of economic and technological development and environmental sustainability. REEs play a crucial role in the development and deployment of renewable energy technologies, contributing significantly to economic growth and technological innovation. This study uniquely integrates the production of REEs, economic complexity indices (ECI and PCI), and their impacts on renewable energy utilization and economic growth. Unlike previous studies that primarily focus on GDP as an economic measure, our research highlights the importance of economic complexity and product complexity as proxies for economic diversification and technological sophistication. By exploring these novel relationships, we provide a comprehensive understanding of how REEs drive sustainable development and industrial advancement. The findings have implications for policymakers, energy companies, and investors, guiding strategic decisions towards promoting renewable energy adoption, fostering economic diversification, and achieving carbon emission reduction targets. The study argues that the synergies between REE production, renewable energy, PCI, ECI, and GDP growth play a pivotal role in driving economic complexities, technological innovation, and environmental sustainability, thereby shaping the trajectory of sustainable economic development. By understanding the primary drivers of green development, governments may devise more effective policy measures to combat climate change and boost economic resilience.

The limitations of this study include its primary focus on countries that produce REEs from primary sources (mining); therefore, the results and implications cannot be directly extrapolated to non-producers. Additionally, the study only utilized data on REE production publicly available on the USGS website, which may not be entirely accurate at the country level. The structure of the paper is segmented as follows: Section 2 discusses the theoretical background of the study, formulating a relationship between the utilization of REEs in renewable energy, trade, and manufacturing sectors, highlighting the paradigm shift in the global energy landscape in recent decades, and emphasizing the need for empirical investigation. Section 3 focuses on the sources and nature of the data and the suitability of the methods used, such as CCE and TCM. Section 4 presents the results of the models and provides their interpretation. Section 5 offers a discussion of the main findings, a comparative analysis with other published studies, and the significance of the results. Finally, Section 6 concludes the paper by providing practical policy implications based on robust empirical findings.

2. Theoretical background

2.1. A paradigm shift in the history of energy transitions

The history of energy transition spans centuries, from the initial adoption of coal in the 18th century (Kemfert et al., 2022) to the oil crises of the 1970s that reshaped modern energy systems (U.S. Energy Information Administration, 2023). The 1973 oil embargo led to a re-evaluation of energy sources and a focus on renewables to diversify energy supplies, enhance security, and reduce CO2 emissions (Abban et al., 2023; Dogan et al., 2020). The 1970s also marked the rise of the environmental movement and the concept of 'climate change,' influencing energy policy and public awareness (Yalew et al., 2020), and expanding the use of nuclear, solar, and wind energy (Marra and Colantonio, 2023), particularly nuclear, solar and wind energy(Yalew et al., 2020). Environmental concerns began to intertwine with energy transition dynamics, driving the pursuit of environmentally sustainable economic growth.

Recently, renewables have come to the forefront of global energy agendas, leading to a paradigm shift in energy transitions. Several pivotal events contributed to this shift. First, the concept of 'Green Growth' emerged in 2005, emphasizing sustainable economic development and the reduction of environmental impacts (United Nations ESCAP, 2005). Second, in 2009, the ECI and PCI were introduced as tools to evaluate industrial capabilities, technological advancement, and economic diversification (Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2010). Third, The U.S. ceased production at the Mountain Pass Mine in 2002 due to environmental concerns, allowing China to dominate the REE market with over 74% share (Ali, 2014). China subsequently emerged as the world's top REE producer, commanding over 74% of the market share (Mancheri, 2015). Fourth, the early 21st century saw new REE producers, such as Myanmar, Madagascar, Thailand, and Vietnam, emerging among the top 10 REE producers simultaneously, the disappearance of the leading REE producers of the 20th century (e.g., Sri Lanka, South Africa, Zaire, Congo, and Canada) (USGS, 2023). This transition highlighted the geopolitical and economic implications of REE production and supply, especially in the context of renewable emerging technologies reliant on REEs.

As a result, global REE production grew from 105,000 metric tons in 2005 to 300,000 metric tons in 2022 (Statista, 2022; USGS, 2023). Solar panel installation capacity surged from 1160 MW in 2004 to 241,000 MW by 2021, with costs decreasing by 90% between 2000 and 2010 (IEA, 2023; IEA, 2022a; IEA, 2022b). Notably, solar panel costs decreased by an impressive 90% between 2000 and 2010 (IEA, 2023), making solar power one of the most rapidly evolving and accessible energy technologies, having been influenced by climate change notion. Wind energy production also increased significantly, from 85.62 TWh in 2004–2005 to 2104.84 TWh by 2021 (IEA, 2023). These expansions in solar and wind energy technologies, driven by climate change concerns, contributed to a 6.5% decrease in CO_2 emissions in 2019, a rate three times faster than the previous decade (Nijsse et al., 2023), helping to mitigate climate change (He et al., 2020; Islam et al., 2022).

Thus, this substantial expansion of renewable energy technologies, in conjunction with other aforementioned concurrent events in the first decade of the 21st century set the stage for a global paradigm shift that hypothetically established a synergistic relationship with the REE industry and renewable energy sector that emphasized the critical role of REEs in energy transitions to achieving decarbonized economic growth and promoting diverse, complex, and innovative domestic industrial and manufacturing sectors. This historical context and pivotal events underscore the evolving landscape of energy transitions, emphasizing the critical role of renewable energy technologies and REEs in achieving sustainable economic growth. Understanding this synergy emphasizes the interplay between the imperatives of technological and economic growth, energy security, REE supply, and environmental sustainability, requiring a strong commitment to reshaping the interplay between society, technology, and the environment to achieve a low-carbon future.

2.2. REEs and techno-economic development

The chemical and magnetic properties of REEs enable clean energy technologies, such as smartphones, tablet computers, computer hard drives, digital cameras, hybrid cars, electric vehicles, solar panels, LEDs (light-emitting diode), solar photovoltaics, and wind turbines (Alonso et al., 2007). Moreover, REEs are crucial for national security and defense, being utilized in guided weapons for precision targeting and guidance systems, and in stealth technology for military aircraft, submarines, and vehicles (Fan et al., 2023). In telecommunications, REEs are vital for developing broadband technology, enhancing data transmission and connectivity. In the smartphone industry, they contribute to the miniaturization of components, creating compact and powerful devices (Zuberbuehler, 2023). In the medical field, REEs advance medical science and healthcare. Gadolinium-based contrast agents in the MRI systems enhance tissue visibility, facilitating accurate diagnosis and monitoring (Klingelhöfer et al., 2022). In diagnostic radiology, REEs improve the radiation detection capabilities of X-ray and CT scanners, enhancing image quality and reducing ionizing radiation exposure (Ascenzi et al., 2020). Medical lasers, employing REEs, are used in procedures such as eye surgeries and skin treatments (Wang and Li, 2022).

REEs are also finding novel applications in quantum computing and material sciences. Quantum computers, leveraging quantum mechanics, perform complex calculations at unprecedented speeds (Kolesov et al., 2012). REEs are used in developing qubits, the fundamental units of quantum information, due to their magnetic properties that create stable qubits for computation (Ogasa, 2023). Material scientists are incorporating REEs into materials with advanced properties, such as luminescent materials for lighting, displays, and sensors (Filho et al., 2023). These modern technologies and gadgets rely on REEs, making them essential for sustaining and driving technological advancements, which in turn foster social and economic development. The dynamic nature of the REE market, with new applications continuously emerging, means that the demand for individual rare earths is subject to change (Henriques and Sadorsky, 2023). The multifaceted applications of REEs in modern technologies highlight their indispensable role in technological advancement, economic growth, and national security, reinforcing the need for sustainable REE production.

2.3. Renewable energy consumption and techno-economic growth

Available empirical literature demonstrates a complex and multidirectional interaction between energy use, technological advancement, and economic growth. Findings underscore energy as a catalyst for technological innovation and economic development. However, this relationship is influenced by various contextual factors, including the energy mix, efficiency policies, and environmental considerations. Numerous studies confirm that energy consumption (both renewable and non-renewable) enhances GDP growth (Ojekemi et al., 2023; Baz et al., 2019, 2020), per capita CO_2 emissions, financial development, and global trade and openness (Anton et al., 2020; Bhattacharya et al., 2016; Ozcan and Ozturk, 2019). Regarding environmental sustainability, researchers have examined the cause-and-effect relationship between fossil fuel consumption, CO2 emissions, greenhouse gases, and climate change (Li et al., 2020a,b; Romano et al., 2017; Murad et al., 2019). Countries prioritizing energy-efficient technologies often witness improvements in productivity and overall technological sophistication (Magazzino et al., 2022).

