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Unveiling the Environmental Efficiency Puzzle: Insights from Global Green Innovations

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Abstract:	The latest surge of global uncertainty and disruptions in global supply networks put policymakers under pressure to emprise green innovations as a vital tool to address environmental concerns. However, producing green innovations doesn't always help in achieving environment-related sustainable development goals. Therefore, in this study, we endeavour to investigate to what extent green innovations are efficient in improving environmental efficiency. To this end, a network bias-corrected data envelopment analysis and clustering analysis is applied. The data used in this study covers 42 countries from different regions, spanning from 2000 to 2020. The results reveal that most countries have not made major advancements in environmental efficiency signifying the low level of green innovations utilization to achieve environment-related sustainable development goals (SDGs). Additionally, the results demonstrate a U efficiency curve for inputs-oriented green innovations efficiency over time, indicating that the initial stages of green innovations production are associated with a decreased return. However, over time, the efficiency exhibits an upward trend. The benchmarking analysis reveals that South American and European Union nations set the bar for other countries in terms of efficiently leveraging green innovations to achieve SDGs. Our findings also suggest that environmental efficiency is more dependent on green-supporting policies such as green energy production and green taxes. As a result, we conclude that achieving environmental SDGs while utilizing green innovations does not always result in the development of other SDGs. Therefore, policymakers need to prioritize pursuing a green developmental approach and supporting policies to achieve environment-related SDGs and other SDGs.

Title Page with all author details (names, universities and affiliations)

Unveiling the Environmental Efficiency Puzzle: Insights from Global Green Innovations

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Statements and Declarations

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To

The editor

Research Policy

Dear Professor,

In the attached file, we have submitted a research paper titled "**Unveiling the Environmental Efficiency Puzzle: Insights from Global Green Innovations**" for the review process at the **Research Policy** journal. In this paper, we investigate the role of green innovations in achieving SDGs from the environmental efficiency perspective. We analyse green patents and other related green policy data in 42 countries from 2000 to 2020. To measure the green innovations efficiency and environmental efficiency, a network bias-corrected data envelopment analysis and clustering analysis are applied. Our findings reveal that a majority of studied countries have not experienced substantial progress in environmental efficiency, indicating a limited utilization of green innovations towards the attainment of sustainable development goals (SDGs) related to the environment. Consequently, we have identified the underlying factors contributing to this low level of environmental efficiency and have formulated policy recommendations and benchmarking insights that can assist policymakers in formulating customized strategies for promoting green development trajectories. The implications of our research are significant for policymakers and stakeholders involved in the management of green innovation systems. Our study is in line with the thematic scope and focal point of the Research Policy journal.

We confirm that we have not submitted this manuscript for possible publication anywhere else nor it has been submitted as a preprint on any servers. We also confirm that we have no conflict of interest.

Thank you for considering our manuscript for publication in your esteemed journal.

Sincerely,

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Abstract

The latest surge of global uncertainty and disruptions in global supply networks put policymakers under pressure to emprise green innovations as a vital tool to address environmental concerns. However, producing green innovations doesn't always help in achieving environment-related sustainable development goals.

Therefore, in this study, we endeavour to investigate to what extent green innovations are efficient in improving environmental efficiency. To this end, a network bias-corrected data envelopment analysis and clustering analysis is applied. The data used in this study covers 42 countries from different regions, spanning from 2000 to 2020.

The results reveal that most countries have not made major advancements in environmental efficiency signifying the low level of green innovations utilization to achieve environment-related sustainable development goals (SDGs). Additionally, the results demonstrate a U efficiency curve for inputs-oriented green innovations efficiency over time, indicating that the initial stages of green innovations production are associated with a decreased return. However, over time, the efficiency exhibits an upward trend. The benchmarking analysis reveals that South American and European Union nations set the bar for other countries in terms of efficiently leveraging green innovations to achieve SDGs.

Our findings also suggest that environmental efficiency is more dependent on green-supporting policies such as green energy production and green taxes. As a result, we conclude that achieving environmental SDGs while utilizing green innovations does not always result in the development of other SDGs. Therefore, policymakers need to prioritize pursuing a green developmental approach and supporting policies to achieve environment-related SDGs and other SDGs.

Key words: green innovations, sustainable development, network DEA, environmental efficiency, SDG-7, SDG-13.

1. Introduction

Environmental sustainability has emerged as a critical concern in recent times, given the increasing global environmental challenges such as ecosystem degradation, natural disasters, and climate change (Thomas, 2023). However, in light of the global instability, uncertainty, and disruptions in global supply chains, policymakers worldwide are facing pressure to shift the structure of developmental priorities at the expense of environmental SDGs (Adediran & Swaray, 2023; Pata et al., 2023). Therefore, it becomes imperative to devise policy mechanisms that enable policymakers to efficiently manage the limited resources available to achieve SDGs in response to the ongoing changes.

In doing so, green innovations, which refer to the development and application of new technologies, aimed at reducing environmental impacts, have been widely promoted as a means to solve this dilemma and achieve environmental sustainability. However, the efficiency of green innovations in improving environmental sustainability remains a subject of debate in the literature (Du & Li, 2019; Sun et al., 2019).

Important contributions to this discussion have been made by several authors. Most of these contributions emphasize the vital role of green innovations in achieving SDGs. Previous studies argue that natural resource consumption efficiency is relatively higher when using green innovations (Miao et al., 2017; X. Zhao et al., 2022). Other scholars suggest that green innovations significantly reduce CO2 emissions per unit of output while holding current technologies constant (Shahzad et al., 2022; W. Zhang et al., 2017). Accordingly, green innovations contribute to environmental efficiency by providing alternative ways of utilizing and implementing existing technology (Du & Li, 2019; Kunapatarawong & Martínez-Ros, 2016). On the other hand, some scholars argue that, in contrast to environmental legislation, an increase in regional green innovation efficiency is found to be entirely dependent on technical advancement (Luo & Zhang, 2021). This implies that green innovations alone are not enough to ensure achieving SDGs. The way countries utilize green innovations and the policies that accompany them are prerequisites for environmental efficiency to be sustained.

According to our knowledge, studies that tried to measure green innovations efficiency and environmental efficiency at the international level are still scarce (Lozano, 2015; Moutinho et al., 2017; P. Zhou et al., 2010), and most related studies in the field measure environmental efficiency at the microeconomic level (Abid et al., 2022; Gao & Li, 2021; Y. Wang & Yang, 2021). Besides, few studies that have tried to measure environmental efficiency are mainly focusing on one main environment-related output, specifically carbon dioxide emissions (Cucchiella et al., 2018; P. Xie & Jamaani, 2022) overlooking other important factors such as environment-related policy, research and development efforts, and clean energy practices.

Therefore, the questions of how green innovations can be produced efficiently and how these innovations can be used to boost the achievement of environment-related SDGs require further exploration. Taking this into consideration, this study endeavours to answer the following research questions:

RQ.1*: Are countries producing green innovations efficiently?*

RQ.2: *What role do green innovations play in achieving the SDGs, in particular SDG-7 and SDG-13?*

RQ.3: *What factors contribute to the environmental efficiency's heterogeneity across different countries?*

This study is motivated by the lack of empirical evidence on the efficiency of green innovations in improving environmental sustainability. By using network bias-corrected DEA, the study attempts to solve the issue of bias in previous studies and provide a more accurate assessment of the green innovations efficiency and their role in improving sustainable environmental efficiency.

This study contributes to the growing literature on the relationship between green innovations and environmental sustainability using a robust methodological approach and a comprehensive dataset. Moreover, to deal with climate change using green innovations, this work contributes to the exploration of environmental efficiency heterogeneity across countries to identify the best practices and strategies that can be adopted to achieve this goal. The results of this study provide policymakers with a tool to identify the source of failure in achieving environment-related SDGs. Accordingly, this study adds to the body of literature in the following aspects. First, a new environmental efficiency measurement framework is provided where the process of achieving environmental efficiency is divided into two sub-processes. Thus, policymakers can identify the weaknesses in their green path. Second, a robust efficiency measurement technique is applied to overcome the shortcomings of the previous studies in terms of bias-correction. Third, clustering analysis is carried out to investigate the heterogeneity among countries, and some tailored policies can be provided by following the best practices of the clustered countries.

The rest of the paper is structured as follows: Section 2 reviews previous studies on environmental efficiency measurement at different analytical levels. Section 3 explains the used data and applied techniques. In Section 4, results are reported and discussed. Section 5 concludes, and policy implications are provided.

2. Literature review

The issue of green innovation has received huge consideration when it comes to reducing the adverse effect of economic activities on the natural environment. By creating innovative ways of production, companies have reduced the consumption of resources, waste generation, and emissions, which has led to more sustainable and efficient use of natural resources (Del Giudice & Della Peruta, 2016; Dubey et al., 2015; Lewis et al., 2014; Singh & El-Kassar, 2019; Hambrick & Quigley, 2014).

Governments across the globe have made commitments to safeguard ecosystems, champion equality, and prioritize sustainable development. They also understand the intertwined nature of these goals in the quest to enhance human well-being (Coscieme et al., 2021). However, this interplay between objectives has given rise to considerable difficulties. Notably, there exist both synergies and conflicts among and within the goals. These conflicts have complicated the pursuit of the SDGs and have presented an obstacle to the execution of cohesive policy solutions for sustainable development. This situation augments the likelihood that the endeavor to equate interests and priorities may fall short (Scherer et al., 2018; Y. Lu et al., 2015; Pham-Truffert et al., 2020). This has led to the problem of policy coherence in Achieving the SDGs(Coscieme et al., 2021). However, some efforts are ongoing to tackle the problem of policy coherence(Janetschek et al., 2020; Ronzon & Sanjuán, 2020; Petersen & Mortensen, 2017).

Green technology innovation is significant to achieving energy efficiency and overall SDGs. For instance, using more sustainable technologies, practices, and products helps achieve climate action, resource efficiency improvement, and biodiversity and ecosystem protection. The SDGs have 5 interconnected goals that directly relate to the environment(UNDP, 2021), and green innovation can contribute to achieving the SDGs in several ways (Ullah et al., 2021). However, this research will focus on green innovation's role in clean energy (SDG 7) and climate change or greenhouse gas emissions (SDG 13).

Green innovations can help improve energy efficiency (Banerjee & Murshed, 2020) by reducing the amount of energy consumed in production processes. According to Wang et al. (2021), promoting energy efficiency avoids excessive energy consumption, and in terms of output, it reduces extreme environmental damage. Several studies have investigated ways to improve energy efficiency (Xie et al., 2014; Xiong et al., 2019; Zhu et al., 2019; Yu, 2020; Yu, 2020; Xiong et al., 2019; Zhu et al., 2019; Fisher-Vanden et al., 2006; Baccarelli et al. 2016; Naranjo et al., 2019; Fisher-Vanden et al. 2006; Hellsmark et al., 2016; Miao et al., 2018). Some of these studies measured green innovation's impact on energy efficiency in industries across countries (Xiong et al., 2019; Zhu et al., 2019; Yu, 2020). For example, Xiong et al. (2019) applied the slacks-based measure model, which incorporates undesirable output, to assess industrial energy efficiency. They conducted this evaluation at both provincial and sectoral levels in China over seven years, from 2010 to 2016. In addition, Zhu et al. (2019) utilized an innovative method that integrates measures of industrial structure adjustment, super-efficiency slacks-based methods with undesirable outputs, and panel regression models. They used this comprehensive approach to investigate the influence of adjustments in industrial structure on the efficiency of green development. Green innovation improves total-factor energy efficiency by employing the environmental Malmquist index, grounded in the SBM-DEA (slack-based measure data envelopment analysis) model (Xie et al., 2014). Meanwhile, Yu (2020) used the modified Super-SBM method to measure China's total-factor energy efficiency, employing the dynamic spatial panel model (DSPM) to validate the impact of industrial structure and technological innovation on total factor energy efficiency. He found no significant correlation between these two factors. Moreover, several studies have suggested that shifts in industrial structure are what improve energy efficiency (Xiong et al., 2019; Zhu et al., 2019; Yu, 2020), rather than technological advancements, as some other research might imply.

