



Spatio-temporal variations, spatial spillover, and driving factors of carbon emission efficiency in RCEP members under the background of carbon neutrality

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Abstract

Improving carbon emission efficiency (CEE) has emerged as a critical way for Regional Comprehensive Economic Partnership (RCEP) members to promote carbon reduction in the context of climate change mitigation and carbon neutrality. The super-efficiency slacks-based measure (SBM) model, which considers non-desired outputs, is adopted to comprehensively assess the current state and trend of CEE in 15 RCEP countries from a spatio-temporal dynamic perspective, and the global Malmquist-Luenberger (GML) index is coupled to quantify the spatial and temporal differences and dynamic changes. Following that, taking into account the spatial characteristics of CEE, the extended STIRPAT model and the spatial Durbin model are combined to further investigate the primary influencing factors of CEE. It is found that (1) the CEE of RCEP members is generally poor and unevenly distributed in temporal and spatial dimensions, with significant room for improvement and an overall positive spatial autocorrelation; (2) CEE varies considerably among RCEP members, with developed countries far outstripping developing countries in terms of both the current status and trend of CEE; (3) on a dynamic level, the GML index exhibits W-shaped fluctuations, with technological progress acting as the dominant force; and (4) in terms of spillover effects, affluence and economic agglomeration inhibit CEE enhancement, whereas technology level and investment capacity facilitate it. The findings will be useful in developing carbon-neutral plans for various countries as well as coordinated sustainable development for RCEP regions.

Keywords Carbon emission efficiency · RCEP countries · Super-efficiency SBM model · Global Malmquist-Luenberger index · STIRPAT · Spatial Durbin model

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Highlights

- The carbon emission efficiency of 15 RCEP members is quantified from 2010 to 2019.
- The super-efficiency undesirable SBM model yields accurate carbon emission efficiency.
- The spatiotemporal variations and dynamic evolution of CEE are analyzed.
- On account of an extended STIRPAT model, 5 driving factors for CEE are identified.
- Spatial spillover effects of drivers on CEE are examined based on effect decomposition.

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Introduction

Global warming-related issues, such as ecosystem destruction, biodiversity loss, natural disasters, and glacier melting, have severely hampered human survival and development (Filho et al. 2019; Bandh et al. 2021). Climate change has emerged as one of the most pressing challenges to global environmental issues today, fueled predominantly by CO₂ and other greenhouse gases emitted due to human activity (Feng et al. 2021; Kazancoglu et al. 2021). In this context, carbon emission reduction is emerging as a critical initiative to address climate change (Feng and Wu 2022). The improvement of carbon emission efficiency (CEE) is regarded as a critical way to promote carbon emission reduction as a proxy for carbon-neutral performance (Zhang and Deng 2022). However, the interaction mechanism between CEE and its driving factors has yet to be fully explored (Gao et al. 2022). Therefore, it is vital to develop an accurate CEE identification and assessment model.

There is already agreement reached on reducing CO₂ emissions and implementing a low-carbon economy, followed by

concrete actions. Several agreements, such as the *Kyoto Protocol* (Nematchoua et al. 2021), the *Copenhagen Accord* (Lau et al. 2012), the *2030 Agenda for Sustainable Development* (Miola and Schiltz 2019), and the *Paris Agreement* (Lu et al. 2022), have been formulated over the years, demonstrating the firm belief of countries worldwide in promoting carbon emission reductions (Zhang et al. 2022a). As of May 2022, 127 countries had proposed or were planning to propose carbon neutrality targets covering 90% of the global GDP, 85% of the total population, and 88% of carbon emissions (Zhao et al. 2022b). As the largest free trade agreement in the world, 13 of the 15 Regional Comprehensive Economic Partnership (RCEP) members have announced carbon neutrality goals. During the General Debate of the 75th Session of the United Nations General Assembly, China, for example, articulated ambitious goals for carbon peaking and carbon neutrality, which corresponds to a 60 to 65% reduction in CO₂ emissions per unit of GDP in 2030 compared to 2005 (Zhang and Deng 2022). As a result, it is critical to investigate the carbon neutrality performance of RCEP members to meet the global carbon neutrality target.

The RCEP agreement, which covers China, Japan, South Korea, Australia, New Zealand, and ten ASEAN countries, was developed by 15 members and comes into effect on January 1, 2022 (Rahman and Ara 2015; Zhang and Wang 2022a, b). In 2019, the RCEP countries accounted for 30% of the total population and 31.3% of GDP, while accounting for 36.8% and 42.1% of total energy consumption and carbon emissions globally, respectively (Qian et al. 2022; Lin et al. 2022; Zhang and Chen 2022). The tariff decrease will significantly increase the short-term pressure on members to reduce their carbon emissions along with the official certification of RCEP. It will also exacerbate the carbon leakage between developed and developing countries. As a result, the RCEP members must now seriously address the rapidly growing carbon emissions (Lin et al. 2022). The fundamental issue regarding low-carbon economic development in RCEP countries at the moment is how to reduce resource consumption and CO₂ emissions while enhancing CEE.

If CEE is enhanced, the RCEP region can undoubtedly benefit from low-carbon development; however, there are several fundamental issues with CEE. Examples include how the CEE of RCEP countries may be measured scientifically, how it has changed over time, and how it varies throughout regions (Zhou and Xu 2022). What causes these temporal and spatial variations? Reliable responses to these questions will not only offer policy suggestions for the carbon-neutral goals of various countries but also offer insightful information on the coordinated and sustainable development of the RCEP region in the current open economy environment (Meng and Qu 2022).

Therefore, the objective of this study is to evaluate the CEE of RCEP members while examining the spatial and temporal characteristics, regional disparities, spatial spillover effects, and driving mechanisms of CEE in the context of carbon neutrality. First, from the standpoint of spatial and temporal

dynamics, the current state and trend of CEE in RCEP members are thoroughly evaluated; and to offer a thorough examination of the regional variations and development trends, the CEE of each nation is compared from a geospatial perspective. Second, from a broad green economy viewpoint, the STIRPAT model incorporates investment capacity and economic agglomeration in light of the significant contribution of the RCEP region to the post-pandemic global economic recovery (Zhang et al. 2023). Finally, to complement the existing studies and provide a theoretical foundation for increasing regional resource use efficiency and achieving carbon neutrality goals, the spatial Durbin model (SDM) and the spatial effect decomposition are applied to explore the key influencing factors of CEE, taking into account the spatial spillover effects.

This essay has the following format. In “[Literature review](#)” section, the literature is reviewed. The methodological framework for examining the spatiotemporal dynamics, spatial spillover, and affecting factors of CEE is presented systematically in “[Methodology](#)” section. “[Variables and data](#)” section describes the study area, variables, and data. In “[Empirical results and discussion](#)” section, the results of the empirical analysis are discussed. Research conclusions and policy suggestions round out the part.

Literature review

Measurement of CEE

Efficiency in the context of economics is understood as the ratio of output produced by a given work to input under specific circumstances (Levihn 2016). Similar to how economic efficiency is defined, CEE can be identified as having a higher economic output while using fewer resources and emitting less CO₂. The measures of CEE are divided into two categories, single factor carbon emission efficiency (SFCEE) and total factor carbon emission efficiency, depending on how production efficiency is measured (TFCEE) (Zhang and Liu 2022).

SFCEE often refers to the relationship between carbon emissions and resource consumption or economic output, such as carbon emission intensity and carbon emission per capita. Carbon intensity, which measures carbon emissions as a percentage of GDP, accounts for both economic progress and carbon emission levels. To investigate the evolving trends of carbon emission intensity and its drivers in China throughout the three 5-year plans at the national, regional, and industry levels, along with projections of the future trends, an integrated decomposition framework based on the IDA model and the PDA model was created (Chen et al. 2022a). Liu et al. (2022) investigated the dynamic spatio-temporal evolution characteristics of carbon emission intensity in 41 counties of Qinghai Province, China, combining nonparametric kernel

density estimation, spatial Markov chain, and spatial variance function models to offer a reliable benchmark for sustainable development. Spatio-temporal heterogeneity and convergence of carbon emissions per capita in the plantation industry, taking into account the carbon sink effect and its affecting factors, were examined using panel data from 31 Chinese provinces from 1997 to 2017 (Cui et al. 2022). SFCEE has the drawback of being incomplete and misrepresenting the true production connection, although being simple to compute and compare (Li et al. 2022c). Next, the TFCEE is derived.