Political and institutional factors also play a significant role. Democracy and corruption substantially influence household and commercial energy consumption. Corrupt practices and lobbying by industrial and manufacturing giants often favour non-renewable energy deployment (Sequeira and Santos, 2018). Conversely, high institutional quality supports energy transitions towards renewable and eco-friendly energy sources, facilitating economic shifts towards sustainability (Uzar, 2020). These empirical pieces of evidence illustrate the complex interplay between energy consumption, technological innovation, and economic growth, underlining the importance of renewable energy in driving sustainable development.

2.4. Filling research gap and novelty

As global initiatives toward sustainable development intensify, ongoing empirical investigation into the relationship between renewable energy utilization, technological progress, and industrial innovation becomes imperative. Such research is crucial for guiding policies that balance economic advancement and environmental stewardship. Many studies have focused on the role of renewable energy consumption in economic growth (Apergis et al., 2010), research innovations (Hille and Oelker, 2023), social development (healthcare, urbanization, and education) (Abbas et al., 2023), the stock market (Monasterolo and Angelis, 2020), foreign direct investment (Hoa et al., 2024), international trade (Lu et al., 2022), and digitalization (Lange et al., 2020).

However, the current literature lacks a comprehensive exploration of the mutual causal dynamics between renewable energy use, REE production, economic complexity, and product complexity. Economic and product complexities, measured by PCI and ECI, gauge economic and trade diversification, reflecting a country's advanced industrial capabilities and diverse trade baskets (OEC, 2023; Harvard University, 2023). These indices provide insights into economic development that GDP alone cannot, capturing the diversity of industries, technological sophistication, and product complexity. Investigating the nexus between energy use, REE production, PCI, ECI, and GDP growth is crucial for several reasons. First, it highlights how energy-intensive critical minerals contribute to technological innovation, product diversification, and economic growth. Second, understanding the energy consumption involved in REE extraction and processing can identify supply chain vulnerabilities and inform responsible resource management. Third, insights into the economic feasibility of REE production processes can guide industrial planning and resource allocation. Fourth, such research supports policymakers in balancing technological and economic growth with environmental protection and societal well-being.

Therefore, this study is pioneering in its approach to integrating REE production, renewable energy consumption, and economic and product complexities using advanced econometric techniques. By employing dynamic Common Correlated Effects (CCE) and Temporal Causal Modelling (TCM), we provide novel empirical evidence on the mutual causal relationships among these variables, which has not been extensively explored in previous literature. It guides sustainable development strategies, informs policy decisions, and advances renewable energy technologies while minimizing environmental impacts. It sheds light on how these factors collectively influence economic diversification, industrial sophistication, and overall economic growth, offering valuable insights for policymakers, economists, and researchers aiming to foster sustainable development pathways. By exploring the synergistic pathways between REE production, renewable energy utilization, economic and product complexities, and GDP growth, this research provides novel insights into sustainable economic development. This study fills a critical gap by exploring the synergistic pathways between REE production, renewable energy utilization, economic and product complexities, and GDP growth, providing novel insights into sustainable economic development.

3. Methods and data

3.1. Data availability

We utilize a comprehensive dataset covering REE production, renewable energy use, ECI, PCI, and GDP growth from 1990 to 2023. The countries under consideration are China, the USA, Myanmar, Malaysia, Brazil, Australia, Thailand, India, Russia, Madagascar, Sri Lanka, and Vietnam. Their selection is based on data availability and their prominence as the primary global REE producers and exporters from 1990 to 2023. The data for this study were sourced from reputable international databases, including the United States Geological Survey (USGS) for REE production statistics, the International Energy Agency (IEA) for renewable energy data, the World Bank for GDP growth(The World Bank, 2022), and the Observatory of Economic Complexity for complexity indices, such as PCI and ECI. These sources ensure the reliability and comprehensiveness of the data used in our analysis. The data for REE production are measured in metric tons. Renewable energy use data, expressed in terawatt-hours (TWh), and economic complexity indices (ECI and PCI) have values representing the complexity and diversity of a country's exports. GDP growth data are measured in percentage. The public data on REE production from the United States Geological Survey (USGS, 2023), serves as the official statistical repository for mineral production. Data on the ECI and PCI from the Observatory of Economic Complexity (OEC, 2023) reflect a country's ranking in terms of technological expertise necessary for manufacturing intricate technological applications or products and the diversity of its export basket based on versatile products. Developed by Harvard University, both indices serve as reliable proxies for assessing a country's diverse trade basket and the complexity of manufactured applications based on their technological and industrial advancement and economic diversification.

3.2. Theoretical framework

The theoretical framework explores an empirical association between renewable energy use, mine production of REEs, product complexity, economic complexity, and economic growth as the main explanatory variables (visualized in Fig. 1), which are grounded in the theories of economic complexity and technological innovation. Economic complexity theory posits that the diversity and sophistication of products a country can produce are indicative of its industrial capabilities and knowledge intensity (Hidalgo and Hausmann, 2009). REEs, being critical components in high-tech and renewable energy products, directly contribute to this complexity. The Resource-Based View (RBV) (Münter, 2024) theory also informs our framework, suggesting that unique resources like REEs can provide competitive advantages and drive innovation. Furthermore, the endogenous growth theory, which emphasizes the role of technological change and innovation in economic growth (Cozzi, 2023), underpins our exploration of how REEs and renewable energy technologies foster economic development.

By integrating these theories, we provide a robust conceptual design that elucidates the multifaceted impact of REEs on economic complexity

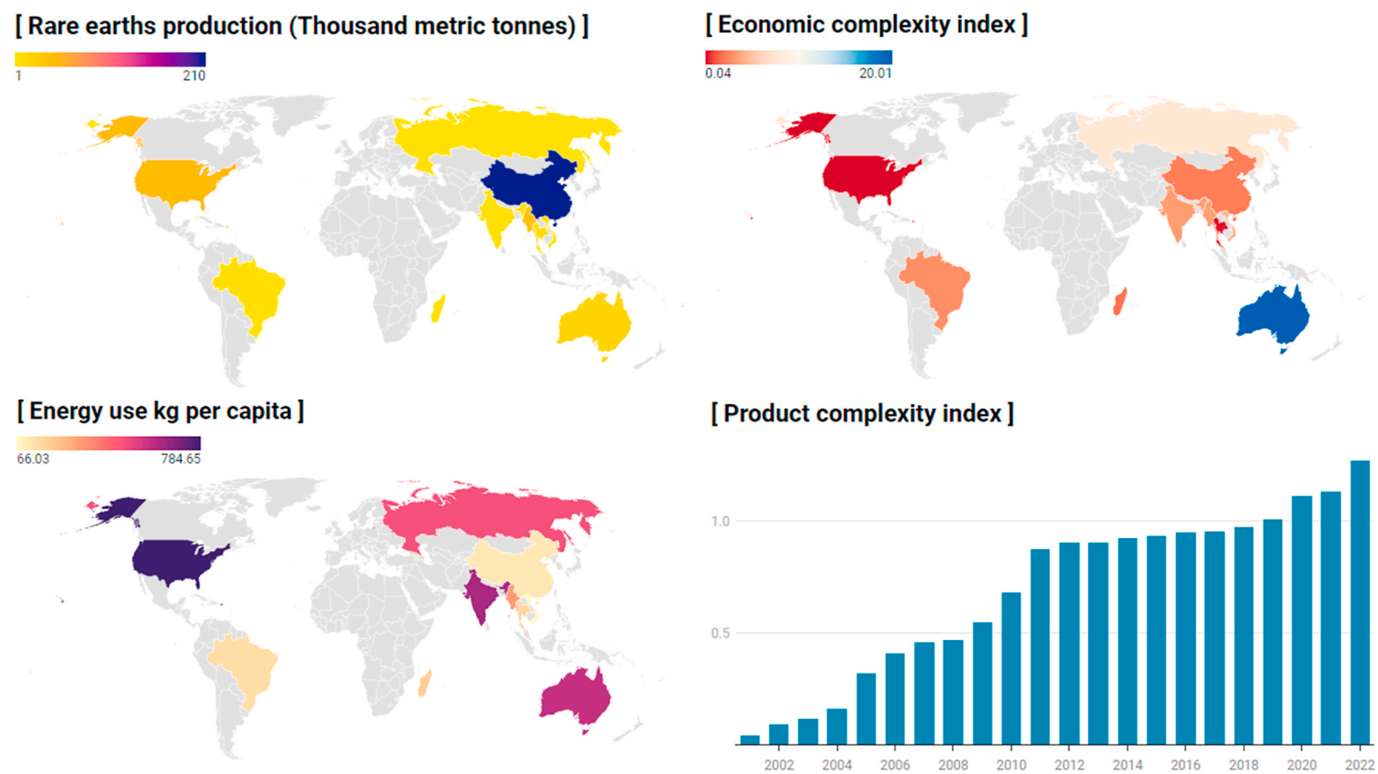

Fig. 1. Graphical representation of data distribution across the variables.

and growth. Therefore, the following equations (1)–(5) explain the functional form of the constructed empirical model.

$$REN_{it} = a_0 + a_1REE_{it} + a_2ECI_{it} + a_3ECG_{it} + a_4PCI_{it} + \varepsilon_{it} \tag{1}$$

$$REE_{it} = a_0 + a_1REN_{it} + a_2ECI_{it} + a_3ECG_{it} + a_4PCI_{it} + \varepsilon_{it} \tag{2}$$

$$ECI_{it} = a_0 + a_1REN_{it} + a_2REE_{it} + a_3ECG_{it} + a_4PCI_{it} + \varepsilon_{it} \tag{3}$$

$$PCI_{it} = a_0 + a_1REN_{it} + a_2REE_{it} + a_3ECG_{it} + a_4ECI_{it} + \varepsilon_{it} \tag{4}$$

$$ECG_{it} = a_0 + a_1REN_{it} + a_2REE_{it} + a_3ECI_{it} + a_4PCI_{it} + \varepsilon_{it} \tag{5}$$

Where t, i, and ε present the time, countries, and error term.