Furthermore, increases in relative energy prices, research and development expenditures, and ownership reform can all contribute to improvements in energy efficiency (Fisher-Vanden et al., 2006), and significant data stream mobile computing combines mobile networking, cloud computing, and big data processing (Baccarelli et al. 2016) are also factors that can improve energy efficiency. Fisher-Vanden et al. (2006) used a uniquely comprehensive data set detailing Chinese firm characteristics and technological innovation activities to pinpoint key drivers of rising energy productivity within China's industrial sector. While many of the papers reviewed had used CO_2 as the measure of energy efficiency, it is a possibility that green innovation impact other environmental-related policy measures differently. This is why it is important to investigate the impact of green innovations on other environmental-related policy measures (i.e., environmental taxes and other renewable energy efforts), which is the focus of this research.

Green innovations help reduce greenhouse gas emissions and other known pollutants. This is by advancing production processes and scaling down the generated waste. More studies have investigated the relationships between green innovation and emission reduction (Xu et al., 2021; Zhang et al., 2017; Huang et al., 2021; Zhao et al., 2023; Wang & Wei, 2020; Bogusz & Howlett, 2008; Roos et al., 2012; Kalkuhl et al., 2012; Voigt et al., 2014; Bogusz & Howlett, 2008; Roos et al., 2012). Many of these studies have demonstrated that green and environmental innovations reduce carbon dioxide emissions (Zhao et al., 2023; Zhang et al., 2017; Huang et al., 2021; Yii & Geetha, 2017). However, a small number of these studies suggest that green innovation or technological advancement may potentially exacerbate CO2 emissions (Xu et al., 2021; Wang & Wei, 2020). Zhang et al. (2017) adopted the system generalized method of moments (SGMM) technique, while Zhao et al. (2023) two-way fixed effects model and interaction model. On the other hand, Wang & Wei (2020) applied the panel smooth transition regression technique to data from OECD countries and emerging economies.Meanwhile, Xu et al. (2021) utilized a two-way fixed effect model, the instrumental variable method, and a spatial econometric model on data from 218 prefecture-level cities in China. Notably, Wang & Wei (2020) pointed out the potential for emerging economies under stringent environmental regulations to fall into a serious 'green paradox.' This paradox refers to a scenario where efforts to reduce emissions prematurely could inadvertently stimulate an increase in emissions in the short term and harm economic development.

Several other studies have also investigated the effect of technological advancement and environmental regulation on CO_2 emissions, significantly as it varies across countries (Bogusz & Howlett, 2008; Roos et al., 2012; Kalkuhl et al., 2012; Voigt et al., 2014). Bogusz & Howlett (2008), Roos et al. (2012), Kalkuhl et al. (2012), and Voigt et al. (2014) have shown the role of green innovation policies (such as taxes on emissions, increased share of renewables, and improvement of energy efficiency, subsidies, quotas, energy intensity trends, and drivers) play in the reduction of greenhouse gas emissions. For example, Kalkuhl et al. (2012) utilized an intertemporal general equilibrium model to demonstrate that even 'small' market imperfections could trigger several decades of dominance by an incumbent energy technology over a dynamically more efficient competitor, assuming that the technologies are perfect substitutes. Meanwhile, Voigt et al. (2014) employed the logarithmic mean Divisia index decomposition to (1) attribute efficiency changes to either changes in technology or alterations in the structure of the economy, (2) examine trends in global energy intensity between 1995 and 2007, and (3) emphasize sectoral and regional disparities.

Many studies in the literature have studied the impact of environmental-related policies on overall environmental efficiency using the Data Envelopment Analysis (DEA) technique (Moutinho et al., 2017; Lozano, 2015; Cucchiella et al., 2018; Biresselioglu et al., 2018; Tsaples et al., 2019; Kwon et al., 2017; Song et al., 2012; Wu et al., 2014; Chang et al., 2014; Zhou et al., 2019; Xie et al., 2017; Wang & Feng, 2015). For instance, an output-oriented model with two specifications (Variable and Constant Returns to Scale) was employed by Moutinho et al. (2017), incorporating inputs such as labour and capital productivity, fossil energy weight, and the GDP's renewable energy share, with GDP per GHG (greenhouse gases) emissions as the output. They found that taxes on emissions have a substantial impact on eco-efficiency scores, and there exist notable discrepancies among European countries. Wu et al. (2014) show that firms use a minimum output improvement strategy to improve their environmental efficiency and reduce their negative impact on the environment. The study highlights the importance of considering output competition between Decision Making Units (DMUs) when evaluating their environmental efficiency, which can help researchers develop more accurate and reliable models for assessing environmental efficiency. This paper demonstrated that it is essential to consider the heterogeneity of industries in proposing emission reduction strategies. Given the divergent thought on the impact of green innovation and environmental efficiency, it is instructive to investigate its role in achieving clean energy and greenhouse gas emission.

Many of the studies reviewed have not adequately addressed the measurement challenges in environmental efficiency literature. For example, most studies only focused on one environmental performance indicator (i.e., CO2 emissions or energy consumption)(Moutinho et al., 2017; Cucchiella et al., 2018; Tsaples et al., 2019) but ignored the potentials impacts of other environmental performance indicators (such as water use or waste management, etc.). Using a single environmental performance indicator in assessing environmental efficiency may lead to inadequate assessment. Also, so many studies used inadequate methods to measure environmental efficiency. For instance, some studies like Afrinaldi (2022) and Chen & Delmas (2012) used simple ratios without considering other external factors that have the potentials to influence environmental efficiency.

3. Data and methodology

3.1. Data

This study includes data from 42 countries across various regions, covering the period from 2000 to 2020. The list of countries analyzed can be found in Appendix A, specifically in table A. 1. The selection of countries for the sample was based on two criteria. The first criterion, as suggested by (Cooper et al., 2006), required the number of countries to be greater than the combined inputs and outputs in order to prevent inflated efficiency evaluations. Secondly, we deliberately chose countries from diverse geographical, economic, and social contexts to enable meaningful comparisons and yield policy insights applicable to various country groups.

Regarding the variables used in this study, different sets of variables were selected to measure different types of environmental efficiency. The list of used variables and their descriptive statistics are reported in Appendix A, Table A. 2. The descriptive statistics show heterogeneity among countries in terms of the SDG-13 achievement process, renewable energy productivity, and environment-related taxes. This provides more motivation to explore how this environment-related heterogeneity can affect environmental efficiency in different contexts.

The process of variables selection is drawn from the conceptual framework of how countries may achieve high levels of environmental efficiency through different channels and processes. Accordingly, variables are divided into two groups. First, the inputs group, where some variables such as research and development expenditures and the published scientific articles in environmental science are selected as proxies for the capabilities of producing green innovations. Other variables, such as environment-related taxes and renewable energy productivity, are selected as proxies for government policy and practices toward achieving the environment-related SDGs. Second, is the outputs group, where variables such as alive environment patents are selected to represent the green innovations production process. Moreover, other variables such as SDG-7, SDG-13, and the overall SDG index are selected as the ultimate goals of governments to enhance the environmental aspects of sustainability.

3.2. Methodology

In this study, we utilize the nonparametric programming model (CCR) developed by (Charnes et al., 1978) and the dual convex model (BCC) introduced by (Banker et al., 1984) for the assessment of environmental efficiency. Data envelopment analysis (DEA) is employed to compute relative efficiency scores for countries within different regions. Our analysis concentrates on measuring both technical and scale efficiency in relation to the efficient frontiers.

The network DEA technique was chosen due to its nonparametric nature, which does not require the assumption of relative weights or specific distribution assumptions for inputs and outputs. Compared to parametric models, this method is less restrictive and offers greater flexibility. Furthermore, network DEA is founded on the principle of Pareto Optimality (Charnes et al., 1985), when another country or a group of countries can achieve the same results with fewer resources than the country in question, that country is considered inefficient.

From a mathematical perspective, the DEA method comprises two primary models based on the type of returns to scale. The first model, known as Constant Return to Scale (CRS), assumes that outputs increase proportionally to inputs, indicating optimal scale operation for all decision-making units (DMUs). In contrast, the second model, Variable Return to Scale (VRS), allows for three different directions of returns: increased, decreased, or constant.

Nevertheless, the existing DEA methods overlook the possibility of breaking down decision-making units (DMUs) into sub-systems, treating them as a single entity. This study employs network DEA to address this limitation and account for the diverse performance levels among various sub-systems within the DMU, as suggested by (Färe & Grosskopf, 2000; C. H. Wang et al., 1997).

To this end, the environmental efficiency measurement process is divided into two sub-processes as shown in figure 1. These two processes are:

- **Green knowledge and innovations production (GIE):** we start with measuring the efficiency of the environment-related knowledge and green innovations production process. The universities, research and development organizations, and private sector companies constitute the three main participants in this process. The inputs of this process are the research and development expenditures as a percentage of GDP, and the number of scientific articles published in environmental science. These inputs should be used efficiently to produce environmental patents as a proxy for green innovations. Otherwise, the system is considered inefficient in producing green innovations that are supposed to play a vital role in achieving the environment-related SDGs.
- **Environmental efficiency (EN):** at this stage, we measure the efficiency of green innovations in achieving the environment-related SDGs. Three aspects of environmental efficiency are taken into consideration. First, technological knowledge is represented by green innovations. Second, environment-related government policy is represented by environment-related taxes. Third, environmental actions are represented by renewable energy production. As shown in Figure 1, green innovations are outputs of the first process, but at the same time, they are used as inputs in the second process. Thus, hypothetically, the performance of the green innovations production efficiency should play a role in improving the performance of environmental efficiency.

Accordingly, the efficiency of the general environmental sustainability is measured using inputs and outputs from both the abovementioned processes. Figure 1 shows the third block, where technological knowledge, green innovations, environment-related policy, and renewable energy are selected as inputs to achieve the overall SDGs. Thus, we can answer the main research question of how green innovations can improve environmental sustainability performance.