TFCEE offers improved persuasion by accounting for the connections between various inputs and outputs (Li et al. 2022c). It establishes a full-factor measurement model to assess CEE from several aspects and integrates several variables, including those related to energy, labor, economic output, and CO₂ emissions. Comparatively to the SFCEE, the TFCEE seems to have a more robust comprehensive evaluation capability, which can successfully prevent bias (Proskuryakova and Kovalev 2015). A dynamic slacks-based measure (SBM) model was implemented to find changes in CEE for China, using total year-end population and energy consumption as inputs, GDP as the desirable output, and CO₂ emissions as the undesired output (Teng et al. 2021). Yu and Zhang (2021) examined a generalized nonconvex meta-frontal DEA model to assess the effects of low-carbon municipal pilot measures on CEE. Zhang et al. (2022c), using the Yangtze River Economic Belt as an example, clarified the formation mechanism of the CEE network and looked into its structural entropy, hierarchical structure, and transmission characteristics, all of which serve as helpful guidance for local carbon reduction efforts.

Various factors influencing the CEE

A systematic and comprehensive index system has not been developed for the study of the factors affecting CEE, and the majority of the literature only looks at a small number of the multiple variables that affect CEE (Zhang and Liu 2022; Li et al. 2022b). The exponential decomposition method, which consists of two general models, is currently what the majority of academics think about when investigating the elements systematically determining CEE.

The first is based on the Kaya identity, which breaks down the components that affect carbon emissions into carbon emissions per unit of energy consumption, energy consumption per unit of GDP, GDP per capita, and population size (Kaya and Yokobori 1997). Carbon emission changes are further decomposed into 9 driving factors using a joint approach based on the Kaya identity exponential decomposition analysis (IDA) and production theory decomposition analysis (PDA) based on a met frontier model (Liu et al. 2019), with a detailed examination of the impact of the 9 factors on national, regional, and provincial

carbon emission changes in China from 2007 to 2016. To measure the impact of changes in each influencing factor on CEE, the Kaya identity is frequently used in conjunction with the log mean Divisia index (LMDI). An extended Kaya-LMDI model is applied to quantitatively analyze how different factors, such as income, population, energy intensity, energy mix, and economic structure, which affect changes in the CEE of three industrial land spaces (agriculture, production and living, and transportation spaces), providing insight into strategies for reducing carbon emissions and land use (Wu et al. 2021b).

The second one is the STIRPAT model, which York et al. (2003) improved from the IPAT model to be a stochastic scalable environmental impact decomposition model. According to the IPAT model, total environmental impact (I) is a function of population (P), affluence (A), and technology (T) (Dietz and Rosa 1997). Whereas, the STIRPAT model adds other variables to investigate the determinants influencing CEE. In contrast to the Kaya equation and the IPAT model which presuppose that all factors affect carbon emissions in the same proportion, the STIRPAT model addresses this flaw and has been broadly applied in research in the field of environmental economics (Zhu et al. 2022). Liu et al. (2021) surveyed the regional variations and influencing factors of carbon emissions in the transportation sector among 30 provinces and added variables including urbanization rate, industrial structure, and energy consumption structure to the STIRPAT model. To investigate the factors influencing CEE in developed and non-high-income countries, respectively, Lin et al. (2017) and Wu et al. (2021a, b) built the extended STIRPAT model based on panel data derived from various types of countries. They quantified the actual contribution of each driver for understanding the emission characteristics and key drivers.

It has been established that there is a connection between the economy and carbon emissions (Lin and Teng 2022), and the efficiency of economic growth and the efficiency of carbon emission reduction is correlated (Sheng et al. 2020). While Yan et al. (2022) employ spatial econometrics and an extended STIRPAT model to investigate the effects of FDI and agglomeration levels on pollution emissions, Lu et al. (2021) build a model to examine how two economic indicators, financial spatial structure and economic agglomeration, affect carbon emission intensity. In order to assess the influencing factors of CEE, the STIRPAT model, which is expanded by integrating more economic indicators based on the three initial influencing variables of affluence, population size, and technological level, is a good choice.

Summary of literature and research gap

A great deal of insight and research ideas has been incorporated into the field of CEE, laying the groundwork for further investigations. However, there is still a lot to explore, particularly in the following areas.

1. The majority of current studies have focused on the spatial–temporal evolution and motivating factors of CEE at the industry, enterprise, and provincial levels; in contrast, there are comparatively few studies on the international or regional level, particularly for RCEP, a new international organization that has only been operational for a brief period. Identifying and scientifically evaluating CEE in RCEP countries contributes to grasping the spatial and temporal evolutionary trends of CEE and bridges the understanding of CEE in the RCEP region.
2. Studies on regional differences in RCEP organizations are relatively under-reported. Due to various historical and natural reasons, RCEP countries differ greatly in terms of geographical location, resource endowment, and market environment, and the CEE is also regionally heterogeneous. Under the goal of carbon neutrality, it is crucial to compare the CEE of various countries and to analyze in depth the regional differences and their evolution patterns of CEE, in order to achieve a coordinated and balanced development among regions.
3. As the largest free trade agreement organization in the world, the RCEP organization is considered to play a non-negligible role in the post-pandemic recovery of the world economy. From a broad green economy perspective, the factors affecting the CEE of the RCEP organization are comprehensively examined by incorporating investment capacity and economic agglomeration into the STIRPAT model, to enrich existing research.
4. Instead of considering spatial spillover effects and radiative effects, there is a tendency for most works regarding RCEP region to treat the research units as independent and homogeneous individuals, ignoring spatial linkages and correlations as well as focusing only on the direct effects of driving factors. In order to complement the existing studies and provide a theoretical foundation for increasing regional resource use efficiency and achieving carbon neutrality goals, the SDM and the spatial effect decomposition are applied to explore the key influencing factors of CEE, taking into account the spatial spillover effects.

Methodology

Static measurement of CEE: super-efficiency SBM model

Data envelopment analysis (DEA) is a relatively objective and accurate method from a total factor perspective for measuring CEE because it better fits the comprehensive evaluation model with various inputs and outputs (Pishgar-Komleh et al. 2020). The super-efficient SBM model taking into account non-desired outputs is able to solve the issue in the presence

of non-desired outputs in comparison to the basic DEA (Tone 2001), while also offering a framework for rating various efficient decision-making units. It also directly includes slack variables in the objective function, making it an excellent choice for CEE measurement (Pishgar-Komleh et al. 2020).

$$\begin{aligned}
 \min \bar{S}_C^{-t} = \min \rho = & \frac{1 + \frac{1}{m} \sum_{i=1}^m s_i^- / x_{ik}}{1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} \cdot \sum_{i=1}^{q_2} s_w^{b-} / b_{ik} \right)} \\
 \text{s.t. } & \begin{cases} \sum_{j=1, j \neq k}^n \lambda_j x_{ij} - s_i^- \leq x_{ik} \\ \sum_{j=1, j \neq k}^n \lambda_j y_{rj} + s_r^+ \geq y_{rk} \\ \sum_{j=1, j \neq k}^n \lambda_j b_{wj} - s_w^{b-} \leq b_{wk} \\ 1 - \frac{1}{q_1 + q_2} \left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} \cdot \sum_{i=1}^{q_2} s_w^{b-} / b_{ik} \right) > 0 \\ \lambda_j, s_i^-, s_r^+, s_w^{b-} \geq 0 \\ i = 1, 2, \dots, m \\ j = 1, 2, \dots, n \\ r = 1, 2, \dots, q_1 \\ w = 1, 2, \dots, q_2 \\ j \neq k \end{cases} \quad (1)
 \end{aligned}$$

where X , Y , and B denote the matrices of inputs, desired outputs, and undesired outputs, respectively; s_i^- , s_r^+ , and s_w^{b-} represent the slack variables for inputs, desired outputs, and undesired outputs; m , q_1 , and q_2 refer to the number of inputs, desired outputs, and undesired outputs; j , k , i , r , and w denote the j th DMU, k th DMU, the i th input, the r th desired outputs, and the w th undesired outputs, respectively; n is the number of DMUs, λ is the nonnegative multiplier vector, and \bar{S}_C is the efficiency value of period t . If $\rho \geq 1$, the corresponding input–output is efficient; otherwise, it is not. And the larger the value of ρ , the higher the efficiency.