The labels and definitions of the variables from the acquired data are provided in Table 1. The supply of REEs is calculated with the total annual production in thousand metric tonnes domestically from primary or secondary sources. The economic growth is estimated with an annual growth rate of GDP and renewable energy consumption with total renewable energy use of the host country.

Table 1
Names and labels of the variables.

Variable	Explanation
REE	Annual production of rare earth elements (in thousand metric tons)
REN	Total Renewable energy use (in megawatts)
ECG	GDP growth (annual %)
ECI	An index that assesses the level of economic diversification and complexity of a country's economy. It is based on the intensity of the diverse, sophisticated, and complex export basket of the country through trade data.
PCI	A calculation rank that evaluates the diversity and sophistication of a nation's manufacturing industry by considering the range and uniqueness of the products it produces. A country with a wide range of manufacturing knowledge (specialized know-how and skilled human capital) may manufacture diverse, complex, and sophisticated technologies.

3.3. Product complexity index

PCI refers to a rank of a product based on the quantity and level of expertise needed to develop a complex and sophisticated mineral commodity, such as high-tech or specialized machinery, petrochemicals and chemicals, electronics and information communication technologies, etc. as compared to the least products (raw materials and simple agrarian products) and economic complexity. Because the manufacturing of highly sophisticated and complex goods needs a diverse range of knowledge, expertise, and resources (human plus capital) compared to simple products. Therefore, a higher index ranking indicates higher production capability of complex and sophisticated minerals commodities. Thus, PCI is measured based on how many other countries can produce the product and the economic complexity of those countries. Technically breaking out (Harvard University, 2023), PCI can be calculated by measuring the average diversity of a state to manufacture a certain product and the average ubiquity of other goods to be produced by these states, as defined in Eq (6).

$$\widetilde{M}^{P}_{p,p'} = \sum_{c} \frac{M_{cp}M_{cp'}}{k_{c,0}k_{p,0}} \tag{6}$$

3.4. Economic complexity index

ECI indicates the rank of the intensity of the diverse and complex export profile of the country. A country with a wide range of manufacturing knowledge, especially specialized know-how, and skilled human capital, may manufacture diverse, complex, and sophisticated technologies. It has been found that the complexity of a country's exports strongly predicts its present income levels. When a country's complexity exceeds expectations for its income level, the country is expected to grow rapidly in the future, which makes it a useful indicator of economic development. Lastly, ECI can be calculated employing the following equations (7)–(10) for ubiquity and diversity to demonstrate recursion (Hidalgo and Hausmann, 2009):

$$k_{c,n} = \frac{1}{k_{kc,0}} \sum_{p} M_{cp} \frac{1}{k_{p,0}} \sum_{c'} M_{c'p} k_{c',n-2} \tag{7}$$

$$= \sum_{c'} k_{c',n-2} \sum_{p} \frac{M_{c'p} M_{cp}}{k_{c,0} k_{p,0}}$$

$$= \sum_{c'} k_{c',n-2} \widetilde{M}^{C}_{c,c'}$$

Where it can be defined

$$\widetilde{M}^{C}_{c,c'} = \sum_{p} \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}} \tag{8}$$

Hence, in a vector notation, if $\overrightarrow{\boldsymbol{k}}_n$ to be the vector whose cth element is $k_{c,n}$ then:

$$\overrightarrow{\boldsymbol{k}}_n = \widetilde{M}^C \times \overrightarrow{\boldsymbol{k}}_{n-2} \tag{9}$$

where $\widetilde{M}^C$ is the matrix whose (c, c') the element is $\widetilde{M}^C_{c,c'}$.

If increasing n infinitely, we get the following distribution, which stays constant up to a scalar factor:

$$\widetilde{M}^C \times \overrightarrow{k} = \lambda \overrightarrow{k} \tag{10}$$

Therefore, $\overrightarrow{k}$ is an eigenvector of $\widetilde{M}^C$. PCI is defined as the eigenvector relating to the second-biggest eigenvalue of the $\widetilde{M}^C$ matrix.

3.5. Panel long-run elasticities

If an econometric model of panel data suffers from issues of cross-sectional dependence, lagged dependent variables, weak exogenous regressors, and heterogeneity or heteroskedasticity it can yield confusing results. In such a scenario, a statistical model that can generate accurate and consistent results by accommodating these aforementioned problems is an optimum choice. We employed the Common Correlated Effects (CCE) method to estimate panel long-run elasticities. This method effectively addresses cross-sectional dependence and heterogeneity among the panel data, offering more robust and reliable estimates. Our approach includes specific modifications to the CCE method tailored to the unique characteristics of our dataset, enhancing its applicability and accuracy in capturing the complex interactions between the variables. CCE estimation was proposed by (Kapetanios et al., 2011) and extended by (Chudik and Pesaran, 2015) to deal with heterogeneous coefficients of dynamic panels (De Vos and Everaert, 2021). The CCE is one of the most conducive models to estimating long-run estimation of variables as compared to other panel models by performing consistently even under the situation of serial correlation, error of CD, and slope heterogeneity or endogeneity (Karabiyik et al., 2019). Also, it is robust for dynamic heterogeneous panels and panel data having lagged endogenous variables and weak exogenous regressors (Pesaran, 2007). Besides, it allows the association of unobserved variables with exogenous regression, does not accommodate unobserved common factors, and permits cross-sectional dependence of error and heterogeneous properties (Eberhardt, 2012). Thus, keeping in mind the comparative advantages of the CCE, the study employs this econometric model to estimate consistent and efficient parameters for the long-run causal association. The CCE can be estimated and explained using the following typical equations (11)–(13).

$$Y_{it} = \sum_{i=1}^{p} \gamma_{ij} y_{i,t-j} + \sum_{i=1}^{q} \delta_{ij} x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{11}$$

$$\Delta y_{it} = \theta_i \left(y_{i,t-1} + \phi_i x + x_i \right) + \sum_{i=1}^{p-1} \gamma_{ij} \Delta y_{i,t-j} + \sum_{i=0}^{p-1} \delta_{ij} \Delta x_{i,t-j} + \mu_i + \varepsilon_{it} \ \theta = \left(- \sum_{j=1}^{p} \gamma ij \right) and\ \phi = \sum_{i=1}^{q} \delta_{ij} \Big/ \left(1 - \sum_{k} \gamma_{ij} \right) \tag{12}$$

$$\gamma^*_{ij} = - \sum_{i=1}^{p} \gamma i, m; j = 1, 2, 3, p-1 \& \delta^*_{ij} = - \sum_{i=1}^{q} \delta i, m; j = 1, 2, 3, q-1 \tag{13}$$

Where, x_i denotes the explanatory variables, μ_i designates the fixed effect, and γ and δ are the vectors of coefficients in the equation whereas ϕ represents the value of past lag of d (dependent variable), alpha and beta series of d present short-run and long-run coefficients, respectively.

3.6. Temporal causal modelling (TCM)

We employ a panel data econometric approach to analyse the relationship between REE production, renewable energy use, economic complexity indices (ECI and PCI), and GDP growth. TCM is a specialized methodology designed for inferring proper panel Granger causality within time series and longitudinal data. TCM offers the advantage of flexibility, allowing for the derivation of country-specific results through the fixation of effects and random causal effects without cross-section control. The choice of panel data models, such as Fixed Effects (FE) and Random Effects (RE) models, is motivated by their ability to control for unobserved heterogeneity and capture the dynamic nature of our variables (Baltagi, 2008). Specifically, the FE model helps account for time-invariant characteristics within countries, while the RE model provides efficiency in estimating the effects of time-variant variables. Our methodological approach is further justified by previous studies that have successfully applied these models to similar contexts (Antonakakis et al., 2017; Apergis and Payne, 2010).