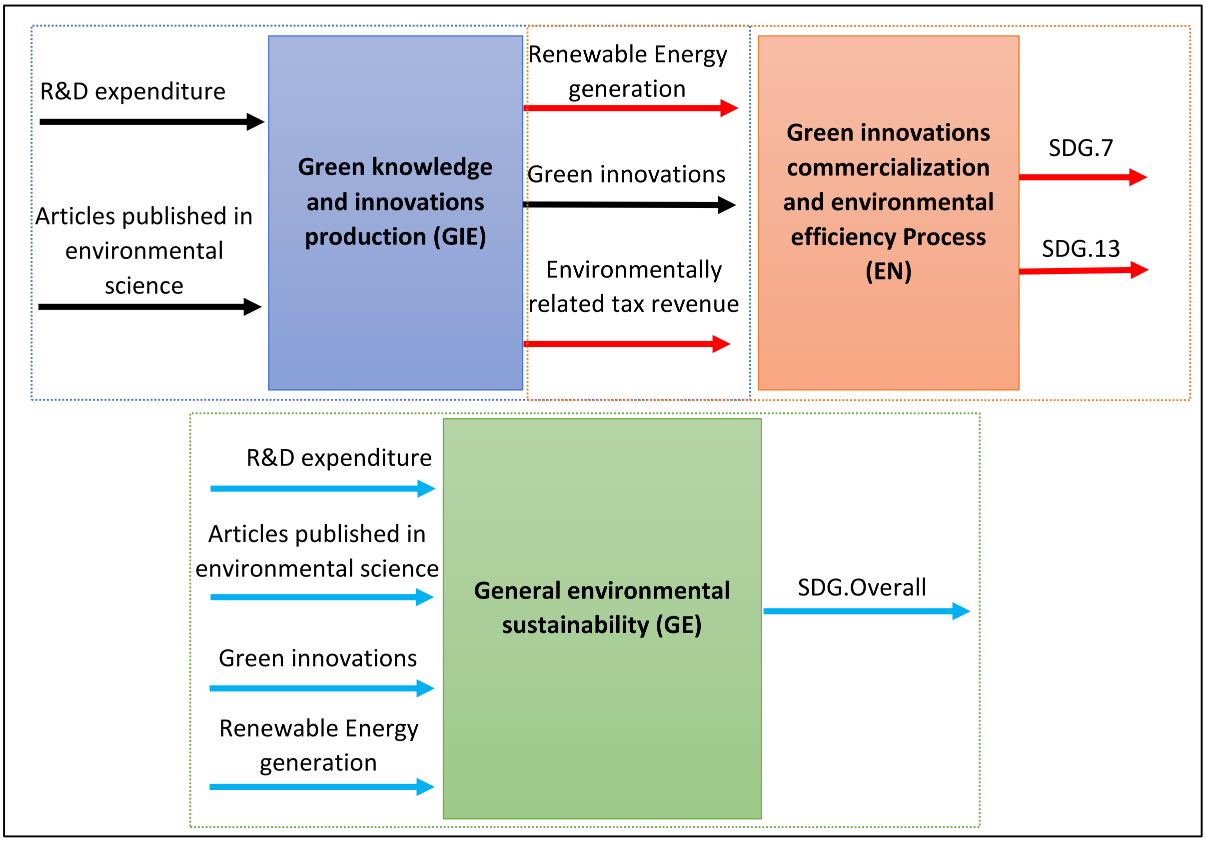

Fig. 1. Environmental efficiency measurement system

The methodology comprises two steps:

A. **Model orientation selection:** inputs and outputs were chosen based on a comprehensive examination of prior empirical studies that utilized various DEA methods to gauge efficiency. As previous studies suggest, inputs-oriented efficiency measurement is preferable since policymakers can control inputs more than outputs (Emrouznejad & Yang, 2018). Therefore, the input-oriented model is selected to measure the efficiency of environmental sustainability. In addition, focusing on the input side of the environmental sustainability achievement process is vital to improve the required national innovation and technological capabilities along with government-related policy and renewable energy capacities.

In the context of static datasets, it is typically necessary to conduct a correlation matrix analysis to establish a meaningful correlation between inputs and outputs, thereby validating the integrity of our model (Golany & Roll, 1989; W.-M. Lu et al., 2014). Nevertheless, in the present study where panel datasets are utilized and the DEA method is applied, this assumption has been relaxed.

B. **Returns selection:** to determine the type of returns to scale to incorporate into our model, we draw on the study conducted by (Kneip et al., 2011) to identify the returns to scale. We employ an RTS test for all three processes, with the null hypothesis being that the suitable returns to scale are constant returns to scale. The outcomes of this test are presented in Appendix A, specifically in Table A.3.

The findings presented in Table A.3 indicate that constant returns to scale (CRS) is the suitable approach for all processes. The p-values for all processes support the acceptance of the null hypothesis at a significance level of α

= 1%. This observation is significant as it suggests that the results of the RTS-test align with the operational structure of the studied countries (DMUs), which are expected to operate at optimal scales. Thus, the efficiency scores obtained can be used to rank the countries in terms of their efficiency, and the results can be used to identify best practices and benchmarking opportunities. Furthermore, the constant returns to scale approach primarily evaluates scale efficiency, but it does not offer insights into the stage or direction of innovation activities' returns. It is important to highlight that the countries examined in this research function under varying institutional structures with incomplete competition. Therefore, the study will employ the CRS methodology to assess comparative environmental efficiency.

3.2.1. Efficiency measurement model

We have three processes, each involving multiple countries. In the first process, each country has m^1 inputs denoted as X_{i^1j} (where i^1ranges from 1 to m^1), and s^1 outputs denoted as Y_{r^1j} (where r^1ranges from 1 to s^1), which pertain to knowledge and green innovations' production (GIE). Similarly, in the second process, each country has m^1 inputs denoted as X_{i^1j} (where i^1ranges from 1 to m^1), and s^1 outputs denoted as Y_{r^1j} (where r^1 ranges from 1 to s^1) for the knowledge and green innovations production (GIE), m^2 inputs X_{i^2j} ($i^2 = 1, \dots, m^2$) and s^2 outputs Y_{r^2j} ($r^2 = 1, \dots, s^2$), which relate to environmental efficiency (EN). Lastly, in the third process, each country has m^3 inputs denoted as X_{i^3j} (where i^3ranges from 1 to m^3), and s^3 outputs denoted as Y_{r^3j} (where r^3 ranges from 1 to s^3) which pertain to general environmental sustainability (GE). Furthermore, a set of P intermediate values, denoted as Z_{pj} (where p ranges from 1 to q), serve as the connection between the (GIE), (EN), and (GE). We represent unknown positive values above ε (a non-Archimedean number) as u_{r^1}, u_{r^2}, u_{r^3}, v_{i^1}, v_{i^2}, v_{i^3} and w_p.

Accordingly, the efficiency score is as follows:

$$E_j = \frac{\sum_{r1=1}^{s^1} u_{r_1} Y_{r^1j} + \sum_{r2=1}^{s^2} u_{r_2} Y_{r^2j} + \sum_{r1=1}^{s^3} u_{r_3} Y_{r^3j} \sum_{p=1}^{q} w_p z_{pj}}{\sum_{i1=1}^{m^1} v_{i_1} x_{i^1j} + \sum_{i2=1}^{m^2} v_{i_2} x_{i^2j} + \sum_{i3=1}^{m^3} v_{i_3} x_{i^3j} \sum_{p=1}^{q} w_p z_{pj}} \qquad \text{(Eq.1)}$$

E_j represents the proportion of the combined weighted outputs to the combined weighted inputs of the two processes. The total efficiency denoted as E_j, encompasses three separate efficiencies: E_j^1 for the *GIE* efficiency score, E_j^2 for the *EN* efficiency score, and E_j^3 for the *GE* efficiency score.

According to (Kao & Hwang, 2008), the results obtained from the initial process, known as GIE, are expected to serve as inputs for the subsequent process, referred to as EN. Consequently, the CRS model (Charnes et al., 1978) can be employed to compute the overall efficiency (GE) of a specific DMU (j_0) using the following formula:

$$E_{j_0} = max \frac{\sum_{r1=1}^{s^1} u_{r_1} Y_{r^1j_0} + \sum_{r2=1}^{s^2} u_{r_2} Y_{r^2j_0} + \sum_{r3=1}^{s^3} u_{r_3} Y_{r^3j_0} + \sum_{p=1}^{q} w_p z_{pj_0}}{\sum_{i1=1}^{m^1} v_{i_1} x_{i^1j_0} + \sum_{i2=1}^{m^2} v_{i_2} x_{i^2j_0} + \sum_{i3=1}^{m^3} v_{i_3} x_{i^3j_0} + \sum_{p=1}^{q} w_p z_{pj_0}} \quad \text{(Eq. 2)}$$

$$\text{s.t.} \qquad \frac{\sum_{r1=1}^{s^1} u_{r_1} Y_{r^1j} + \sum_{r2=1}^{s^2} u_{r_2} Y_{r^2j} + \sum_{r3=1}^{s^3} u_{r_3} Y_{r^3j} + \sum_{p=1}^{q} w_p z_{pj}}{\sum_{i1=1}^{m^1} v_{i_1} x_{i^1j} + \sum_{i2=1}^{m^2} v_{i_2} x_{i^2j} + \sum_{i3=1}^{m^3} v_{i_3} x_{i^3j} + \sum_{p=1}^{q} w_p z_{pj}} \leq 1$$

$$\frac{\sum_{r1=1}^{s^1} u_{r_1} Y_{r^1j} + \sum_{p=1}^{q} w_p z_{pj}}{\sum_{i1=1}^{m^1} v_{i_1} x_{i^1j}} \leq 1$$

$$\frac{\sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j}}{\sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj}} \leq 1$$

$$\frac{\sum_{r^3=1}^{s^3} u_{r_3} Y_{r^3 j}}{\sum_{i^3=1}^{m^3} v_{i_3} x_{i^3 j} + \sum_{p=1}^{q} w_p z_{pj}} \leq 1$$

where u_{r^1}, u_{r^2}, u_{r^3}, v_{i^1}, v_{i^2}, v_{i^3} and $w_p \geq \varepsilon$; $j = 1, 2, \dots, n$

To solve the conversion of the previous model into a linear program model, the model can formed as follows:

$$E_{j_0} = \max \sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} + \sum_{r^3=1}^{s^3} u_{r_3} Y_{r^3 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \qquad \text{(Eq. 3)}$$

$$\text{s.t.} \quad \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{i^3=1}^{m^3} v_{i_3} x_{i^3 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} = 1$$

$$\left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj}\right) - \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} \leq 0$$

$$\sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} - \left(\sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j} + \sum_{p=1}^{q} w_p z_{pj}\right) \leq 0$$

$$\sum_{r^3=1}^{s^3} u_{r_3} Y_{r^3 j} - \left(\sum_{i^3=1}^{m^3} v_{i_3} x_{i^3 j} + \sum_{p=1}^{q} w_p z_{pj}\right) \leq 0$$

where u_{r^1}, u_{r^2}, u_{r^3}, v_{i^1}, v_{i^2}, v_{i^3} and $w_p \geq \varepsilon$; $j = 1, 2, \dots, n$

Similarly, we determine the efficiency of two sub-processes (GIE and EN) using the same approach.