Dynamic measurement of CEE: GML index

The super-efficient SBM model falls short of accurately capturing the dynamic changing characteristics based on the cross-sectional measurement of static CEE for a single year. To reflect the dynamic changes in the CEE of RCEP members from 2010 to 2019, the global Malmquist-Luenberger (GML) index is used (Malmquist 1953; Fare et al. 1994; Chung et al. 1997). The GML index can be further broken down into technical efficiency (GML_{effch}) and technical progress (GML_{tech}) indices, allowing analysis of the key driving elements, rather than just looking at the change in CEE over time.

$$GML(x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t) = \left[\frac{\bar{S}_C^{-t}(x^{t+1}, y^{t+1}, b^{t+1})}{\bar{S}_C^{-t}(x^t, y^t, b^t)} \times \frac{\bar{S}_C^{-t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{\bar{S}_C^{-t+1}(x^t, y^t, b^t)} \right]^{\frac{1}{2}} \quad (2)$$

$$GML(x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t) = GML\text{effch}_t^{t+1} \times GML\text{tech}_t^{t+1} \tag{3}$$

$$GML\text{effch}_t^{t+1} = \frac{\bar{S}_C^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{\bar{S}_C^t(x^t, y^t, b^t)} \tag{4}$$

$$GML\text{tech}_t^{t+1} = \left[\frac{\bar{S}_C^t(x^{t+1}, y^{t+1}, b^{t+1})}{\bar{S}_C^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \frac{\bar{S}_C^t(x^t, y^t, b^t)}{\bar{S}_C^{t+1}(x^t, y^t, b^t)} \right]^{\frac{1}{2}} \tag{5}$$

Identification of the driving factors: STIRPAT model

Ehrlich and Holdren first proposed the IPAT model in 1971, which resulted in an equation between carbon emissions and population, per capita income, and technological level (Dietz and Rosa 1997; Ma et al. 2022), as shown in Eq. (6). Building on the IPAT equation, the stochastic impacts by regression on population, affluence, and technology (STIRPAT) was proposed (York et al. 2003) and is represented in Eq. (7). The STIRPAT model has been widely applied to various environmental economics research because it can quantify the impact of factors on environmental loads. Additionally, it can be stochastically expanded by including other influencing factors in accordance with the actual situations (Zhang et al. 2022b).

$$I = P \times B \times T \tag{6}$$

$$I = a \times P^b \times B^c \times T^d \times e \tag{7}$$

where *I* denotes the environmental load; *P*, *B*, and *T* characterize the population, affluence, and technology level, respectively, and *b*, *c*, and *d* are the corresponding index terms; *a* is the constant term and *e* is the error term.

Modeling of the driving factors: spatial regression model

Continuous trade globalization has resulted in a strengthening of international economic and trade relations as well as an increase in the frequency of industrial transfers and a corresponding large-scale movement of carbon emissions (Dong et al. 2022). Spatial econometric models have proven to be the best option for handling such spatial effects. The selection of spatial econometric models is critical because the model setup significantly affects the validity of the model estimates. The spatial Durbin model (SDM), spatial error model (SEM), and spatial lag model (SAR) are some of the well-known spatial econometric models (Chen et al. 2022b). SEM

explores the interaction between the spatial error terms, whereas SAR assesses spatial dependence by taking into account the endogenous interaction of the explanatory variables. The spatial correlation of the explained variables and the spatial correlation of the explanatory variables are both taken into consideration by SDM, which is a combined extended form of the models mentioned above (Feng and Wang 2020).

$$SAR : Y_{it} = \delta \sum_{j=1}^n W_{ij} Y_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{8}$$

$$SEM : Y_{it} = \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \varepsilon_{it} = \rho \sum_{j=1}^n W_{ij} \varepsilon_{it} + \nu_{it} \tag{9}$$

$$SDM : Y_{it} = \delta \sum_{j=1}^n W_{ij} Y_{it} + \theta \sum_{j=1}^n W_{ij} X_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{10}$$

where δ is the spatial autoregressive coefficient; μ_i , λ_t , and ε_{it} denote the individual effect, time effect, and random error, respectively; and ν_{it} denotes the spatial autocorrelation error term.

Variables and data

Study area

The RCEP agreement was first introduced by ASEAN in 2012 to encourage regional economic integration and free trade. The 15-member RCEP agreement, which covers China, Japan, South Korea, Australia, New Zealand, and 10 ASEAN nations (Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam) entered into force on January 1, 2022 (Li and Moon 2018). The RCEP is the largest free trade agreement, including 30.0% of the world’s population and 31.3% of GDP in 2019. However, energy consumption and carbon emissions account for 36.8% and 42.1% of the global totals, respectively, and the CEE urgently needs to be improved (Zhang and Chen 2022).

Abundant energy and mineral reserves and high exploitation serve as essential foundations for the decarbonization transition in the RCEP region (Zhang and Chen 2022). Australia ranks second globally as an exporter of liquefied natural gas and coal, while Indonesia, Malaysia, and New Zealand are rich in oil, gas, timber, and coal reserves. Besides, the advanced technology in Japan and South Korea, powerful production capacity and mega market size in China, and relative labor cost advantage in most ASEAN countries are evident (Lin et al. 2022). Under

favorable measures such as significant reduction of tariff barriers, adoption of cumulative rules of origin, and negative list investment access (Ding et al. 2022), it is possible for RCEP to give full play to the comparative advantages of countries, accelerate the flow and effective allocation of technology and resources, and promote the process of regional integration and sustainable development (Zhou and Xu 2022). Studying the carbon-neutral performance of RCEP members bears vital significance for fulfilling the carbon neutrality target worldwide.

Variable selection

Input and output variables

To calculate the CEE in the RCEP region, the super-efficiency SBM model mentioned in “Static measurement of CEE: super-efficiency SBM model” section was used. According to earlier studies (Zhao et al. 2022a; Zhang and Liu 2022), GDP and CO₂ emissions are chosen as outputs. GDP and CO₂ emissions are chosen as outputs, while capital stock, labor force, and total energy consumption are chosen as inputs (Table 1).

Driving factors

When studying CEE using the STIRPAT model, an extended STIRPAT model can be created by including additional components that have an impact on CEE in accordance with real-world settings. It has been proven that there is a link between the economy and carbon emissions (Lin and Teng 2022) and that there is a direct correlation between economic growth efficiency and the efficiency of carbon emission reduction (Sheng et al. 2020). The RCEP agreement, which was formalized in September 2020 and is seen as playing a significant part in the post-pandemic recovery of the global economy, is the largest free trade agreement organization in the world (Zhang et al. 2023). There will be more engagement between participating nations in the actual economy and capital markets as a result of tariff reductions and negative listings (Li et al. 2022a). In light of the three basic influencing elements of affluence, population size, and technology level, the STIRPAT model is extended by choosing two economic factors, namely investment capacity and economic agglomeration, as

independent variables (Lu et al. 2021; Yan et al. 2022). Affluence (AFF) and investment capacity (ATI) are two of them, and they are quantified, respectively, by gross fixed capital creation and GDP (constant 2010 US\$) (Wang et al. 2017; Ma et al. 2022). The population density indicator and the labor density indicator, which measure the number of people and employees per unit of land area, respectively, are applied to describe population (POP) and economic agglomeration (EAL) (Gani 2021; Xu et al. 2022). The energy intensity, specifically represented as energy consumption per unit of GDP, often captures the technology level (ENR), since a decline in energy intensity typically reflects a rise in technical innovation and advancement (Zhu et al. 2022).