Another notable feature of TCM is its adaptability to simultaneously consider a variable as both input and target. This modelling approach involves identifying a specific group of target time series and their potential influencing factors. Subsequently, autoregressive time series models are developed for each target, incorporating only those potential influences that show a genuine causal connection with the respective target. In the context of temporal causal modelling (TCM), the term “causal” specifically refers to Granger causality (Tiwari et al., 2023). Granger causality suggests that one-time series, denoted as X, is considered to “Granger cause” another time series, denoted as Y, if regressing Y while considering both past values of X and Y results in a more effective model for Y compared to a regression that relies solely on previous values of Y (Runge et al., 2019). This concept is illustrated in equations (14) and (15). IBM SPSS Statistics v.26 was utilized to implement TCM for assessing the mutual, individual, and synergistic causal impacts of all variables. The variable representing periodic observations (Year) was processed into the period field, and the variable country ID was removed to obtain panel causality results. Missing values, if any, were included by computing based on the linear interpolation method. The confidence interval and threshold for outliers were set to 95%, while the model tolerance was set to 0.001 by default. The automatic option was selected to determine the number of lags for each input. The F-statistic was used to assess the significance level of causality, subsequently accepting or rejecting the null hypothesis, and R2 and RMSE were used to evaluate the overall quality and performance of the TCM model.

$$Y_t = a + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + \beta_4 Y_{t-4} + \ldots + \beta_p Y_{t-p} + \varepsilon_{it} \tag{14}$$

$$Y_t = a + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_p Y_{t-p} + \ldots + \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \gamma_q X_{t-q} + \varepsilon_{it} \quad (15)$$

If the second model (which includes past values of both X and Y) provides a better fit for predicting Y compared to the first model (which includes only past values of Y), then it is concluded that X Granger causes Y. In other words, the past values of X contain information that improves predictions of Y beyond what can be achieved with only past values of Y.

4. Results

4.1. Statistical summary and correlation

Table 2 shows a statistical summary of all variables demonstrating the normal distribution of data across the variables, except for the REE, REN, and ECG variables where standard deviations surpassed a typically acceptable threshold, suggesting a considerable discrepancy in the distribution of observations. Besides, the skewness of REE exceeded the acceptable thresholds of normality, indicating comparatively heavy left-tailed data. The normality statistics indicate a significant degree of variability and deviation in the data of these variables. This variability can largely be attributed to significant disparities in the production capacity or quantities of REEs. For example, China's substantial production of 210,000 metric tons in 2022, which accounts for approximately 70% of the total, stands in stark contrast to Madagascar's relatively modest output of 960 metric tons, representing a mere 0.03% of the total production. These substantial production discrepancies highlight the wide-ranging nature of REE production across different regions. The rest of the variables show a normal distribution of data. Similarly, the renewable energy production of China reached 87 GW in recent years, however, it is only 3.18 GW for Vietnam, showing a substantial discrepancy. The same is the case with ECG as well. However, except for REE, the statistics indicated no significant skewed data in the variables. Furthermore, Fig. 2 portrays the correlation matrix using a heatmap technique.

4.2. CD and heterogeneity

Before employing advanced statistical analysis of panel data or determining the course of causality, it is very important to check the error of cross-sectional dependence in the panels. This study applied two tests for cross-sectional dependency (Friedman, 2012; Pesaran, 2021) and another for checking the heterogeneity of coefficients (Blomquist and Westerlund, 2013). The test of slope heterogeneity proposed by Pesaran and Yamagata (2008) is very popular for large panels. The results of cross-sectional dependence and slope heterogeneity tests are described in Table 3. The statistics of CD tests reject the null hypothesis confirming the presence of cross-sectional dependence in the panels, suggesting that the selected variables of the sample have considerable interdependence across the panel dynamics/sections. Besides, statistical significance at both fixed and random effects models suggests that there is not a substantial discrepancy between both, inferring the random effects model would be appropriate to infer causality.

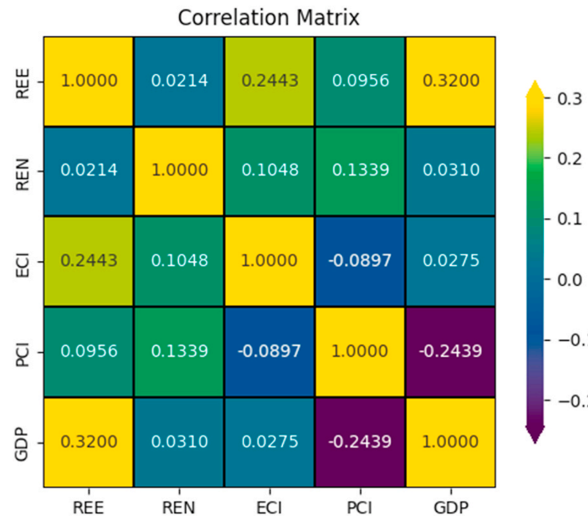

Fig. 2. Correlation matrix with heatmap.

Table 3
CD tests.

Cross-sectional dependence tests	Friedman	Pesaran
Fixed effects	40.795[a] (0.0000)	4.225[a] (0.0000)
Random effects	40.868[a] (0.0000)	4.157[a] (0.0000)

Note.
[a] Presents a significance level of 1%.

4.3. Stationarity

As the previous findings revealed the presence of cross-sectional dependence in heterogenous panels, the subsequent step is to employ the unit root tests to check the stationarity of the data. The modern economist is typically not restricted to univariate time series but employs analysis using panel data. Many panel series have a shorter time dimension but are observed over many cross-sections. The steep assumption of cross-sectional homogeneity prevents the application of just first-generation unit root tests that may not produce efficient results. Therefore, we use first and second-generation unit root tests to have robust results (Pesaran et al., 2013; Pesaran, 2012). The outcomes of 1st (IPS) and 2nd generation (CIPS) stationarity tests in Table 4 rejected the null hypothesis by a thumb rule of the majority, suggesting the presence of unit roots in the panels at the level I(0) and 1st difference I(1). In other words, the data is stationary both at level I(0) and the 1st difference I(1), which leads us to perform cointegration tests to check the integration of variables in the same order.

Table 2
Statistical summary of the group sample.

	REE	REN	PCI	ECI	ECG
Mean	14.78	33.59	0.72	0.85	5.28
Median	2.00	23.98	0.90	0.88	4.82
Maximum	168	87.35	1.27	1.99	17.98
Minimum	0.1	3.18	0.1	0.01	0.004
Std. Dev.	34.19	27.13	0.34	0.55	3.23
Skewness	2.69	0.73	−0.45	0.16	0.82
Kurtosis	8.98	2.27	1.94	1.87	3.67
Jarque-Bera	567.36	23.23	16.91	12.08	27.96
Probability	0.0000	0.0000	0.0000	‘0.0000	0.0000

Table 4
Results of 1st and 2nd generation panel unit root tests.

Variable	IPS		CIPS	
	I(0)	I(1)	I(0)	I(1)
REE	1.14 (0.8740)	−4.42* (0.0000)	−1.22	−3.35*
ECI	−3.58* (0.0002)	−10.57* (0.0000)	−3.01*	−5.29*
PCI	−3.78* (0.0001)	−11.74* (0.0000)	−4.21*	−5.67*
ECG	−2.97** (0.0015)	−9.51* (0.0000)	−3.43*	−5.32*
REN	−1.17 (0.1205)	−3.52* (0.0002)	−1.22	−3.44*

Note: * and ** refer to significance levels at 1% and 5%.

4.4. Cointegration

Westerlund and Edgerton (2008), Pedroni (2004), and Johansen (1991) cointegration tests were applied to assess equilibrium procedures in long-run relationships (see whether the stationary panels are integrated in the same order or not). As shown in Table 5, the statistical significance of both applied tests again rejects the null hypothesis, which means that panels are cointegrated in order and the existence of long-run association is confirmed. It is evident that the heterogeneous panels have cross-sectional dependence, stationarity at I(0) and I(1), and long-run cointegration equilibrium.

4.5. Panel long-run elasticities

Keeping in mind that the panels are cross-sectionally dependent, heterogenous, dynamically integrated, and stationery at least at the level I(0) or 1st difference I(1), the next step is to employ CCE in STATA^{MP} v.16, which is one of the most conducive models to estimating long-run estimation of variables as compared to other panel models by performing consistently even under the situation of serial correlation, error of CD, heteroskedasticity, and slope heterogeneity as in our case as shown in Table 7. Therefore, Table 6 summarizes panel long-run estimations, indicating the long-run elasticities of all causal models. The empirical findings imply that renewable energy use stimulates the production of REEs, economic growth, economic complexity (ECI), and product complexity (PCI) in the long run. Similarly, the supply of REE promotes renewable energy expansion, product and economic complexity, and economic growth. Going into details, the results show a positive relationship between renewable energy use and REE supply, revealing that a 1% rise in renewable energy use raises REE supply by 0.53% in the long run, which infers that renewable energy consumption plays a pivotal role in influencing the production of REEs, driven by its direct impact on various stages of the REE supply chain. Moreover, a 1% increase in renewable energy use contributes to increasing economic complexity, product complexity, and economic growth by 3.07%, 4.86%, and 0.18% in the long run respectively, which suggests that renewable energy use plays an instrumental role in enhancing industrial and manufacturing capabilities, diversity of complex and high-tech exports and trade sector, and overall economic growth by increasing green productivity.