$$E_{j_0}^1 = \max \sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \qquad \text{(Eq. 4)}$$

$$\text{s.t.} \quad \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} = 1$$

$$\left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0}\right) - E_{j_0} \left(\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0}\right) = 0$$

$$\left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj}\right) - \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} \leq 0$$

$$\sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} - \left(\sum_{p=1}^{q} w_p z_{pj} + \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j}\right) \leq 0$$

where u_{r^1}, u_{r^2}, u_{r^3}, v_{i^1}, v_{i^2}, v_{i^3} and $w_p \geq \varepsilon$; $j = 1, 2, \dots, n$

and

$$E_{j_0}^2 = \max \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \qquad \text{(Eq. 5)}$$

$$\text{s.t.} \quad \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} = 1$$

$$\left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} + \sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j_0}\right) - E_{j_0} \left(\sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j_0} + \sum_{i^2=1}^{m^2} v_{i_2} x_{i^2 j_0} + \sum_{p=1}^{q} w_p z_{p j_0}\right) = 0$$

$$\left(\sum_{r^1=1}^{s^1} u_{r_1} Y_{r^1 j} + \sum_{p=1}^{q} w_p z_{pj}\right) - \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j} \le 0$$

$$\sum_{r^2=1}^{s^2} u_{r_2} Y_{r^2 j} - \left(\sum_{p=1}^{q} w_p z_{pj} + \sum_{i^1=1}^{m^1} v_{i_1} x_{i^1 j}\right) \le 0$$

where $u_{r^1}, u_{r^2}, u_{r^3}, v_{i^1}, v_{i^2}, v_{i^3}$ and $w_p \geq \varepsilon$; $j = 1, 2, \ldots, n$

and

$$E_{j_0}^3 = \max \sum_{r^3=1}^{s^3} u_{r_3} Y_{r^3 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} \qquad \text{(Eq. 6)}$$

$$\text{s.t.} \quad \sum_{i^3=1}^{m^3} v_{i_3} x_{i^3 j_0} = 1$$

$$\left(\sum_{r^3=1}^{s^3} u_{r_3} Y_{r^3 j_0} + \sum_{p=1}^{q} w_p z_{p j_0} + \sum_{r^3=1}^{s^3} u_{r_3} Y_{r^3 j_0}\right) - E_{j_0}\left(\sum_{i^3=1}^{m^3} v_{i_3} x_{i^3 j_0} + \sum_{i^3=1}^{m^3} v_{i_3} x_{i^3 j_0} + \sum_{p=1}^{q} w_p z_{p j_0}\right) = 0$$

$$\left(\sum_{r^3=1}^{s^3} u_{r_3} Y_{r^3 j} + \sum_{p=1}^{q} w_p z_{pj}\right) - \sum_{i^3=1}^{m^3} v_{i_3} x_{i^3 j} \le 0$$

$$\sum_{r^3=1}^{s^3} u_{r_3} Y_{r^3 j} - \left(\sum_{p=1}^{q} w_p z_{pj} + \sum_{i^3=1}^{m^3} v_{i_3} x_{i^3 j}\right) \le 0$$

where $u_{r^1}, u_{r^2}, u_{r^3}, v_{i^1}, v_{i^2}, v_{i^3}$ and $w_p \geq \varepsilon$; $j = 1, 2, \ldots, n$

The equations formulated earlier lack bias correction, which means that the efficiency scores obtained through DEA can be influenced by sampling variations in the frontier (Tsolas, 2011). Consequently, to remove any bias in the results, a bootstrapping estimation is utilized.

The equations that have been formulated before do not incorporate bias correction, which means that the efficiency scores obtained from DEA are influenced by the sampling variation of the frontier. Therefore, a bootstrapping estimate will be applied to eliminate the bias in the results. The fundamental concept of bootstrapping involves estimating efficiency scores through multiple sampling procedures (Simar & Wilson, 1998). In order to mitigate the bias of the estimated value $\widehat{\theta_\iota}$, we create simulated data that closely resembles the original dataset following (Kneip et al., 2011; Simar & Wilson, 2007). The bootstrapped samples exhibit distributions and standard deviations that closely resemble those of the original data. Consequently, the efficiency score, adjusted for bias, can be expressed in the following manner:

$$\tilde{\theta}_j = \hat{\theta}_j - Bias\left(\hat{\theta}_j\right) \qquad \text{(Eq. 7)}$$

$$\text{Where} \quad Bias\left(\hat{\theta}_j\right) = E\left(\hat{\theta}_j\right) - \hat{\theta}_j = B^{-1} \sum_{b=1}^{B} \hat{\theta}^*{}_{jb} - \hat{\theta}_j$$

$$\tilde{\theta}_j = 2\hat{\theta}_j - B^{-1} \sum_{b=1}^{B} \hat{\theta}_{jb}^* \left(\hat{\theta}_j\right) \qquad \text{(Eq. 8)}$$

Where b is any value from 1 to B, representing a sample generated from $\hat{\theta}_1$ to $\hat{\theta}_j$.

4. Results and discussion

4.1. Green innovations efficiency

The results of the green innovation production efficiency measurement are reported in Table 4. The results presented in column (1) show that in 2020, only six of 41 countries were efficient in producing green innovations and knowledge (GIE). However, after taking the bias into account (column 2), the results have changed dramatically, with only 3 countries being efficient. The case of China is a good example of how the scale of the economy can produce biased efficiency results, with a 0.05 reduction in its efficiency score justifying the use of the bias-corrected efficiency model.

The results reveal that the USA, India, and Russia have the lowest efficiency scores in terms of green innovations production, indicating a low performance of these countries in using the financial and human resources they have to produce more alive green patents. On the other hand, the results show that countries such as Lithuania, Croatia, and Slovenia are the most efficient in utilizing their inputs to produce more green innovations.

Table 4. CRS-inputs-oriented efficiency results in 2020

Country	(1) **GIE.CRS.I**	(2) **GIE.CRS.I Bias corrected**	(3) **EN.CRS.I**	(4) **EN.CRS.I Bias corrected**	(5) **GE.CRS.I**	(6) **GE.CRS.I Bias.corrested**
Argentina	0.99	0.98	0.97	0.95	0.88	0.86
Australia	0.89	0.88	0.73	0.70	0.84	0.83
Austria	0.98	0.98	0.93	0.90	0.92	0.89
Belgium	0.97	0.97	0.83	0.82	0.87	0.84
Brazil	0.90	0.89	1.00	0.93	0.83	0.82
Canada	0.90	0.90	0.77	0.73	0.91	0.90
Chile	0.99	0.98	0.99	0.97	1.00	0.97
China	1.00	0.95	0.85	0.81	0.64	0.63
Colombia	0.99	0.98	0.99	0.95	0.84	0.82
Croatia	1.00	1.00	0.99	0.98	0.97	0.95
Czech Republic	0.98	0.97	0.89	0.88	0.95	0.92
Denmark	0.97	0.97	0.98	0.95	0.98	0.94
Finland	0.98	0.97	0.99	0.96	1.00	0.96
France	0.91	0.91	0.87	0.85	0.93	0.92
Germany	0.87	0.87	0.78	0.74	0.92	0.89
Hungary	0.99	0.99	0.90	0.88	0.94	0.92
India	0.84	0.83	1.00	0.98	0.58	0.57
Israel	0.99	0.99	0.83	0.82	0.76	0.74
Italy	0.88	0.88	0.91	0.89	0.93	0.92
Japan	0.93	0.93	0.84	0.82	0.86	0.83
Korea	0.94	0.94	0.84	0.82	0.82	0.80
Lithuania	1.00	1.00	0.79	0.77	0.90	0.88
Malaysia	0.95	0.95	0.88	0.85	0.80	0.79
Mexico	0.97	0.96	0.95	0.93	0.84	0.82
Morocco	1.00	0.99	1.00	0.97	0.79	0.77

Netherlands	0.94	0.94	0.81	0.80	0.92	0.89
New Zealand	0.98	0.98	1.00	0.95	0.95	0.93
Norway	0.97	0.97	1.00	0.93	0.97	0.94
Peru	1.00	0.99	1.00	0.96	0.89	0.87
Poland	0.94	0.94	0.87	0.86	0.98	0.96
Portugal	0.96	0.96	0.99	0.98	0.94	0.92
Russia	0.87	0.86	0.86	0.84	0.87	0.86
Singapore	0.99	0.98	0.84	0.80	0.77	0.75
Slovenia	1.00	1.00	0.91	0.89	0.94	0.91
South Africa	0.97	0.96	0.93	0.91	0.67	0.65
Spain	0.88	0.88	0.90	0.88	0.97	0.96
Sweden	0.95	0.95	1.00	0.95	0.98	0.95
Thailand	0.98	0.97	1.00	0.94	0.91	0.89
Ukraine	0.99	0.98	0.98	0.95	0.95	0.92
United Kingdom	0.84	0.84	0.85	0.83	0.98	0.97
USA	0.68	0.67	0.71	0.68	0.75	0.73
Vietnam	0.98	0.97	0.99	0.97	0.88	0.86

Regarding environmental efficiency, the results presented in Table 4, Column 3, show that in 2020, eight countries were efficient. However, after considering the bias (column 4), none of the studied countries was efficient in using green innovations to achieve SDG-7 and SDG-13. The findings also indicate that South American countries have the highest environmental efficiency scores when compared to countries from other continents that were examined. On the other hand, industrial countries such as the USA, Germany, and Canada have the lowest environmental performance. This indicates a weakness in utilizing green innovations toward achieving SDG-7 and SDG-13. Moreover, this group of countries falls behind other countries in terms of utilizing renewable energy production and implementing environment-related taxes, which are crucial policy instruments for attaining SDGs for the environment. These findings validate the previous research findings that emphasize the crucial importance of environmental taxes and associated policies in enhancing environmental efficiency (Lozano, 2015; Moutinho et al., 2017).

The results also indicate that certain countries, like Lithuania and Australia, exhibit strong scores in terms of green innovation efficiency but struggle to effectively utilize these innovations in attaining SDG-7 and SDG-13. This result depicts a system failure related to the government's efforts to substitute oil and gas energy with renewable energy, in addition to weak environmental policies and regulations (Kalkuhl et al., 2012).

Regarding the overall environmental efficiency related to countries' efforts to produce more green innovations and make progress in achieving the environment-related SDGs, the results presented in Table 4, Column 5, show that, in 2020, only Chile and Finland were efficient in comparison with other countries. However, when we corrected the measurement by eliminating the bias, the results (column 6) revealed that none of the studied countries were efficient.

The results reveal that South Africa, the USA, India, and China have the lowest total environmental efficiency scores in comparison with the other studied countries. Various factors contribute to this observed low-efficiency score. For instance, in South Africa, the lack of financial resources and inadequate environmental regulations can account for this phenomenon. Similarly, in China and the USA, the presence of extensive industrialization and insufficient environmental policies can help explain the low-efficiency score.

On the other hand, the results show that the United Kingdom and Chile have the highest total environmental efficiency scores. Each country presents a special case from a policymaking point of view. The United Kingdom, for example, has a high-efficiency score in neither producing green innovations nor using them to achieve SDG-7 and SDG-13. But it has a high total environmental efficiency score. This can be explained by the fact that other SDGs are achieved through other economic and social policies, not environment-oriented ones. In Chile, the case is different, where the SDGs are being achieved by following environmentally friendly policies. Thus, countries can achieve environment-related SDGs, and this has a developmental spillover effect on other SDGs. These results indicate that being efficient at producing green innovations or using green innovations to achieve environment-related SDGs does not necessarily mean having developmental spillovers to other SDGs.

To track the progress made in all types of environment-related efficiencies, we first take the total average efficiency score of all efficiencies scores, second, we measure the growth or decline of each efficiency between 2000 and 2020. The efficiency progress analysis results are presented in Table 5.

The results reported in Table 5 show that the majority of advancements made primarily revolve around knowledge and the production of green innovations (GIE). The average improvement rate for the efficiency of knowledge and green innovations (GIE) is determined to be 27%. Nevertheless, a considerable number of countries have not made noteworthy strides in environmental efficiency (EN) through the optimal utilization of green innovations to attain SDGs related to the environment.

The results also reveal that the high level of overall environmental efficiency (GE) in the best countries, such as Finland, Denmark, and France, is the result of an improvement in the GIE efficiency of green innovations rather than an improvement in their utilization. Furthermore, the best-performing countries in terms of using green innovations to achieve SDGs related to the environment are Spain, Denmark, Mexico, and France. Meanwhile, the worst-performing countries are China and the United States.

Overall, the results suggest that some countries have made significant progress in environmental efficiency, but substantial efforts are still required to tackle the current global environmental challenges that confront our planet.