Data source

The data on the CEE of the 15 RCEP members were chosen as completely as possible, taking into account the availability. Table 2 contains a list of the assessment samples chosen for RCEP participants. The *United States (US) Energy Information Administration* (<https://www.eia.gov/international/data/world>) and the *World Bank database* (<https://data.worldbank.org/>) both provided the data, and the sample period included 2010 to 2019. MATLAB 2016 software was utilized to perform interpolation for a few missing data points. Additionally, MATLAB 2016 software was used to implement the super-efficiency SBM model taking into account undesirable outputs and the decomposition of the GML index. GeoDa software was employed to create the spatial weight matrix, and Stata 16.0 was used to establish the SDM. The drivers are taken as logarithms to address the heteroskedasticity and lessen the instability of panel data. Table 3 displays the statistical summaries of each variable.

Empirical results and discussion

Spatio-temporal evolution of CEE for 15 RCEP members

Spatial feature analysis

The panel data of 15 RCEP members from 2010 to 2019 are estimated based on the super-efficiency SBM model and the

Table 1 Explanations for the input and output variables

Variable	Indicator	Source	Definition
Input variables	Capital	WDI	The capital stock is calculated using the perpetual inventory method (current US\$)
	Labor	WDI	The number of employees
	Energy	EIA	Total energy consumption (terajoules)
Desirable output	GDP	WDI	The gross domestic product (current US\$)
Undesirable output	CO ₂ emissions	EIA	Carbon dioxide emissions from the consumption of energy (MMtons)

Table 2 Selection of assessment samples in RCEP members

Region	Country
ASEAN (10)	Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam
Non-ASEAN (5)	China, Japan, Korea, Australia, New Zealand

Table 3 Descriptive statistics for all variables

Variables	Obs	Mean	Std. dev	Min	Max
CEE	150	0.7137	0.2703	0.2840	1.0420
lnAFF	150	26.358	1.9451	23.017	30.291
lnPOP	150	17.309	1.8821	12.870	21.065
lnENR	150	-11.618	0.4555	-12.360	-10.416
lnATI	150	3.3219	0.2104	2.8390	3.8429
lnEAL	150	4.1823	1.7090	0.4176	8.5155

input–output variables shown in Table 1, and the CEE of each country is measured, as outlined in Table 4. The average value of CEE in RCEP members from 2010 to 2019 was determined to be 0.714, which is considered to be low and gives significant room for future improvement.

The CEE of 15 RCEP countries was visualized via ArcGIS software, and a map of the spatial distribution of four-time nodes was generated to intuitively depict the spatial characteristics (Fig. 1). Overall, the CEE features spatial non-equilibrium and variable spatial patterns, gradually shifting from high in the center and low at both ends to low in the middle and high at both ends from south to north.

More specifically, at the country level, more than half of the nations, including Australia, Singapore, Korea,

Malaysia, Indonesia, Philippines, Vietnam, and China, have seen an increase in CEE. It demonstrates that countries are attempting to strike a balance between the economy, society, and environment by implementing greener transformations of economic conceptions and development patterns and paying closer attention to carbon emissions. The CEE of China has increased more rapidly since 2010, going from 0.499 in 2010 to 1.030 in 2019 at an average annual growth rate of 10.64%. Laos and Myanmar, on the other hand, show a more pronounced reduction in CEE, with a loss of over 50%. It demonstrates the growing incompatibility between population, resources, and the environment as well as the mounting pressure for sustainable development. An area of great concern is Myanmar. The CEE index of Myanmar in 2012 suddenly changed dramatically, which may be related to the ongoing military conflict. The region has been in upheaval since the riots in Rakhine State in May 2012. Studies have revealed that protracted conflict not only hinders economic growth but also significantly increases greenhouse gas emissions and air pollution, with wartime carbon emissions being the most intensive and concentrated of all human activities.

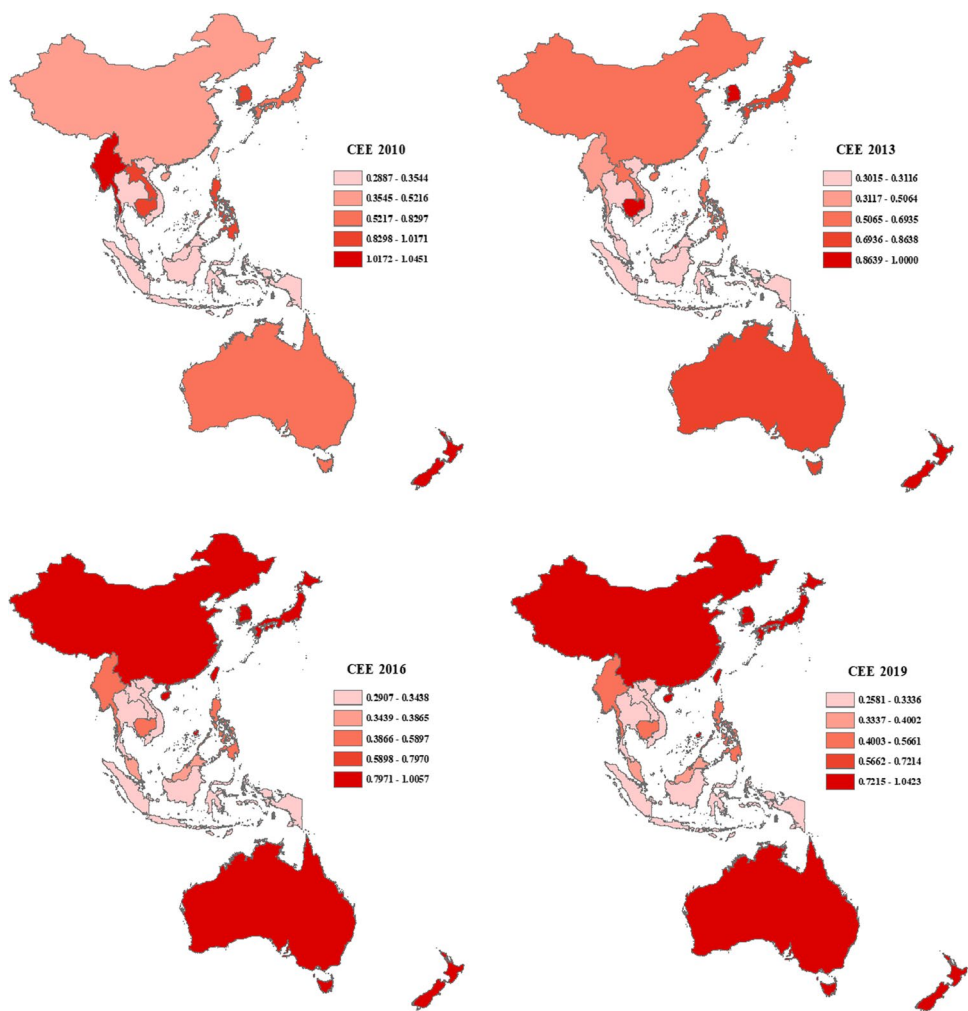
Temporal evolution pattern

The trend of the average CEE is displayed in Fig. 2 in terms of the temporal dimension. In general, the CEE of RCEP countries went through two stages of declining and then increasing over the 10 years, demonstrating U-shaped change characteristics. The average efficiency fell from 0.755 in 2010 to 0.692 in 2016, which is the changing decrease stage (2010–2016). The second phase, gradual growth (2017–2019), sees an increase in average efficiency from 0.692 in 2016 to 0.695 in 2019.