The research findings indicate that a 1% increase in REE production is associated with a long-term increase of 0.42% in the utilization of renewable energy. This relationship stems from the essential role of REEs in the manufacturing of green energy technologies, leading to higher demand and subsequent production of REEs. Moreover, the production of REEs contributes to a rise in product and economic complexity by 11.93% and 3.83%, respectively, in the long-term equilibrium. Additionally, an increase in product complexity by 0.1% leads to a 0.05% increase in both REE production and the use of renewable energy, as well as a 0.05% growth in GDP. Furthermore, economic growth positively influences REE supply and renewable energy use by 0.01% each. Consequently, GDP growth contributes positively to REE production and product complexity by 0.03% and 2.92%, respectively, in sequential order.

Table 5
Cointegration estimations.

	Westerlund	Pedroni	Johansen
Variance ratio	6.55[a] (0.0000)		
Modified Phillips-Perron t		3.83[a] (0.0001)	
Phillips-Perron t		4.03[a] (0.0000)	
ADF t		3.58[a] (0.0002)	
Trace test			240.4[a] (0.0000)
Max-eigen test			161.5[a] (0.0000)

Note.
[a] Presents a significance level of 1%.

Table 6
Panel long-run estimations with CCE.

Regressors	→REN	→REE	→PCI	→ECI	→ECG
REN	–	0.53** (2.38)	4.86* (7.23)	3.07* (4.88)	0.18** (1.92)
REE	0.42** (2.12)	–	11.93* (5.43)	3.83*** (1.84)	0.82* (2.71)
PCI	0.1* (5.27)	0.01* (5.81)	–	0.01 (0.16)	0.05* (7.35)
ECI	0.01** (2.67)	0.01** (2.66)	−0.03 (−0.51)	–	−0.01 (−0.27)
ECG	0.02 (1.00)	0.03** (2.20)	2.92* (7.87)	−0.18 (−0.49)	–

Note: * and ** refer to significance levels of 1% and 5%.

Table 7
Diagnostic tests.

Residual Serial Correlation LM Tests	
LRE* stat	72.97 (0.0000)
Rao F-stat	3.02 (0.0000)
Slope heterogeneity tests	
Delta	−0.346 (0.729)
adj.	−0.414 (0.679)
Residual Heteroskedasticity Tests	
Chi-sq	24.22 (0.0070)
F-statisics	2.60 (0.0055)

4.6. Results of panel causality with TCM

As aforementioned, CCE is not primarily intended as a proper panel causality model; rather, its purpose lies in addressing issues of unobserved heterogeneity and endogeneity in longitudinal data analysis in the long run. It aims to account for unobserved variables that may influence the variables of interest in longitudinal data, thereby mitigating potential biases in estimating coefficients. Thus, we use TCM as a suitable causality model for analysing panel data. It enables the exploration of causal relationships among variables over time, facilitating the investigation of both the direction and magnitude of causal effects between variables in a longitudinal context, while considering both cross-sectional and temporal interdependencies.

Therefore, we implement TCM to derive comprehensive panel causality results, incorporating the Granger causality approach to analyse both time series and panel data. We used IBM SPSS Statistics v.26 to run TCM and generate the results. Given the utilization of panel data from 10 countries from 2000 to 2023, we eliminated a categorical country variable within the dimensions to rectify country identity issues. The Year variable transformed a period field to delineate cyclic periods. We processed all variables both as input and target variables to determine mutual causality. Any missing values (not exceeding 25% of the maximum percentage) were addressed through linear interpolation as a substitution method. The confidence interval was set at 95%, with a model tolerance of 0.001 and an outlier threshold of 95%. The determination of the number of lags was conducted automatically there were 5 maximums. Fig. 3 provides an overview of the overall causal outcomes yielded by the TCM models, while Table 8 presents a comprehensive evaluation of the overall model's quality, considering fit statistics, such as RMSE, AIC, BIC, and R-square. These metrics are utilized to assess the overall quality of the models for each target variable.

Overall, the TCM model demonstrates high accuracy, indicating an excellent fit for all target variables with RMSE values below 0.10 and R-square values exceeding 0.90, except for economic complexity, which stands at 0.82, still indicative of a good fit. This suggests that all models achieved more than 90% accuracy whereas the ECI model still achieved 82% prediction accuracy for causal inference. Another frequently

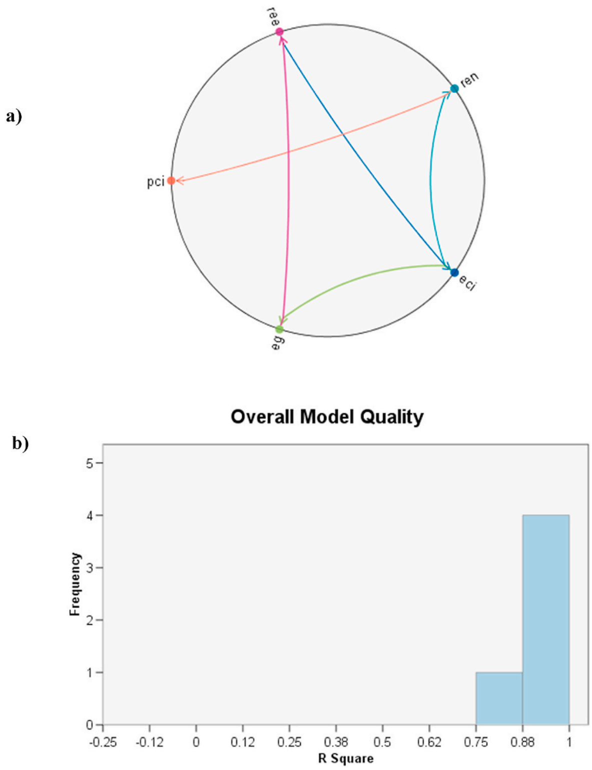

Fig. 3. Overall model system and overall quality assessment with R-square.

Table 8
Fit statistics for top models taking each variable as a target variable.

Model for target	RMSE	AIC	BIC	R-square
REN	3.20	40.62	49.12	0.99
REE	8.76	72.85	81.34	0.99
PCI	0.45	−22.19	−13.69	0.99
ECG	5.37	57.16	65.66	0.92
ECI	0.41	−25.28	−16.78	0.82

employed method to assess the accuracy of a model's predictions involves plotting observed values against predicted series to evaluate the degree of alignment between them (Piñeiro et al., 2008). In Fig. 4, visual representations are provided regarding the alignment of observed values with predicted series. This visualization confirms that the model effectively captures the underlying patterns and relationships inherent in the data, as evidenced by the close correspondence between observed and predicted values.

Moreover, Fig. 5 provides a comprehensive overview of the mutual causal relationships identified through the TCM, presented in three three-level impact diagrams. The findings presented in Fig. 5**a** reveal that REE production exhibits positive Granger causal effects on the utilization of renewable energy. Furthermore, Fig. 5**b** illustrates that REEs indirectly influence product complexity through their impact on renewable energy consumption. Similarly, in Fig. 5**c**, it is evident that renewable energy use stimulates growth in the product complexity index. Moving forward, Fig. 5**d** elucidates that economic growth directly Granger causes REE production, and indirectly affects economic complexity through REE supplies. This suggests that economic growth fosters an increase in REE production, thereby elevating economic complexity, which serves as an indicator of trade diversification. Additionally, Fig. 5**e** demonstrates that renewable energy Granger causes product complexity, highlighting that the expansion of the renewable energy sector fosters manufacturing and industrial capabilities for producing high-tech applications.

Moreover, in Fig. 5**e**, the effects of REE supply on economic complexity, renewable energy, and economic growth are depicted. This suggests that the availability of REEs contributes to trade diversification, potentially through the manufacturing and export of renewable energy technologies, thereby stimulating overall economic growth. Finally, Fig. 5**f** portrays that economic complexity directly impacts renewable energy use and indirectly influences economic growth. This indicates that a higher economic complexity ranking expands the renewable energy sector and promotes overall economic growth. Furthermore, economic complexity indirectly affects product complexity and REE production, implying that it enhances industrial and manufacturing capabilities to produce complex products utilizing rare earths as critical raw materials. The results derived from the TCM model provide profound insights, aligning closely with the findings obtained from the CCE model.