Table 5. Environmental efficiency progress

Country	GIE 2000	EN 2000	GE 2000	GIE 2010	EN 2010	GE 2010	GIE 2020	EN 2020	GE 2020	Total 2000	Total 2010	Total 2020	GIE Progress	EN Progress	GE Progress	Total Progress
Argentina	0.85	0.92	0.90	0.67	0.92	0.90	0.98	0.95	0.86	0.89	0.83	0.93	15%	3%	-4%	4%
Australia	0.91	0.77	0.83	0.63	0.65	0.82	0.88	0.70	0.83	0.84	0.70	0.80	-3%	-9%	0%	-5%
Austria	0.81	0.87	0.92	0.55	0.91	0.91	0.98	0.90	0.89	0.87	0.79	0.92	21%	3%	-3%	6%
Belgium	0.63	0.87	0.84	0.57	0.82	0.93	0.97	0.82	0.84	0.78	0.77	0.88	54%	-6%	0%	13%
Brazil	0.79	0.93	0.84	0.72	0.92	0.82	0.89	0.93	0.82	0.85	0.82	0.88	13%	0%	-2%	4%
Canada	0.82	0.79	0.84	0.67	0.77	0.83	0.90	0.73	0.90	0.82	0.76	0.84	10%	-8%	7%	2%
Chile	0.82	0.96	0.97	0.68	0.96	0.97	0.98	0.97	0.97	0.92	0.87	0.97	20%	1%	0%	5%
China	0.88	0.91	0.77	0.87	0.73	0.62	0.95	0.81	0.63	0.85	0.74	0.80	8%	-11%	-18%	-6%
Colombia	0.87	0.97	0.86	0.68	0.96	0.88	0.98	0.95	0.82	0.90	0.84	0.92	13%	-2%	-5%	2%
Croatia	0.74	0.98	0.92	0.66	0.98	0.97	1.00	0.98	0.95	0.88	0.87	0.98	35%	0%	3%	11%
Czech Republic	0.73	0.88	0.93	0.62	0.86	0.96	0.97	0.88	0.92	0.85	0.81	0.92	33%	0%	-1%	8%
Denmark	0.62	0.88	0.94	0.57	0.88	0.96	0.97	0.95	0.94	0.81	0.80	0.95	56%	8%	0%	17%
Finland	0.61	0.95	0.95	0.55	0.91	0.94	0.97	0.96	0.96	0.84	0.80	0.96	59%	1%	1%	14%
France	0.67	0.81	0.83	0.57	0.83	0.89	0.91	0.85	0.92	0.77	0.76	0.89	36%	5%	11%	16%
Germany	0.92	0.76	0.82	0.59	0.69	0.82	0.87	0.74	0.89	0.83	0.70	0.83	-5%	-3%	9%	0%
Hungary	0.77	0.94	0.97	0.65	0.93	0.97	0.99	0.88	0.92	0.89	0.85	0.93	29%	-6%	-5%	4%
India	0.77	0.97	0.58	0.69	0.85	0.55	0.83	0.98	0.57	0.77	0.70	0.79	8%	1%	-2%	3%
Israel	0.64	0.88	0.79	0.58	0.83	0.75	0.99	0.82	0.74	0.77	0.72	0.85	55%	-7%	-6%	10%
Italy	0.73	0.88	0.93	0.61	0.87	0.92	0.88	0.89	0.92	0.85	0.80	0.90	21%	1%	-1%	6%
Japan	0.93	0.79	0.79	0.90	0.77	0.81	0.93	0.82	0.83	0.84	0.83	0.86	0%	4%	5%	2%
Korea	0.69	0.92	0.83	0.86	0.87	0.84	0.94	0.82	0.80	0.81	0.86	0.85	36%	-11%	-4%	5%
Lithuania	0.80	0.94	0.91	0.66	0.84	0.94	1.00	0.77	0.88	0.88	0.81	0.88	25%	-18%	-3%	0%
Malaysia	0.83	0.95	0.85	0.66	0.89	0.78	0.95	0.85	0.79	0.88	0.78	0.86	14%	-11%	-7%	-2%
Mexico	0.90	0.85	0.83	0.72	0.96	0.82	0.96	0.93	0.82	0.86	0.83	0.90	7%	9%	-1%	5%
Morocco	0.79	0.97	0.73	0.67	0.96	0.78	0.99	0.97	0.77	0.83	0.80	0.91	25%	0%	5%	10%

Netherlands	0.66	0.84	0.92	0.58	0.79	0.97	0.94	0.80	0.89	0.81	0.78	0.88	42%	-5%	-3%	9%
New Zealand	0.73	0.94	0.98	0.64	0.92	0.98	0.98	0.95	0.93	0.88	0.85	0.95	34%	1%	-5%	8%
Norway	0.67	0.93	0.95	0.60	0.95	0.96	0.97	0.93	0.94	0.85	0.84	0.95	45%	0%	-1%	12%
Peru	0.87	0.96	0.89	0.68	0.95	0.93	0.99	0.96	0.87	0.91	0.85	0.94	14%	0%	-2%	3%
Poland	0.80	0.92	0.97	0.70	0.88	0.96	0.94	0.86	0.96	0.90	0.85	0.92	18%	-7%	-1%	2%
Portugal	0.81	0.94	0.93	0.62	0.97	0.92	0.96	0.98	0.92	0.89	0.84	0.95	19%	4%	-1%	7%
Russia	0.75	0.86	0.83	0.72	0.73	0.82	0.86	0.84	0.86	0.81	0.76	0.85	15%	-2%	4%	5%
Singapore	0.66	0.93	0.80	0.61	0.85	0.84	0.98	0.80	0.75	0.80	0.77	0.84	48%	-14%	-6%	5%
Slovenia	0.70	0.95	0.91	0.58	0.90	0.92	1.00	0.89	0.91	0.85	0.80	0.93	43%	-6%	0%	9%
South Africa	0.78	0.89	0.69	0.70	0.88	0.68	0.96	0.91	0.65	0.79	0.75	0.84	23%	2%	-6%	6%
Spain	0.86	0.80	0.94	0.65	0.82	0.89	0.88	0.88	0.96	0.87	0.79	0.91	2%	10%	2%	5%
Sweden	0.63	0.92	0.97	0.54	0.96	0.96	0.95	0.95	0.95	0.84	0.82	0.95	51%	3%	-2%	13%
Thailand	0.85	0.94	0.97	0.70	0.94	0.93	0.97	0.94	0.89	0.92	0.86	0.93	14%	0%	-8%	1%
Ukraine	0.75	0.94	0.89	0.68	0.92	0.91	0.98	0.95	0.92	0.86	0.84	0.95	31%	1%	3%	10%
United Kingdom	0.79	0.85	0.93	0.55	0.81	0.96	0.84	0.83	0.97	0.86	0.77	0.88	6%	-2%	4%	2%
USA	0.91	0.71	0.64	0.71	0.70	0.62	0.67	0.68	0.73	0.75	0.68	0.69	-26%	-4%	14%	-8%
Vietnam	0.84	0.95	0.86	0.69	0.95	0.87	0.97	0.97	0.86	0.88	0.84	0.93	15%	2%	0%	6%
Average	**0.78**	**0.90**	**0.87**	**0.66**	**0.87**	**0.87**	**0.94**	**0.88**	**0.86**	**0.85**	**0.80**	**0.89**	**27%**	**4%**	**6%**	**6%**

The colored cells represent values above or below the average. The green color indicates the progress made between 2000 and 2020, while the red color represents a decline in the process of improving environmental efficiency.

An aggregation was performed based on their proximity to investigating the progress patterns of the countries under study. Starting with knowledge and green innovation efficiency. Figure 2 shows an inverted efficiency curve, indicating that policymakers have focused on optimizing input utilization to improve efficiency, which has been found to yield better long-term results. The results also suggest that during the initial stages of knowledge and green innovations production, the utilization of inputs is associated with a decrease in efficiency. However, over time, the efficiency of the process exhibits an upward trend.

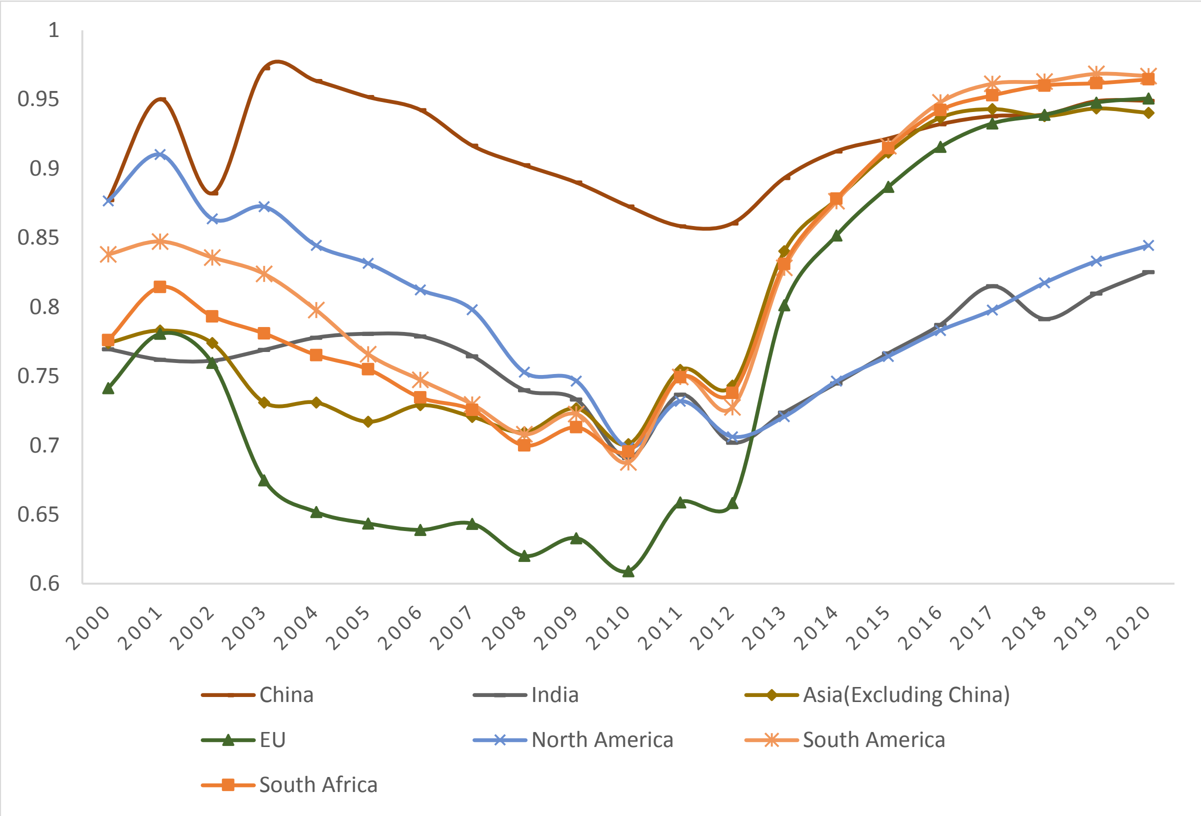

Fig. 2. International GIE.CRS.I comparison

Our findings highlight that China, South American countries, and European nations exhibit superior performance in terms of green innovations production. Conversely, North American countries and India demonstrate relatively lower levels of efficiency compared to the other countries examined. Recent studies that revealed that R&D spending and intellectual outputs were the primary predictors of the production of green technologies confirm this finding.(Cao et al., 2023).