Table 4 The CEE of the RCEP countries, 2010–2019

Country	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
Australia	1.010	0.969	0.951	0.921	0.949	0.955	0.955	0.952	0.988	1.011	0.966
New Zealand	1.011	1.002	1.002	0.987	0.961	1.000	0.991	0.981	1.009	0.983	0.993
Laos	1.000	1.000	0.874	0.785	0.782	0.558	0.434	0.405	0.366	0.326	0.653
Brunei	1.000	1.000	1.000	1.000	0.854	0.786	0.747	0.744	0.696	0.712	0.854
Singapore	0.584	0.592	0.595	0.603	0.605	0.602	0.599	0.612	0.627	0.619	0.604
Cambodia	1.000	1.008	1.002	1.008	0.977	0.891	0.764	0.746	0.670	0.623	0.869
Myanmar	1.010	1.009	0.684	0.612	0.550	0.538	0.556	0.467	0.462	0.504	0.639
Japan	1.019	0.951	0.917	0.930	0.930	0.971	0.967	1.004	1.001	1.013	0.970
Korea	1.002	1.005	0.922	1.003	1.003	1.000	1.001	1.007	1.001	1.042	0.999
Malaysia	0.382	0.387	0.391	0.386	0.391	0.407	0.418	0.427	0.426	0.434	0.405
Indonesia	0.334	0.348	0.354	0.362	0.367	0.379	0.390	0.396	0.389	0.390	0.371
Philippines	0.793	0.801	0.894	0.934	1.016	1.001	1.006	1.003	1.003	1.004	0.945
Thailand	0.385	0.369	0.377	0.369	0.361	0.365	0.370	0.377	0.383	0.384	0.374
Vietnam	0.289	0.284	0.291	0.308	0.306	0.308	0.310	0.322	0.327	0.345	0.309
China	0.499	0.543	0.578	0.621	0.673	0.740	0.865	1.002	1.001	1.030	0.755

Fig. 1 Spatial distribution pattern of CEE in RCEP countries in major years



To further analyze the regional variations in CEE, the 15 RCEP nations are split into two groups based on the economic development level, from highest to lowest. Five nations—Japan, South Korea, Australia, New Zealand, and Singapore—are included in the first tier of developed countries; the remaining nations are included in the second tier of developing countries. As can be seen from Fig. 2, from 2010 to 2019, the CEE of the first-tier countries likewise had two stages of declining and then growing, following the general trend and hitting a low of 0.877 in 2012. This is known as a U-shaped fluctuation. The second-tier nations, however, displayed a varying declining tendency, ranging from 0.669 to 0.575.

The CEE of the first tier is significantly higher than the second tier in terms of regional differences. This result shows how the RCEP countries are currently doing with regard to sustainable development. With advantages in economy, science, and technology, the first-tier countries, represented by developed nations, have closely linked environmental issues with economic development and developed long-term policies to balance economic growth, rational

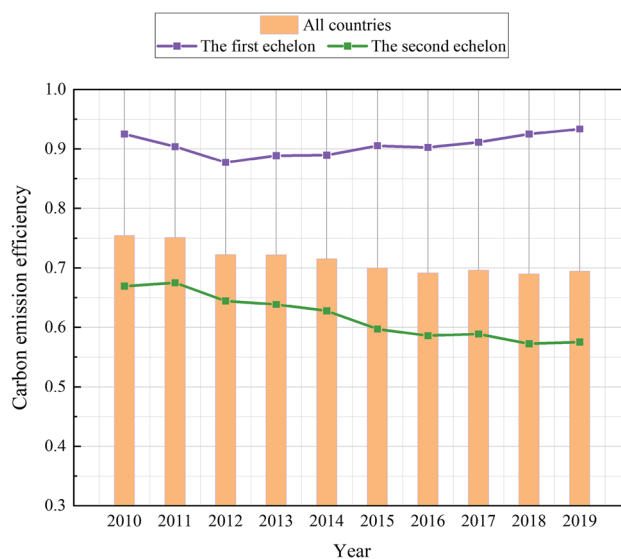


Fig. 2 Trends in the average CEE of the RCEP countries, 2010–2019

resource exploitation, and environmental protection. The second tier, on the other hand, is made up of all developing nations that, during the study period, were at the height of their development, prioritizing economic development and accelerating industrialization and urbanization while paying insufficient attention to the adverse effects on the environment. A downward trend has been caused by the large utilization of fossil fuels, relatively antiquated technologies, and ineffective managerial capabilities. In light of this, as the RCEP agreement develops, developing countries in the RCEP members should focus on ecological and environmental protection, make wise use of the benefits of regional cooperation and knowledge and technology spillover effects, facilitate the implementation of regional sustainable construction and policy, and further promote the RCEP region as a new force in the development of low-carbon technological innovation.

The dynamics of CEE for 15 RCEP members

The static efficiency was obtained in “Spatio-temporal evolution of CEE for 15 RCEP members” section through the super-efficient SBM model. This section will assess the dynamic CEE for RCEP members using the non-parametric GML index based on DEA. The GML index and its decompositions into the index of technical efficiency change (GML_{effch}) and the index of technical progress (GML_{tech}) are depicted in Figs. 3 and 4.

The GML index has a W-shaped fluctuation that decreases, then increases, then decreases, then climbs once more from 2010 to 2019. The GML index has a value of 0.988, which is less than 1, and indicates that the RCEP members appear to be declining in CEE. The average change in the technical efficiency change index for RCEP members is 0.996, showing negative average growth and a little reduction, while the average change in the technical progress is 1.011, suggesting stable growth, according to a further breakdown of the GML index.

It is clear that technological progress, particularly innovation and advancement, is the primary force behind CEE improvement in RCEP countries. During the inspection period, the RCEP nations focused their efforts on the introduction of efficient technologies, the substitution of new energy fuels, and the development of novel solutions for environmental protection and energy saving. Nevertheless, there are still issues in technology application and operation management. Poor diffusion, harsh operating conditions, and difficult management of energy-saving and emission reduction technologies are a few potential causes. Therefore, in order to improve CEE, it is necessary to place a greater emphasis on technical efficiency and continuously improve industrial structure and operation size.

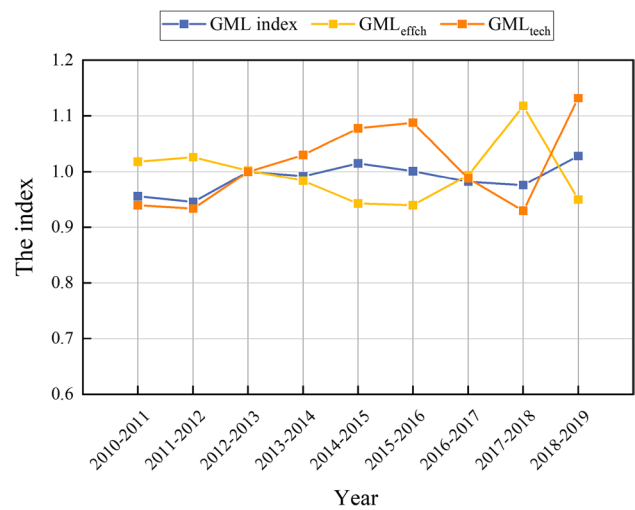


Fig. 3 The GML index and decomposition index from 2010 to 2019

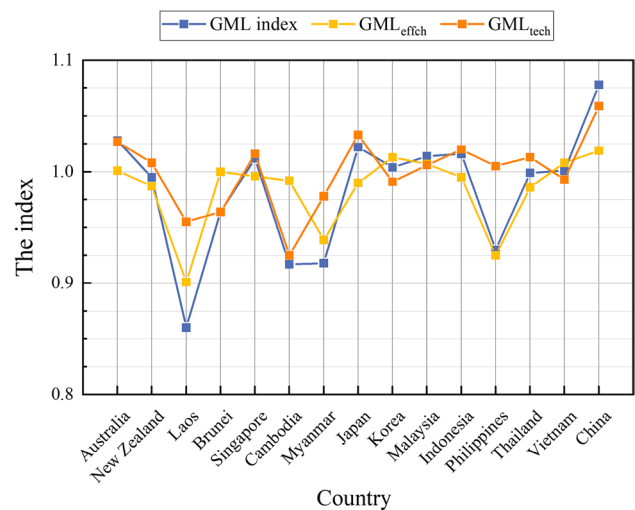


Fig. 4 The GML index and decomposition index for 15 RCEP countries

From 2010 to 2019, eight of the 15 countries in the RCEP region have a CEE change index greater than 1, indicating positive CEE growth (Fig. 4). China, Australia, and Japan are the three countries with the highest cumulative increase in the GML index, with growth rates of 7.8%, 2.8%, and 2.2%, respectively.