5. Discussion

Our results reveal significant relationships between REE production, renewable energy utilization, and economic complexities. Compared to previous studies, which primarily focused on direct economic impacts, our findings highlight the nuanced synergistic pathways that drive economic diversification and technological advancement. Notably, our study uncovers the pivotal role of REE production in fostering renewable energy adoption, which in turn enhances both product and economic complexities. This contrasts with earlier research that often treated these elements in isolation. We discussion our findings point by point while comparing each result with the previous studies on this topic.

5.1. REE supply promotes renewable energy and product and economic complexities

The results indicate that the production of REEs contributes to an increase in renewable energy use. This highlights the critical role of REE supply in the manufacturing and expansion of renewable energy technologies, such as wind turbines, hybrid electric vehicles (EVs), and solar modules. Our results indicate that the production of REEs significantly contributes to the expansion of renewable energy technologies, which aligns with findings by Sovacool et al. (2020) and Geng et al. (2023). Key REEs, such as neodymium, praseodymium, dysprosium, and terbium, enhance the magnetic efficiency of wind turbines, while samarium, europium, and terbium are essential for solar panels. This is consistent with Apergis and Apergis (2017), who highlighted the importance of lanthanum, cerium, and praseodymium in manufacturing rechargeable batteries for energy storage in renewable systems.

Additionally, our findings corroborate Gramling (2023), who emphasized the role of rare earth phosphors like europium and yttrium in energy-efficient lighting technologies. The application of neodymium-iron-boron magnets in geothermal power plants, as discussed by Zhou et al. (2016) and Alonso et al. (2012), further supports the critical role of REEs in renewable energy technologies. By facilitating the development and deployment of these technologies, REE supply enhances renewable energy production, promoting a transition to a low-carbon future and supporting the achievement of Sustainable Development Goals (SDGs). Moreover, our research extends the work of Zapp et al. (2022), by demonstrating how the utilization of REEs in high-tech product manufacturing contributes to product complexity and economic growth. As industries incorporate REEs, they stimulate innovation and research, fostering economic complexity and enhancing trade diversification and competitiveness (Serpell et al., 2021; Islam et al., 2022). Investments in research and development aimed at improving the efficiency and performance of renewable energy technologies contribute to technological advancements and economic complexity.

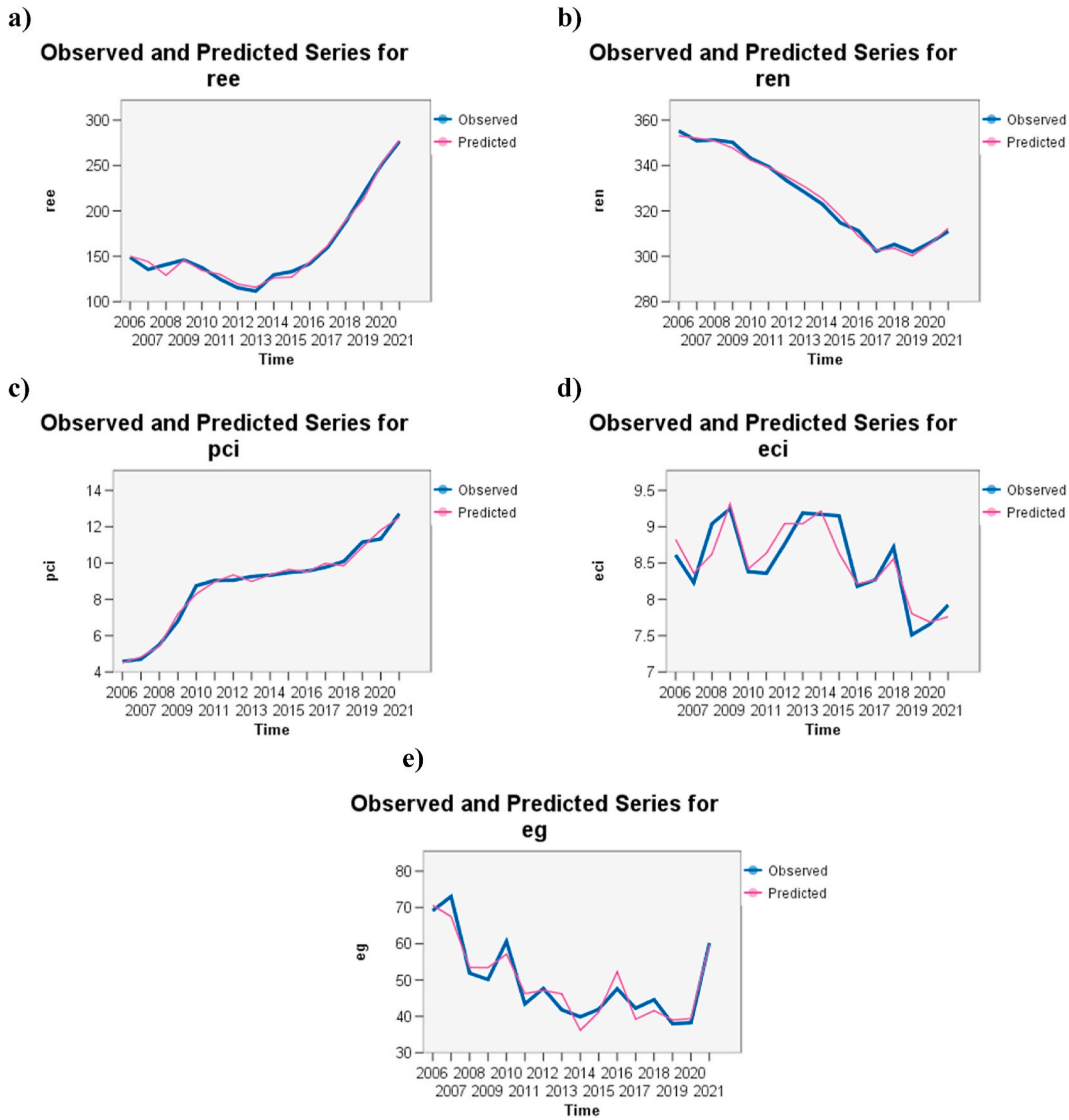

Fig. 4. Observed versus predicted series for all variables.

5.2. Renewable energy use elevates product complexity index

Consistent with previous studies by Lorente (2020), Pata (2021), and Buhari et al. (2020), our findings affirm that renewable energy use promotes economic complexity. Renewable energy utilization drives product complexity by necessitating advanced industrial capabilities and knowledge to manufacture sophisticated technologies. The constant need for energy efficiency and environmental sustainability requires research and innovation for advancing renewable energy technologies and storage systems (Baz et al., 2022), which necessitates the development of intricate components, thereby contributing to the complexity of exported products. This aligns with Min (2022), and Bouteska et al. (2023), who observed that the exportation of advanced renewable energy technologies fosters economic diversification. As countries adeptly manufacture and export these technologies, opportunities for product complexity growth arise, exemplified by the exportation of advanced wind turbines and solar cells to nations seeking to expand their renewable energy capacity. Investments in renewable energy prompt diversification in manufacturing capabilities, as countries expand their production capacities to meet the demand for renewable energy components. These findings further endorse the findings of Abbas et al. (2024) and Solangi et al. (2024) that the use of renewable energy technologies drives technological advancement (Technology complexity) and research and development (Research complexity), leading to industrial diversification, and innovation, contributing positively to the product complexity index (PCI).