To get more insights from the green innovation systems, the output-oriented model was also applied, so we can measure not only how efficient countries are in using their inputs, but also to what extent they are efficient in maximizing their outputs no matter how much input they use. The results of the CRS-output-oriented model show that North American countries, India, and European countries are the most efficient economies at maximizing their green innovations outputs. However, this high output-oriented efficiency is achieved at the expense of the inputs required to produce the same number of green innovations. Therefore, output-oriented efficiency does not depict the environmental behaviour of economies in terms of the rational use of financial and human resources

(Alnafrah, 2021). In other words, in countries with low CRS-input-oriented efficiency, the number of inputs required to produce one alive environment-related patent is much higher than those required in other countries.

The production of environmental knowledge is a complex process that requires resources, time, and effort. Figure 3 shows that even though the green innovations efficiency may increase over time, the relationship between the resources allocated and the resulting outputs is not straightforward. This process is subject to the law of diminishing returns (Barbero et al., 2021), indicating that beyond a certain threshold, augmenting the inputs will not yield a commensurate rise in the outputs. This pattern has been documented across all analyzed nations.

In other words, while it may initially be easy to produce green alive patents, over time, it becomes more difficult to do so, even with increased resource allocation. Therefore, policymakers need to focus on optimizing the use of inputs in the production process. This is because inputs, such as research and development expenditures and human resources, are within their control, while outputs, such as green patents, are influenced by various factors beyond their control. Thus, policymakers should shift their focus from output-oriented efficiency to input-oriented efficiency in the field of green innovations production. By doing so, they can ensure that the available resources are used most effectively and efficiently as possible.

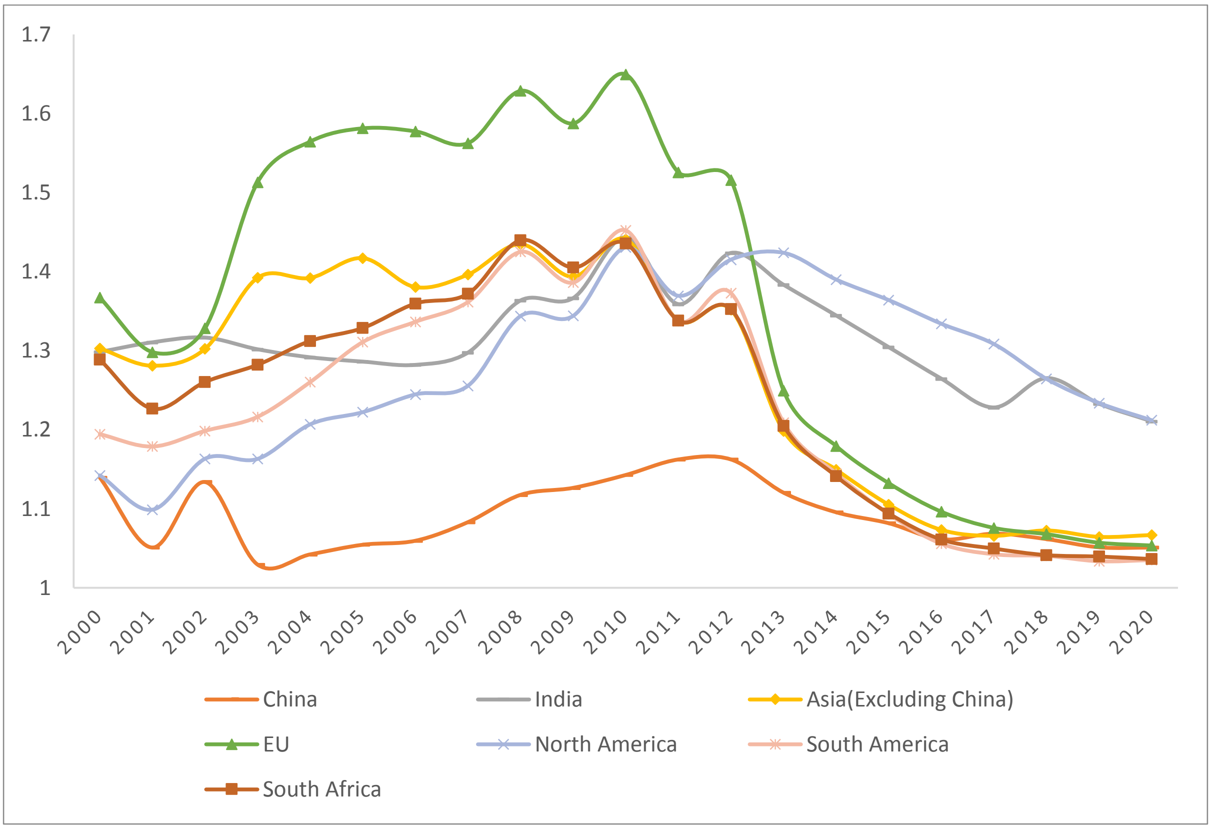

Fig. 3. International GIE.CRS.O comparison

Regarding environmental efficiency, figure 4 shows that China and North America have the lowest efficiency scores for achieving environmental SDGs, namely SDG-7 and SDG-13. In contrast, India, South America, and South Africa have the highest efficiency scores for achieving these two goals. This implies that major industrialized nations such as China, the USA, and the European Union do not exploit green innovations to improve their sustainable development performance.

For instance, China lags in renewable energy production compared to Brazil, which negatively affects its environmental efficiency. This indicates a lack of commitment by the Chinese government to increase clean energy production despite the existence of numerous green patents. Furthermore, green tax policies have been proven ineffective in major industrialized countries in achieving SDGs. In contrast, South American countries demonstrate how green innovations can enhance renewable energy production, thereby improving the efficiency of resource utilization for SDGs (Tchorzewska et al., 2022).

The case of India appears unexpected, but it is a result of a different approach to interpreting efficiency. In this context, the high level of efficiency stems from the government's increased focus on improving green taxes' structure and raising them for non-environmentally friendly activities. The latest data shows that the Indian government doubled green tax revenues between 2017 and 2020, resulting in improved environmental efficiency. The latest Sustainable Development Report also indicates that India has achieved SDG-13 Sustainable, while still facing challenges in achieving SDG-7 (Sachs et al., 2022).

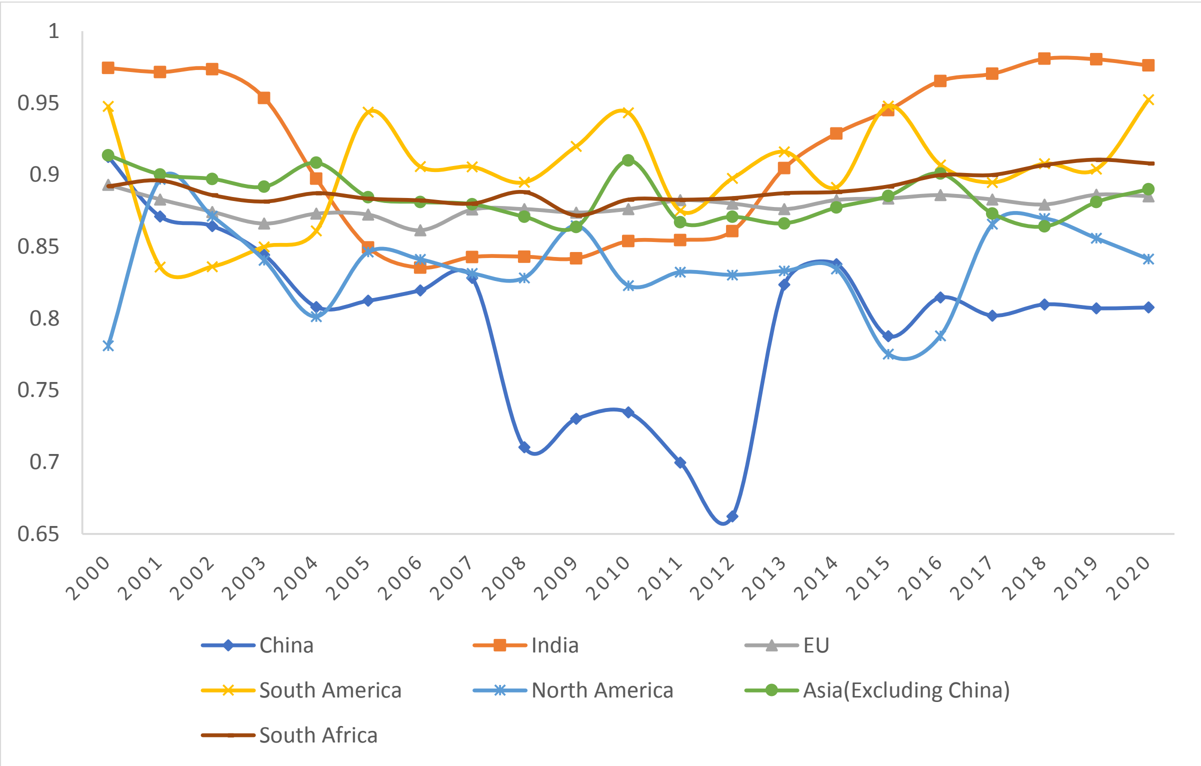

Fig. 4. International EN.CRS.I comparison

Conversely, when evaluating output-oriented environmental efficiency, figure 5 shows that certain countries like India and North America exhibit contradictory outcomes. Specifically, industrialized nations are more effective at maximizing output from a given input. Nevertheless, the latest Sustainable Development Report reveals that these countries still face significant challenges in achieving SDG-7 and SDG-13. Consequently, output-oriented efficiency fails to depict the true progress made by governments towards environmental sustainable development. Instead, the input-oriented efficiency analysis provides a more accurate representation of governmental efforts and policies geared towards green innovations and renewable energy to achieve environmental SDGs.

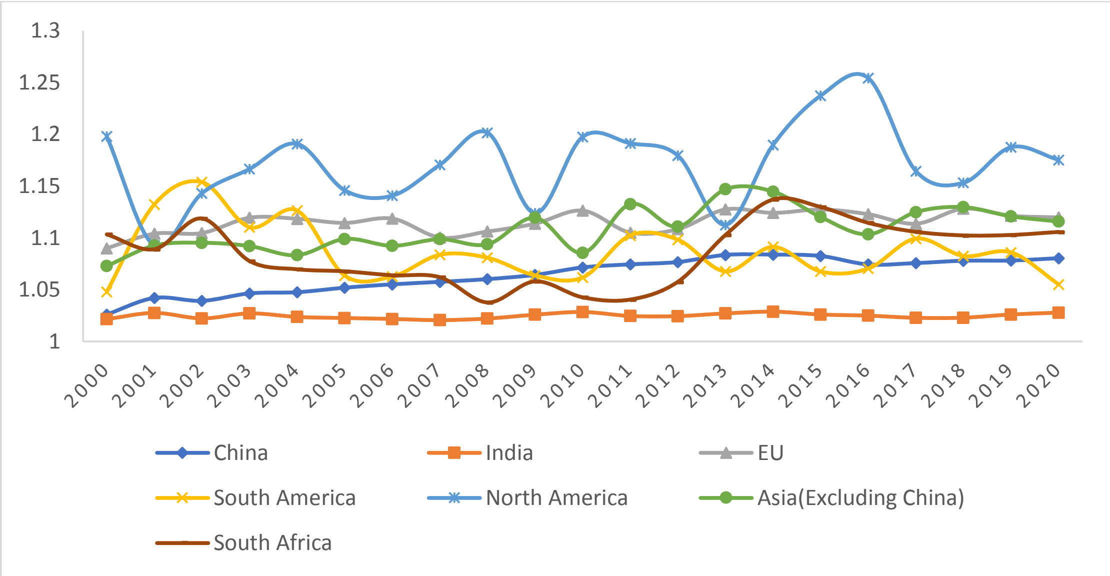

Fig. 5. International EN.VRS.O comparison

Regarding the role of environmental efficiency and green innovations efficiency in achieving SDGs, the results presented in Figure 6 reveal mixed results. The cases of China and India serve as notable illustrations of the contradictory connection between green innovations and sustainable development.