In terms of drivers, a combination of technical efficiency and technology advancement has led to improvements in CEE in Malaysia, China, and Australia. With rising environmental technology development and utilization, these nations are in the process of transitioning and upgrading their industrial and energy structures. This serves as a model for other countries. While Laos, Cambodia, and Myanmar are three countries where technological advancement and

efficiency still need to be enhanced. While speeding up the development of a high-quality economy during the research period, traditional industrial sectors in these countries increased in size, which raised the overall CO₂ emissions. At the same time, there are problems such as growing difficulty in emission management and low utilization of process equipment, resulting in low technical efficiency. The improvement of technical efficiency has had a significant impact on CEE in Brunei, Korea, and Vietnam, indicating a gradual industrial upgrading and transition. Technical advancements help six nations—Indonesia, Philippines, Singapore, Thailand, Japan, and New Zealand—improve their CEE, but there is a pressing need to enhance technical efficiency.

Analysis of the driving factors on CEE

Spatial correlation test

Moran's *I* index and scatter plots are chosen to observe the spatial autocorrelation and spatial aggregation of CEE globally and locally (Kashlak and Yuan 2022), resulting in Table 5 and Fig. 5, respectively. This is done in order to confirm the existence of spatial effects caused by significant shifts in carbon emission among RCEP countries. In the majority of the sample years, Moran's *I* index is positive, passing the significance test. The CEE of the 15 RCEP countries shows positive spatial autocorrelation from smooth to enhanced, and there is a more pronounced regularity, which is primarily distributed in the first quadrant (high-high aggregation) and the third quadrant (low-low aggregation).

The aforementioned findings show that the spatial agglomeration effect and level of spatial autocorrelation are both rising with time. Due to the fact that CEE is influenced by industrial structure, production factor combinations, and technological level, there is some industrial structure uniformity among nearby nations with comparable resource endowments. Countries are becoming more mindful of low carbon emission reduction as the conflict between economic development and environmental pressure intensifies. As a result, they have been developing particular environmental protection regulations and low-carbon development plans. The production relationship between resource input and output is moving in the direction of convergence, which promotes the convergence of CEE among RCEP region neighbors.

Model identification test

It is advisable to use the spatial econometric analysis approach because it is known from the findings of the spatial correlation test that the CEE of RCEP nations is

Table 5 Spatial correlation test of CEE in 15 RCEP members, 2010–2019

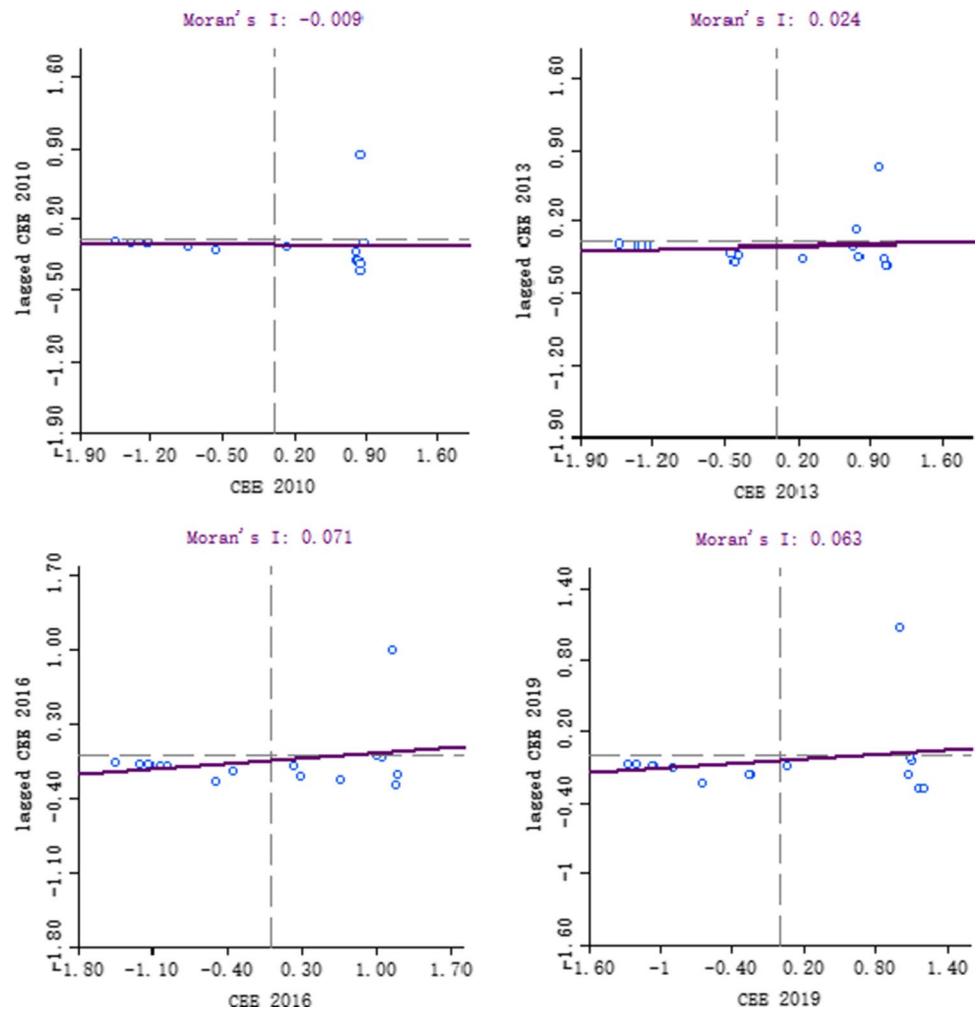
Year	Moran's <i>I</i>	<i>p</i> value
2010	−0.009	0.243
2011	−0.018	0.273
2012	0.033	0.096
2013	0.024	0.120
2014	0.033	0.099
2015	0.071	0.045
2016	0.071	0.044
2017	0.056	0.074
2018	0.078	0.041
2019	0.063	0.064

spatially associated. The LM test (Engle 1982), LR test, Wald test (Wang et al. 2019), and Hausman test (Zhao and Sun 2022) were carried out in order to further confirm the spatial correlation of CEE in the RCEP region and determine whether this correlation is related to the lag term or the error term. Prior to that, the multicollinearity test (Ariyajunya et al. 2021) and Pearson correlation test were also performed. The findings supported the claim that there is no multicollinearity concern in the regression analysis and that the explanatory variables were selected in a logical and meaningful manner by demonstrating that the variance inflation factor (VIF) for each variable was under 2.8 and the correlation coefficient between the variables was less than 0.85.

First, the LM test was performed to determine whether the spatial lagged dependent variable or the spatial autocorrelation error term should be included in the model. The results disprove the original hypothesis and support the inclusion of spatial effects by showing that the LM lag and LM error are significant at the 10% and 5% levels, respectively. Second, to check whether SDM could be simplified to SAR and SEM, the Wald test and LR test were both employed. Additionally, at a 1% level of significance, the Ward lag, LR lag, Ward error, and LR error all refute the initial hypothesis, indicating that SDM is superior to SAR and SEM (Table 6).