5.3. Economic growth increases REE demands and promotes the economic complexity index

The outcomes provide concrete evidence that economic growth increases REE supply and enhances economic complexity. As economies grow, the demand for technologies reliant on REEs increases, driving REE production and supporting economic complexity, such as renewable energy systems, electronics, electric vehicles, cybernetics, telecommunications, space apparatus, and health equipment. This is supported by Czerwinski (2022), and Balaram (2019), who noted that REE production requires sophisticated technological capabilities, fostering innovation and skill development. Furthermore, our research aligns with Filho et al. (2023), who highlighted that the production and export of REE-related products diversify industrial portfolios and enhance economic complexity. Economic growth stimulates R&D investments, exploring new applications and processes for REEs Mohamed et al. (2022), which further elevates the economic complexity index (ECI) through multiple channels. Firstly, the production of REEs necessitates sophisticated technological capabilities, leading to the

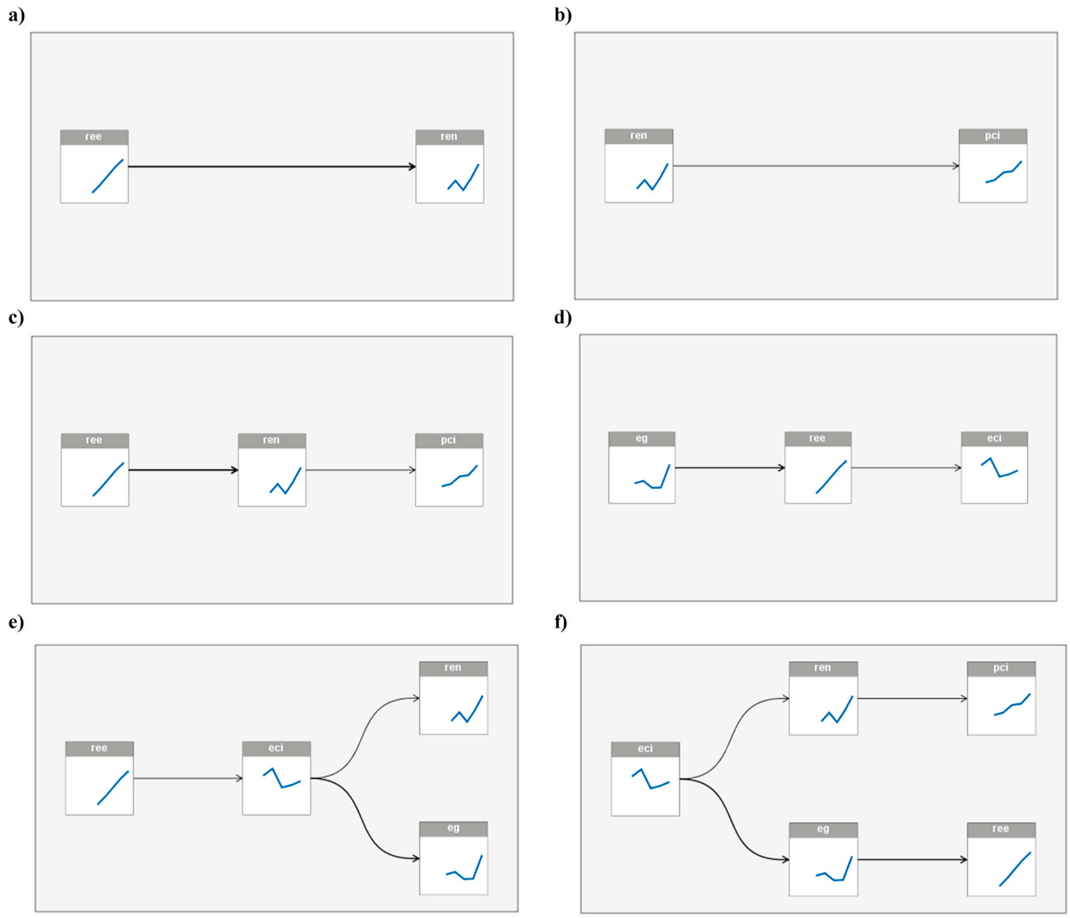

Fig. 5. The total outputs of the causal effect model provide an assessment of the causes and effects of the series using a three-level impact diagram: **a)** It reveals the causal effects of REE production on renewable energy use, **b)** It shows the effects of renewable energy on product complexity, **c)** It visualizes the causes of REE production on product complexity through renewable energy use, **d)** It shows the causes and effects of economic growth with respect to REE production and economic complexity, **e)** It illustrates the causes and effects of REE production in relation to economic complexity, economic growth, and renewable energy, and subsequently, **f)** It demonstrates the causes and effects of economic complexity concerning renewable energy, economic growth, product complexity, and REE production.
Note: the blue curve indicates the trend of causality: however, the bold dark arrow curve refers to statistically significant causation.

development of a skilled workforce and fostering innovation in manufacturing processes (Ada et al., 2021). These advancements contribute to the overall complexity of economic activities, thereby elevating the ECI. Secondly, as countries engage in the production and export of REE-related products, such as advanced materials and high-performance magnets, they diversify their industrial portfolios (Dutta et al., 2016). This diversification, coupled with the intricate nature of REE-related manufacturing processes, enriches the overall economic landscape and bolsters the ECI. Finally, the pursuit of economic expansion fosters investments in technological innovation and industrial diversification, ultimately promoting a higher level of economic complexity as indicated by the ECI.

5.4. Economic complexity increases renewable energy use and economic growth

The findings also highlight that economic complexity contributes to raising renewable energy use and economic growth, showcasing how economic complexity fosters the expansion of renewable energy use and drives overall economic growth. Our findings indicate that economic complexity fosters renewable energy use and economic growth, in line with Numan et al. (2023). Economies with diverse and sophisticated industrial capabilities are better equipped to produce and adopt renewable energy technologies. This facilitates the development of skills, expertise, and infrastructure necessary for manufacturing these technologies, promoting their widespread adoption. Moreover, the growth of renewable energy sectors contributes to economic diversification and job creation, further augmenting economic complexity. Additionally, a complex and diverse economy is better equipped to leverage renewable energy investments, leading to enhanced productivity, reduced energy waste, and lower production costs. This, in turn, fosters innovation, stimulates economic growth, and reinforces the cycle of economic complexity, renewable energy utilization, and overall economic development. These findings are consistent with Hoa et al. (2024), who observed that economic complexity leverages renewable energy investments to enhance productivity and reduce production costs. This fosters innovation and stimulates economic growth, reinforcing the cycle of economic complexity, renewable energy utilization, and overall economic development. Our findings contribute significantly to the existing body of knowledge by demonstrating the crucial role of REEs in facilitating renewable energy adoption and economic complexities. This research provides policymakers and industry stakeholders with actionable insights into the synergies between REE supply and renewable energy technologies, essential for strategic planning and sustainable development.

6. Conclusion and policy implications

The primary objective of this empirical study was to explore the interconnected pathways between REE production, renewable energy utilization, economic and product complexities, and GDP growth that can facilitate the transition towards a low-carbon future. Employing TCM on panel data spanning from 1990 to 2023 from major REE-producing nations, our investigation revealed robust insights into these dynamics. This study significantly contributes to the existing literature by unveiling the intricate synergistic pathways between REE production, renewable energy utilization, and economic complexities. The innovative application of CCE and TCM methods provides deeper insights into these relationships, offering valuable guidance for policymakers and industry stakeholders. Our findings suggest that strategic investments in REE production and renewable energy technologies can drive economic diversification and technological sophistication, crucial for achieving sustainable economic growth. Specifically, the increased production of REEs significantly boosts the development and deployment of renewable energy technologies, contributing to economic and product complexities. This underscores the critical importance of strategic management of REE resources in fostering sustainable economic growth. Moreover, our results demonstrate that renewable energy use positively impacts economic complexity by promoting industrial diversification and technological advancement. This finding aligns with the broader literature emphasizing the role of renewable energy in enhancing economic resilience and innovation. Additionally, the study shows that economic complexity facilitates the adoption of renewable energy technologies, creating a positive feedback loop that further stimulates economic growth.

The implications of these findings are profound for policymakers and industry stakeholders. Prioritizing investments in REE production and renewable energy technologies can drive industrial development, enhance economic diversification, and support the transition to a low-carbon economy. This accentuates the imperative of investing in green energy sources to diversify renewable energy supplies, necessitating the expansion of sophisticated clean energy technologies reliant on REEs. Solar photovoltaic panels, wind turbines, nuclear reactors, batteries, fuel cells, and electric vehicles exemplify indispensable components essential for realizing a low-carbon future and achieving sustainable development objectives (Sovacool et al., 2020). This, on the one hand, will ensure environmental sustainability and reduce carbon footprints and emission intensity. On the other hand, it will strengthen the government's grip on controlling energy poverty and potential health issues by providing efficient and clean energy at household and macro levels (Abbas et al., 2020). However, the magnitude of these impacts hinges on multifaceted factors such as the scale of REE production, global supply chain management, resource governance, and energy costs. In addition, the energy-intensive nature of REE production underscores its sensitivity to variations in energy availability and cost (Considine et al., 2023). Such variations can downgrade the product and economic complexity rankings of a country, especially for industries directly affected by REE prices. Addressing the anticipated surge in demand for REEs necessitates proactive measures to mitigate supply chain vulnerabilities and environmental impacts associated with traditional extraction practices (Bai et al., 2022).

Therefore, an adequate and consistent supply of clean energy and rare earth minerals become fundamentally important for inclusive green growth with challenges lying in their best extraction and processing of REEs. These attached risks can be minimized by considering the following policy steps. Firstly, the critical role of REEs in renewable energy technologies necessitates the development of strategic policies to ensure a stable and sustainable supply of these elements. In this context, diversification of REE supplies through eco-friendly mining techniques and enhanced recycling initiatives emerges as a viable solution. These strategies encompass exploring additional REE deposits under the seabed and continental shelves (Takaya et al., 2018), recycling electronic waste (Binnemans et al., 2013) at the industrial level, and implementing modern extraction practices, such as biomining (Dawson, 2021), hydrometallurgical method (Ruiz et al., 2020), agromining (Mirkouei, 2021), electrokinetic mining (Wang et al., 2022), droplet-based microfluidic technique (Chen et al., 2022) and reusable biosurfactant (Li et al., 2020a,b), etc. Bolstering efficient recycling endeavors not only mitigates geopolitical tensions and supply chain disruptions but also promotes a circular economy paradigm. Consequently, this ensures a sustainable REE supply chain while reducing the adverse environmental impacts of extraction activities (Geng et al., 2023; Du and Graedel, 2011).