In China, despite high knowledge and green innovations efficiency, the efficiency did not translate into better environmental sustainable development (Ma et al., 2021). India, on the other hand, shows weak efficiency in producing environmental knowledge and green innovations, but recent government policies helped improve environmental efficiency in achieving certain SDGs. However, India's overall sustainable development efficiency remained low due to poor performance in other SDGs indicators (B.-C. Xie et al., 2014).

The European Union, despite having a high level of knowledge and green innovations efficiency, shows moderate environmental efficiency. Nevertheless, the EU's overall environmental efficiency remains high, indicating that green innovations have positive spillovers on achieving other SDGs. European government policies aimed at achieving SDGs currently prioritize the environmental aspect to a certain extent. However, an increased focus on green investments could greatly enhance the sustainability opportunities of the European Union. The current model of prioritizing industrial activities has had negative impacts on policy outcomes, which could be mitigated by prioritizing environmentally friendly practices, particularly given recent events such as the Russian-Ukrainian war and disruptions in energy supply chains. These circumstances have prompted some European Union countries to adopt energy policies that are not environmentally sustainable, highlighting the need for a shift towards more environmentally conscious practices (Biresselioglu et al., 2018).

South American countries, particularly Brazil, provide a good example of high efficiency in producing green innovations and sustainable environmental efficiency. This translated into high overall sustainable efficiency, reflecting the optimal utilization of environmentally friendly policies and tools (Banerjee & Murshed, 2020).

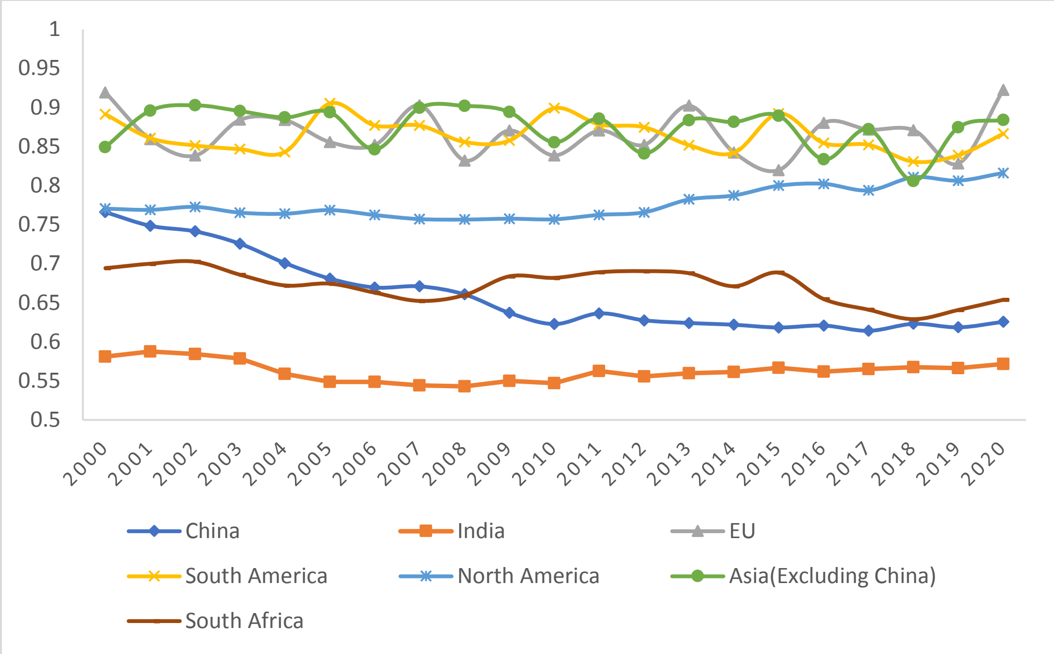

Fig. 6. International GE.CRS.I comparison

To acquire a thorough evaluation of countries' environmental efficiency, we calculate the average of their previous environmental efficiency scores. The outcomes are showcased in Figure 7, revealing subpar levels of environmental efficiency in industrial economies like the USA, China, and India. These lower levels can be ascribed to a variety of factors. In India, it could be due to the low production efficiency of green innovations, while in China, it could be due to the weak implementation of green innovations and environmental policies to achieve SDGs (Cao et al., 2023; Huang et al., 2021). In the case of the USA, the low overall environmental efficiency results from the weakness of both factors (Shapiro, 2022).

On the other hand, South American and European Union countries serve as exemplary models for other countries. These countries exhibit superior environmental efficiency levels by effectively utilizing their financial and human resources to produce green innovations and efficiently implementing them to achieve SDGs, not only limited to the environment but also beyond.

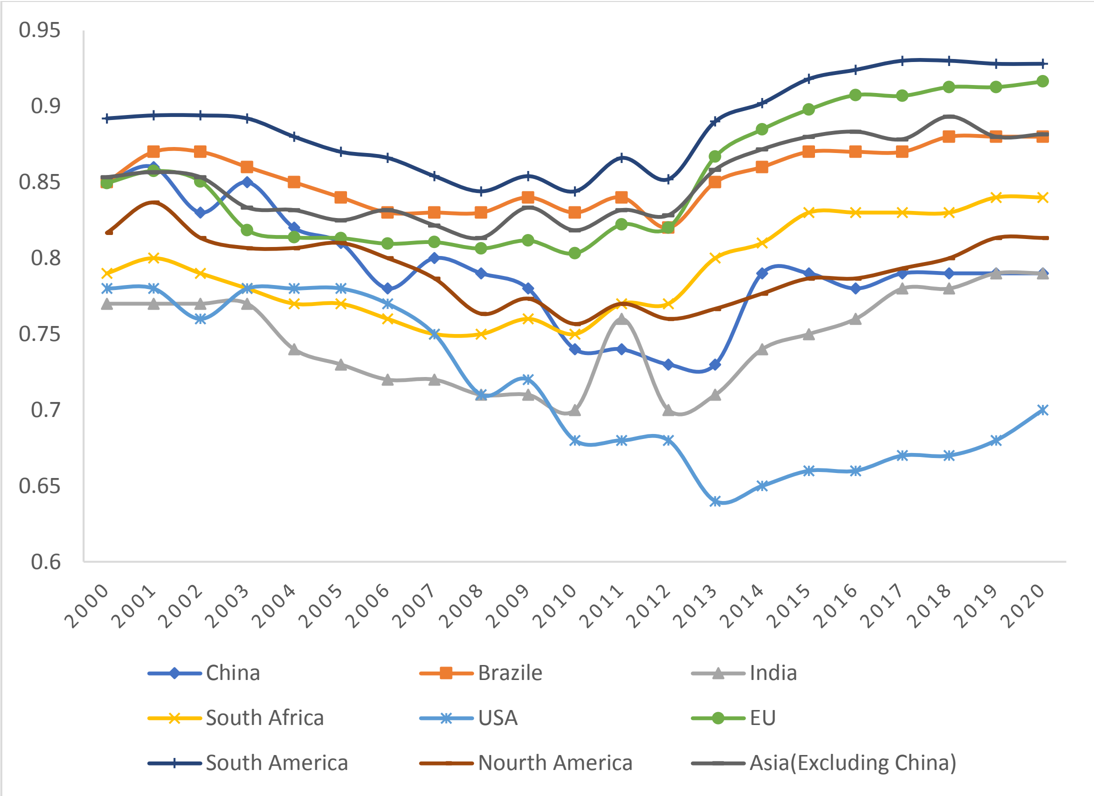

Fig. 7. Total average of environmental efficiencies

We examined the correlation between efficiency values to assess the impact of green innovations on enhancing the overall efficiency of sustainable development. Figure 8 shows a positive relationship between green innovations and the level of overall sustainable development efficiency. This confirms the main hypothesis on which the research was based. This means that increasing the green innovations efficiency plays an important role in improving and accelerating the process of achieving the overall SDGs.

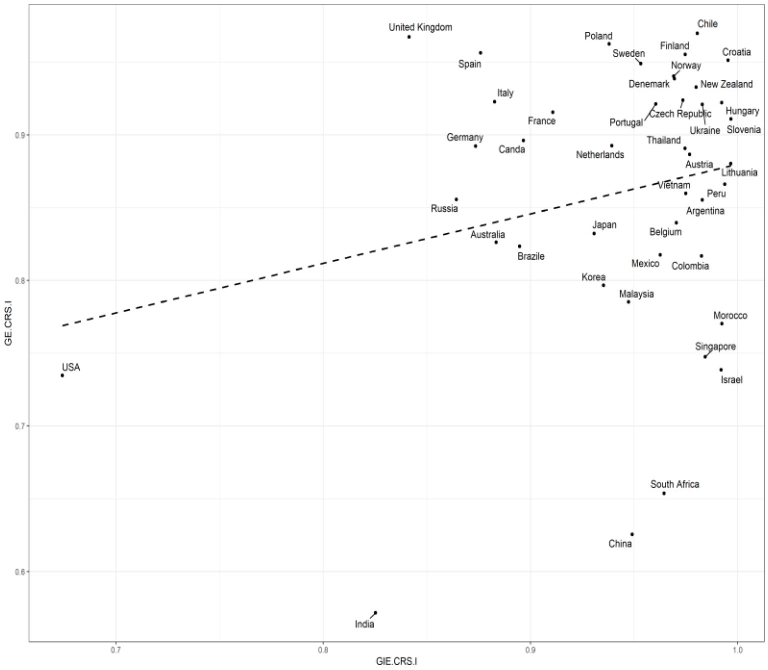

Fig. 8. The relationship between GE and GIE

Concerning the relationship between the environmental efficiency associated with achieving SDG7 and SDG13 (EN) and the total environmental efficiency (GE), Figure 9 illustrates a positive correlation. However, some deviations from this pattern were observed in the cases of China, the USA, and India, which are characterized by high industrial production intensity, a significant carbon footprint, and inadequate government policies concerning the environment. The low level of environmental efficiency in these countries undermines progress towards achieving the two aforementioned SDGs, and, consequently, the overall SDGs (Shapiro & Walker, 2020).

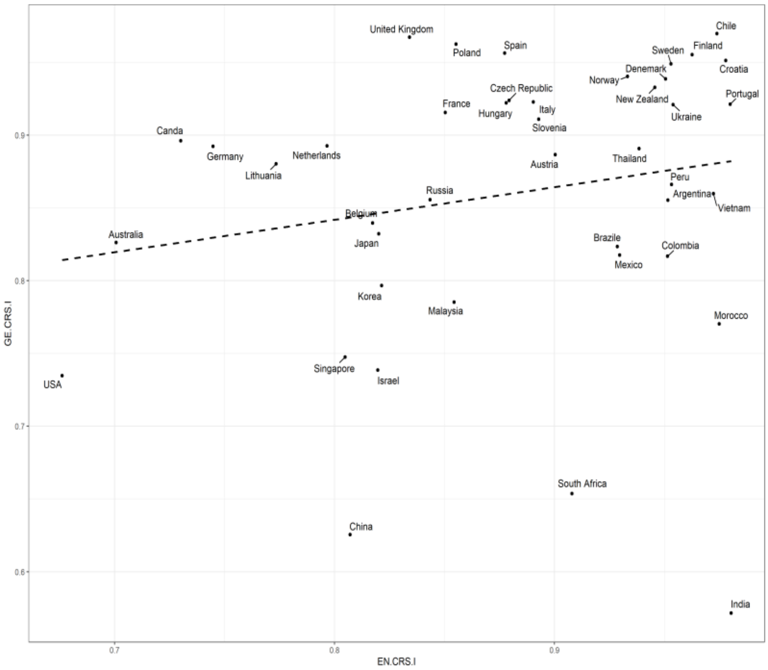

Fig. 9. The relationship between GE and EN

On the other hand, in figure 10, a more pronounced positive correlation can be observed between the overall environmental efficiency (GE) and the efficiency of green innovations (GIE). Again, some countries like Germany, Canada, and Australia provide different cases, where producing more green innovations does not lead to achieving the SDG-7 and SDG-13. These countries have a high level of green innovations efficiency, but their performance in terms of environmental efficiency (EN) is low in comparison with other studied countries. This situation calls for an environmental approach to achieve the SDGs including, but not limited to, increasing renewable energy production and reforming the environment-related taxation system.