The choice between the random-effect model and the fixed-effect model is a critical one for SDM as a type of panel data model. At a 1% level of significance, the Hausman test rejects the null hypothesis, indicating that fixed effects outperform random effects. Additionally, the various fixed-effect models must still be examined and chosen, which are realized by the LR test. There are three different categories of fixed-effect models: spatial fixed effect, time fixed effect, as well as both time and spatial fixed effects. The original hypotheses that the spatial fixed effect and the time fixed effect are stronger than both the time and spatial fixed effects are both clearly rejected in Table 7, suggesting that the SDM containing both time and spatial fixed effects is the best choice.

Fig. 5 Moran scatter plot of the CEE in 15 RCEP members, 2010–2019



The direct and spatial spillover effects of driving factors

Due to the presence of spatial lags, the regression coefficients of SDM are unable to accurately represent the impacts of explanatory variables on the explained variables. In order to parse the spatial spillover effects in three dimensions, the total, direct, and spillover effects were estimated and decomposed in accordance with the variance–covariance matrix of the SDM estimate results (Zhai et al. 2022), as shown in Table 8.

First, the coefficients of two variables, affluence, and economic agglomeration, with respective values of -1.0437 and -1.8317 , pass the z test at the 1% and 10% significance levels. Affluence is particularly noteworthy for its simultaneously remarkable direct and spillover effects, demonstrating that it is the primary factor affecting CEE in RCEP countries. With coefficients of 0.4053 , 1.7763 , -0.8480 , and -0.2770 , respectively, the four variables of wealth, population size, technology level, and investment capacity pass the z test for direct impacts at a 1% significance level. With

values of -1.4490 and 0.9321 , the two variables of affluence and technology level pass the z test for spillover effects at a 1% significance level. Investment capacity and economic agglomeration have regression coefficients of 0.4553 and -1.5628 , with the former having a 5% significance level on CEE and the latter having a 10% one, respectively.

Table 6 Estimation results for the spatial panel regression model

Variables	Coefficients	<i>p</i> value
LM error	3.343	0.068
LM lag	4.692	0.030
Robust LM error	0.034	0.853
Robust LM lag	1.384	0.239
Ward spatial lag	30.87	0.000
LR spatial lag	27.75	0.000
Ward spatial error	40.31	0.000
LR spatial error	29.10	0.000
Hausman test	29.28	0.002

Table 7 Fixed-effect test based on the SDM

Variables	Spatial fixed	Time fixed	Both time and spatial fixed
lnAFF	0.3302*** (5.35)	−0.0151 (−0.76)	0.2595*** (4.52)
lnPOP	1.4723*** (3.25)	−0.0500*** (−3.47)	1.6760*** (3.34)
lnENR	−0.7089*** (−19.64)	−0.3669*** (−5.91)	−0.7577*** (−20.88)
lnATI	−0.2601*** (−5.60)	0.0096 (0.10)	−0.2294*** (−4.84)
lnEAL	−0.5484** (−2.33)	0.0320** (2.54)	−0.4182* (−1.73)
Wx lnAFF	−0.3008* (−1.76)	−0.1524 (−1.25)	−1.9448*** (−4.44)
Wx lnPOP	−0.1053 (−0.10)	0.0335 (0.30)	−0.5334 (−0.38)
Wx lnENR	0.4376** (2.26)	−0.4969 (−1.20)	0.8876*** (2.87)
Wx lnATI	−0.0548 (−0.33)	−2.0014*** (−3.49)	0.5134** (1.99)
Wx lnEAL	−1.0384 (−1.09)	0.0444 (1.34)	−2.5203** (−2.06)
Rho / lambda	−0.5905*** (−3.30)	−0.5915*** (−2.59)	−0.6064*** (−3.00)
sigma2_e	0.0020***	0.0226***	0.0016***

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, with the *z* statistics in parentheses

Affluence (AFF). The positive regression coefficient of affluence shows that increasing GDP in RCEP countries has a definite beneficial impact on CEE. This is in line with the underlying theory. As the GDP of RCEP countries rises, economic quality is pursued along with rapid economic growth, and increased investments in science, technology, and improved infrastructure are prioritized, which improves resource use and CEE. Although affluence raises the CEE of RCEP countries obviously, the affluence of neighboring countries suppresses the CEE of the home country. This suggests that whether or not the economic development structure of neighboring regions is rational affects the CEE of the home nation.

Population (POP). The direct and indirect effects of population on CEE are positive and negative, and the former satisfies the significance test at the 1% level. This shows that population density has a positive impact on the CEE of the home country and a negative but insignificant impact on the CEE of neighboring countries. Within a certain threshold, densely populated places are more likely to experience agglomeration effects, which is favorable to the effective use of resources and infrastructure. Additionally, since development concepts and practices have undergone a green metamorphosis, inhabitants' consumption patterns have tended to

be low carbon, which has a positive impact on CEE. On the other hand, population mobility is mostly responsible for the population's impact on the CEE of neighboring countries. Cross-border and cross-country population migrations are unavoidable in an open economy. Due to their similar social structures and resource endowments, adjacent nations are preferable options for population migration. When there is an excessive concentration of people, pressure on the environment and the resources increases, which leads to ineffective resource use and harms CEE.

Technology level (ENR). A negative direct effect of technology level implies that the higher the energy consumption per unit of GDP, the lower the CEE of RCEP members. The elasticity coefficient of the direct effect is −0.8480, passing a 1% level of significance testing. This indicates that, when all other variables are held constant, the CEE increases by 0.848% for every 1% decrease in energy consumption per unit of GDP. Energy is a necessary input for national production. Dropping energy intensity is a sign of technological advancement and improved production facilities, which enable higher outputs and benefits with less resource input. Continuously emerging energy-saving and consumption-reduction technologies assist in gradually offsetting the negative environmental externalities at the early stage of development and improving CEE. With an

Table 8 Direct effects, indirect effects, and total effects of the SDM

Variables	Direct effect	Indirect effect	Total effect
lnREI	0.0390*** (3.42)	0.1000*** (3.77)	0.1390*** (4.74)
lnEAD	−0.1790** (−2.15)	−2.3920** (−2.43)	−2.5720** (−2.55)
lnGDP	0.3560*** (6.97)	−1.2590** (−2.44)	−0.9030* (−1.73)
lnCIF	−0.1250*** (−8.17)	0.3190* (1.70)	0.1940 (1.01)
lnATI	−0.0910*** (−3.61)	−0.3810** (−2.06)	−0.4720** (−2.49)

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, with the *z* statistics in parentheses

indirect effect elasticity value of 0.9321, the spillover effect of the technology level is positive. To improve CEE, it is crucial to reduce energy consumption per unit of GDP; as a result, sophisticated low-carbon technologies should be introduced and investment in them should be encouraged.

Investment capacity (ATI). Investment intensity has a detrimental impact on the CEE of RCEP countries, most likely as a result of each nation's current preference for investing in fixed assets related to energy infrastructures like steel, cement, and electricity. There are resource and environmental costs associated with the creation of this fixed capital. The acquisition of industrial production apparatus and equipment rises in response to the increase of fixed-asset investment, which directly drives the rapid expansion of energy carbon emissions. The indirect impact of investment intensity is favorable, nevertheless, meaning that the more fixed assets are invested in the neighboring nations, the greater the CEE of the home country. A reasonable explanation is that the beneficial spillover effects of technology and knowledge from fixed asset investments in nearby regions outweigh the negative effects of energy infrastructure, improving CEE. Future infrastructure construction projects should address environmental considerations, and green investments with a focus on ecological preservation and environmental management should be given attention.