Secondly, policymakers should incentivize the adoption of renewable energy technologies through subsidies, tax incentives, and regulatory frameworks that support the development of green energy infrastructure. By fostering a favorable investment climate for renewable energy, countries can enhance their economic complexity and drive sustainable industrial growth. This will also stabilize the skyrocketing price fluctuation of REEs and manufactured high-tech commodities in the global market, which will eventually have positive impacts on industrial diversification, technological sophistication, and overall economic development improving ECI and PCI ranking a country. The expansion of the diversified energy sector driven by the vital utility of REE also underscores the critical role of renewable energy in industrial and manufacturing activities, affordable access to clean energy plays an instrumental role in achieving sustainable and versatile technological and economic growth. Without this, the technological progress of energy transitions may slow down, and efforts to reduce costs could be hindered. Stable REE prices resulting from improved supply chain resilience will foster industrial diversification, technological sophistication, and overall economic development. A stable energy supply, coupled with investment incentives in energy-intensive industries, including manufacturing and mining, will stimulate job creation and foster favorable business prospects domestically. Thirdly, international cooperation is essential to manage the global supply chain of REEs and renewable energy technologies. Collaborative efforts can help mitigate supply risks, enhance technological innovation, and promote sustainable practices across the value chain. Finally, integrating renewable energy policies with broader economic development strategies can maximize the benefits of economic complexity. This includes investing in education and training programs to develop a skilled workforce capable of supporting advanced manufacturing and technological innovation. These policy recommendations provide a roadmap for leveraging REE production and renewable energy adoption to achieve sustainable economic growth and diversification.

Finally, this study enriches the scientific community's understanding by empirically validating the interconnectedness of REE production, renewable energy, and economic growth. Our results underscore the importance of sustainable REE supply chains to support the clean energy transition and economic diversification, thereby guiding future research and policy initiatives in these critical areas. This holistic approach aligns with the overarching goals of sustainable development, paving the way for a resilient, complex, and sustainable global economy. However, the study's limitations, such as its focus on primary REE-producing countries and potential data inaccuracies, highlight the need for further research. Future studies should explore these dynamics in a broader context, incorporating a wider range of countries and more precise data to validate and extend our conclusions. The study further emphasizes the exploration of the environmental impacts of REE production, the potential for recycling, and reuse of REEs in renewable energy technologies, and sustainable utilization of specific REEs used in energy and transportation sectors through life cycle assessment. Future research should also explore the long-term impacts of these dynamics and consider the role of emerging technologies and global market trends.

CRediT authorship contribution statement

Khizar Abbas: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shisi Zou:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Conceptualization. **Deyi Xu:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Khalid Manzoor Butt:** Validation, Supervision, Project administration, Investigation. **Qing Han:** Visualization, Methodology, Investigation, Conceptualization. **Khan Baz:** Visualization, Validation, Supervision, Software, Conceptualization. **Jinhua Cheng:** Visualization, Validation, Software, Project administration, Methodology, Investigation. **Yongguang Zhu:** Validation, Project administration, Methodology, Investigation, Conceptualization. **Sanwal Hussain Kharl:** Visualization, Validation, Software, Investigation, Data curation.

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.

Data availability

Data will be made available on request.

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Appendix

Appendix 1
Parameter estimates for economic complexity

Model Term		Coefficient	Std. Error	T	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept		14.73	7.30	2.02	0.099	−4.02	33.49
eci	Lag 1	0.01	0.39	0.03	0.974	−0.98	1.01
	Lag 2	−0.39	0.38	−1.01	0.359	−1.38	0.60
	Lag 3	0.19	0.39	0.48	0.651	−0.81	1.19
	Lag 4	−0.50	0.37	−1.35	0.236	−1.46	0.46
	Lag 5	0.16	0.37	0.43	0.688	−0.79	1.10
ree	Lag 1	−0.01	0.01	−1.30	0.251	−0.04	0.01
	Lag 2	−0.01	0.02	−0.67	0.532	−0.06	0.04
	Lag 3	0.02	0.02	0.83	0.444	−0.04	0.07
	Lag 4	0.01	0.02	0.24	0.818	−0.05	0.06
	Lag 5	−0.01	0.02	−0.49	0.642	−0.05	0.03

Appendix 2
Parameter estimates for economic growth

1		Coefficient	Std. Error	T	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept		168.31	90.27	1.86	0.121	−63.73	400.35
eg	Lag 1	−0.18	0.33	−0.54	0.610	−1.02	0.66
	Lag 2	−0.06	0.24	−0.24	0.820	−0.67	0.55
	Lag 3	0.67	0.37	1.82	0.128	−0.27	1.62
	Lag 4	0.41	0.38	1.07	0.335	−0.57	1.39
	Lag 5	−0.60	0.24	−2.49	0.055	−1.23	0.02
eci	Lag 1	−1.33	3.82	−0.35	0.742	−11.15	8.50
	Lag 2	−4.69	4.18	−1.12	0.313	−15.45	6.06
	Lag 3	7.81	7.74	1.01	0.359	−12.09	27.71
	Lag 4	−1.46	6.98	−0.21	0.843	−19.39	16.47
	Lag 5	−15.72	7.06	−2.23	0.642	−33.86	2.42

Appendix 3
Parameter estimates for product complexity

Model Term		Coefficient	Std. Error	T	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept		10.23	10.64	0.96	0.380	−17.12	37.59
pci	Lag 1	0.77	0.35	2.18	0.081	−0.14	1.67
	Lag 2	−0.13	0.50	−0.27	0.798	−1.41	1.14
	Lag 3	−0.05	0.50	−0.10	0.925	−1.33	1.23
	Lag 4	0.22	0.46	0.47	0.659	−0.96	1.40
	Lag 5	−0.01	0.33	−0.04	0.973	−0.86	0.83
ren	Lag 1	0.06	0.05	1.36	0.231	−0.06	0.18
	Lag 2	−0.03	0.05	−0.58	0.585	−0.16	0.10
	Lag 3	0.03	0.06	0.46	0.667	−0.12	0.17
	Lag 4	0.01	0.05	0.10	0.923	−0.12	0.13
	Lag 5	−0.09	0.05	−1.82	0.128	−0.21	0.03

Appendix 4
Parameter estimates for rare earth elements.

Model Term		Coefficient	Std. Error	T	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept		50.62	63.54	0.80	0.462	−112.70	213.95
ree	Lag 1	1.31	0.30	4.39	0.007	0.54	2.08
	Lag 2	−0.59	0.55	−1.08	0.331	−1.99	0.82
	Lag 3	0.57	0.58	1.00	0.365	−0.91	2.05
	Lag 4	0.01	0.75	0.02	0.988	−1.93	1.95
	Lag 5	−0.23	0.56	−0.40	0.702	−1.67	1.21
eg	Lag 1	−0.02	0.78	−0.02	0.985	−2.01	1.98
	Lag 2	0.38	0.68	0.55	0.604	−1.37	2.12
	Lag 3	−0.64	0.64	−1.01	0.360	−2.29	1.00
	Lag 4	0.30	0.59	0.51	0.630	−1.22	1.83
	Lag 5	−1.02	0.45	−2.25	0.074	−2.19	0.14

Appendix 5
Parameter estimates for renewable energy use

Model Term		Coefficient	Std. Error	T	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept		156.64	70.08	2.24	0.076	−23.51	336.79
ren	Lag 1	0.44	0.41	1.07	0.332	−0.61	1.49
	Lag 2	0.63	0.42	1.52	0.189	−0.44	1.71
	Lag 3	−0.17	0.44	−0.39	0.713	−1.31	0.96
	Lag 4	−0.04	0.42	−0.10	0.924	−1.11	1.03
	Lag 5	0.10	0.27	0.39	0.714	−0.59	0.80
eci	Lag 1	−2.31	2.34	−0.99	0.370	−8.32	3.71
	Lag 2	−6.80	2.51	−2.71	0.042	−13.25	−0.35
	Lag 3	−2.35	4.63	−0.51	0.633	−14.25	9.55
	Lag 4	−4.55	3.05	−1.49	0.196	−12.38	3.29
	Lag 5	−1.26	3.76	−0.33	0.751	−2.19	0.14

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