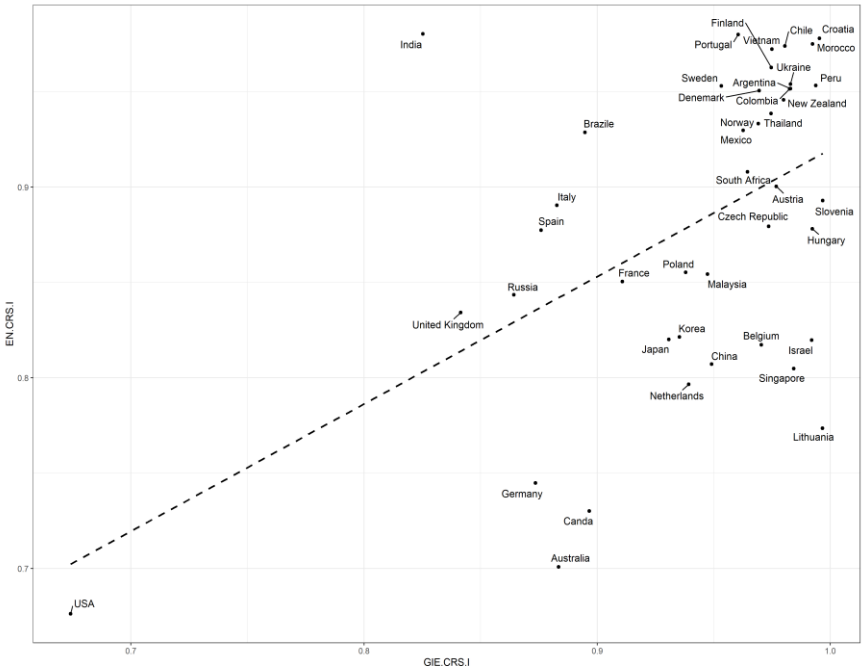

Fig. 10. The relationship between GIE and EN

To provide more profound policy benchmarking, a clustering analysis is conducted to explore the environmental frontiers in each cluster. The K-means clustering results shown in Figure 11 reveal that countries are clustered into three groups based on their efficiency scores.

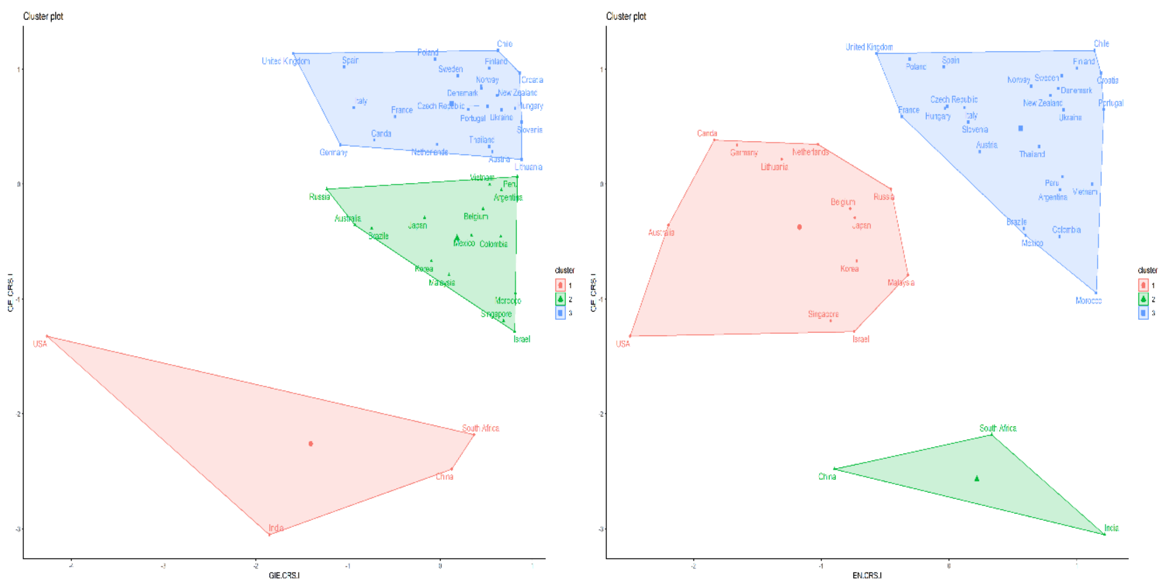

Fig. 11. Countries clustering based on their GIE and EN

In Figure 11, the left plot illustrates that countries within the cluster exhibit varying levels of green innovations efficiency and overall environmental efficiency. For instance, Russia is clustered together with South Korea and Australia, but its policy benchmarks are derived from cluster 2, which comprises Germany, Canada, and the Netherlands. This particular group of countries serves as a reference point for Russia to embrace more environmentally friendly policies, allowing it to approach the center of the optimal cluster and align with countries like Finland, Denmark, and Sweden, ultimately achieving a higher score in green innovations efficiency. Similarly, in the right plot of Figure 11, the USA should adopt policies and practices pertaining to the environment that resemble those implemented by benchmarking countries such as Japan, Belgium, and the Netherlands.

The abovementioned benchmarking cases serve as mere illustrations of how policymakers can address the low levels of different environment-related efficiencies. Therefore, it is imperative for future researchers to undertake comprehensive analyses when examining benchmarking studies pertaining to the environment.

5. Conclusion and policy implications

This study was intended to investigate to what extent countries are efficient in producing green innovations, and how these green innovations have been used to achieve environment-related SDGs, SDG-7 and SDG-13. To do so, a biased-corrected network DEA was applied to a set of environment-related variables. To capture the system failure of utilizing green innovations to achieve the SDGs, three types of efficiency were measured across different countries from several regions. Our study contributes to the policymaking process by revealing the heterogenous environmental performance across countries in the course of green economy and green innovations production. We primarily contribute to the debate on the role of green innovations in achieving the SDGs, and what policy interventions are required to stimulate the environmental performance of countries.

Our findings revealed that being efficient in creating or utilizing green innovation to achieve environment-related SDGs does not guarantee that there will be positive developmental spillovers to other SDGs. Therefore, policymakers should accompany green innovations with other policies such as command and control environmental policy, environment-related taxes, and support for renewable energy production. Additionally, our findings indicate that a high overall score for environmental efficiency may not always correspond to greater sustainability in certain countries. Through analysing the structural aspects of both green innovations efficiency and environmental efficiency, we found that countries with high-efficiency scores may have achieved non-environmental SDGs through economic and social policies rather than environmental initiatives or approaches. As a result, this high score may mislead policymakers.

Our study also revealed that the majority of progress has been made in knowledge and green innovations production (GIE). On the other hand, most countries have not made significant advancements in environmental efficiency (EN) by effectively utilizing green innovations to attain SDGs related to the environment. Therefore, policymakers should focus on implementing policies that prioritize environment-oriented SDGs to enhance environmental efficiency. This can be achieved by investing in green technologies, promoting sustainable practices, and encouraging businesses to adopt environmentally friendly approaches. Moreover, policymakers should consider integrating non-environmental SDGs with environment-oriented ones to avoid misleading high-efficiency scores.

More importantly, analysing the progress made in environmental efficiency suggested that during the early stages of knowledge and green innovations production, input utilization may initially result in decreased efficiency. However, over time, this process will become more efficient. Therefore, policymakers should also consider the inverted efficiency curve when developing policies and allocate resources accordingly. This means that more focus should be placed on promoting the optimal utilization of green innovations to achieve SDGs related to the environment, rather than solely relying on economic and social policies.

Finally, we found that green innovations efficiency plays a more decisive role than environmental efficiency, which is related only to SDG-7 and SDG-13, in achieving the SDGs. This signifies the importance of green innovations in achieving multidimensional sustainability. Policymakers should therefore prioritize green innovation-based solutions in their SDGs-related policies to tackle various challenges in the sustainable development process. Our study demonstrates that a few countries have made noteworthy progress in this pursuit, but there is still a lot of work to be done in addressing the global environmental challenges confronting the world at present.

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Appendix A.

Table A. 1 List of studied countries

Region	Countries
EU and other European countries	Austria, Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Lithuania, Netherlands, Norway, Poland, Portugal,

	Russia, Slovenia, Spain, Sweden, Ukraine, United Kingdom
Asia	China, India, Israel, Japan, Korea, Malaysia, Singapore, Thailand, Vietnam
South America	Argentina, Brazil, Chile, Colombia, Peru
North America	Canada, Mexico, USA
Africa	Morocco, South Africa
Others	Australia, New Zealand

Table A. 2 Data source and descriptive statistics

Variable	Code	Source	Mean	Std. dev. overall	Std. dev between	Std. dev within
Research and development expenditure as % of GDP (RD)	RD	WDI database	1.64	1.05	1.02	0.27
Articles published in environmental science (AP)	AP	Scopus database	3168	6241	5191	3552
Number of alive environment patents (GI)	GI	Orbit Intelligence database	1023	7517	3855	6479
Environmentally related tax revenue (Etax)	Etax	OECD database	1.97	1.09	1.10	0.35
Renewable Energy generation (GWh) (RenEn)	RenEn	OECD database	29258.26	68742.1	56041.12	40696
SDG.7 – Affordable and clean energy	SDG.7	Sustainable development report	73.22	8.56	8.29	2.47
SDG.13 – Climate action	SDG.13	Sustainable development report	66.21	20.66	20.76	2.38
SDG.Overall	SDG	Sustainable development report	73.43	6.53	6.27	2.04

Number of observations	882
Number of countries	42

Table A. 3 RTS test results

Year	Orientation test p-value		
	KE	EN	GE
2000	0.02	0.02	0.02
2001	0.02	0.02	0.02
2002	0.02	0.02	0.02
2003	0.02	0.02	0.02
2004	0.02	0.02	0.02
2005	0.02	0.02	0.02
2006	0.02	0.02	0.02
2007	0.02	0.02	0.02
2008	0.02	0.02	0.02
2009	0.02	0.02	0.02
2010	0.02	0.02	0.02
2011	0.02	0.02	0.02
2012	0.02	0.02	0.02
2013	0.02	0.02	0.02
2014	0.1	0.02	0.02
2015	0.005	0.02	0.02
2016	0.48	0.02	0.02
2017	0.48	0.02	0.02
2018	0.6	0.02	0.02
2019	0.6	0.02	0.02
2020	0.5	0.02	0.02

Declaration of interests

☒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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Research Highlights

- Output-oriented green innovations production is subject to the law of diminishing returns.
- Policymakers should redirect their attention from output-oriented efficiency to input-oriented efficiency when it comes to producing green innovations.
- Achieving SDGs goals in industrial economies comes at the cost of negative environmental impacts.
- South American and European Union countries are at the forefront in terms of efficiency in green innovations.