Economic agglomeration (EAL). The impact of economic agglomeration is dual. On the one hand, the growth in economic agglomeration will concentrate assets, technology, and experts in a more concentrated location, which will help businesses specialize and centralize their production. It simultaneously minimizes the cost of product and raw material transportation while maximizing the effects of technological innovation and knowledge spillover, which will further improve production efficiency and CEE. However, excessive economic agglomeration also produces several unfavorable externalities, such as a lack of resources and hampered transportation. When the crowding effect outweighs the favorable benefit, CEE is negatively affected. According to the findings, both the direct and indirect effects of economic agglomeration behave negatively, demonstrating that the crowding effect has already manifested and drastically inhibits production efficiency and CEE.

Robustness tests

The following two methods are used for robustness detection in order to guarantee the validity of the aforementioned empirical results.

1. Introduction of control variables. To avoid endogeneity issues due to possible omitted variables, additional control variables are further included in the regressions, including urbanization level (urban population share (URB)), foreign

direct investment (percentage of foreign direct investment in GDP, FDI), and the combination of both. The results are summarized in models (1), (2), and (3) of Table 9, respectively. The signs and significance levels of all explanatory variables remain consistent with the previous results, and there are still robust effects for CEE in RCEP countries, meaning a reliable and sound result.

2. Replace the explanatory variables. According to research, the development and utilization of renewable energy have become a key strategy for ensuring energy security, strengthening environmental protection, and addressing climate change. As a result, the technological development of renewable energy serves as an important gauge (Pham et al. 2020). Therefore, the GDP per capita (GDP) and the share of renewable energy consumption (RCP) are substituted for GDP and energy consumption per unit of GDP to characterize the affluence (AFF) and technology level (ENR), respectively (Wang and Li 2021; Wu et al. 2021a). The empirical results are still supported by the regression results, which are shown in models (4) and (5) in Table 9.

Conclusion and policy recommendations

Conclusions

Given the critical role of CEE in achieving carbon neutrality targets, the super-efficiency SBM model, which takes into account undesirable outputs, is employed to comprehensively assess the current state and trend of CEE in 15 RCEP countries from a spatio-temporal dynamic perspective, and the GML index is coupled to quantify the spatial and temporal differences and dynamic changes. The extended STIRPAT model and SDM are then integrated to further investigate the main influencing factors of CEE from a wide green economy perspective while taking into account the spatial characteristics of CEE. It is discovered that.

1. There is a tremendous opportunity for improvement in the CEE of RCEP members, which is generally poor and unevenly distributed in temporal and spatial dimensions. Meanwhile, the CEE of RCEP members exhibits positive spatial autocorrelation and the spatial association accumulates over time.
2. There are significant differences in CEE among RCEP members, with developed countries, who make up the first tier, significantly outpacing developing countries, who comprise the second tier. The latter should utilize the benefits of regional collaboration and knowledge and technological spillover effects suitably, facilitate

Table 9 Robustness test of the SDM containing both time and spatial fixed effects

Variables	(1)	(2)	(3)	(4)	(5)
lnAFF	0.2071*** (2.60)	0.2610*** (4.52)	0.2108*** (2.60)	-	0.2685** (2.42)
lnPOP	1.9407*** (3.42)	1.6814*** (3.34)	1.9422*** (3.42)	1.9355*** (3.92)	2.6069*** (2.75)
lnENR	-0.7649*** (-19.31)	-0.7564*** (-20.75)	-0.7647*** (-19.31)	-0.7577*** (-20.88)	
lnATI	-0.2267*** (-4.58)	-0.2275*** (-4.71)	-0.2270*** (-4.55)	-0.2294*** (-4.84)	-0.4541*** (-4.99)
lnEAL	-0.4449* (-1.83)	-0.4164* (-1.72)	-0.4445* (-1.83)	-0.4182* (-1.73)	-1.7364*** (-3.68)
lnURB	0.3019 (0.92)	-	0.2885 (0.85)	-	-
lnFDI	-	-0.002 (-0.26)	-0.0008 (-0.10)	-	-
lnGDP	-	-	-	0.2595*** (4.52)	-
lnREI	-	-	-	-	0.1707*** (4.7)
Wx lnAFF	-2.2041*** (-3.21)	-1.9639*** (-4.29)	-2.2213*** (-3.10)	-	0.4337 (0.81)
Wx lnPOP	0.3002 (0.18)	-0.4401 (-0.31)	0.3168 (0.19)	-2.4782* (-1.71)	6.2999** (2.34)
Wx lnENR	0.626 (1.36)	0.9079*** (2.88)	0.6319 (1.37)	0.8875*** (2.87)	-
Wx lnATI	0.4851* (1.86)	0.5115* (1.9)	0.4739* (1.74)	0.5134** (1.99)	-0.3424 (-0.69)
Wx lnEAL	-2.3716* (-1.81)	-2.5825** (-2.08)	-2.3823* (-1.81)	-2.5203** (-2.06)	-4.7241** (-2.01)
Wx lnURB	1.9799 (0.77)	-	2.0255 (0.79)	-	-
Wx lnFDI	-	0.0052 (0.19)	0.0067 (0.24)	-	-
Wx lnGDP	-	-	-	-1.9448*** (-4.44)	-
Wx lnREI	-	-	-	-	-0.4927** (-2.14)
Rho/lambda	-0.6294*** (-3.05)	-0.6078*** (-3.01)	-0.6314*** (-3.05)	-0.6064*** (-3.00)	-0.7779*** (-3.66)
sigma2_e	0.0016***	0.0016***	0.0016***	0.0016***	0.0060***

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, with the z statistics in parentheses

regional sustainable development, and support policy execution.

3. The GML index displays W-shaped variations on a dynamic level. It is clear from the decomposition results that technological progress is the primary force driving CEE improvement in RCEP countries and that technical efficiency needs to be improved.
4. Although each of the five drivers has an impact on the CEE of RCEP members, the impact differs. Technology level and investment capacity have negative direct effects on national CEE, whereas affluence and population have favorable direct effects. Affluence and economic agglomeration hinder CEE enhancement, although the technological level and investment capacity favor it in terms of spillover effects.

Policy recommendations

The implementation of carbon neutrality plans and regionally coordinated sustainable development strategies by RCEP nations under the current free economic environment must take into account closing the inter-regional gap while enhancing the CEE of RCEP members.

1. To ensure regional low-carbon synergistic development, countries should cooperate and exchange ideas more; there are significant differences among the

nations in the RCEP region, and developed countries have a number of advantages in this area. As the RCEP agreement continues to advance, it is necessary to gradually build exchange platforms and promote the flow of capital, technology, management talent, and experience in the region through economic policies such as fiscal, financial, and investment policies. The RCEP region should be strengthened as a new force in the development of low-carbon technology innovation by giving full play to the radiation-driven role and knowledge and technology spillover effects of highly efficient countries, promoting sustainable regional construction and policy implementation, and narrowing internal efficiency differences.

2. Increase the emphasis on the efficiency of energy-saving and emission reduction technologies. The current low technical efficiency of RCEP members is the main barrier to CEE improvement. Energy-saving and emission reduction technologies face several issues, including poor diffusion, challenging management, and harsh working circumstances. As a result, while fostering technological innovation for reducing carbon emissions, greater focus should be placed on promoting and effectively using technology. One way is to strengthen managerial skills, scale up inputs, and leverage the scale effect to improve economic efficiency. On the other hand, efforts are made to remedy the decline in techni-

cal effectiveness to further encourage the force behind technological innovation. The existing scenario where technical efficiency and technological advancement are unable to coexist can be improved by creating a productive method of positive interaction between technology R&D and management services.

3. The secret to advancing CEE is controlling economic agglomeration levels and lowering investment in high-carbon industries. Economic agglomeration significantly reduces emissions, but scale diseconomies brought by excessive agglomeration will cause a drop in regional CEE. Therefore, when establishing energy-saving and emission reduction targets, on the one hand, green investments with the primary goal of ecological protection and environmental management should be highlighted, and investments in high-carbon industries such as electricity, iron, and steel, and cement should be reduced; on the other hand, the regional economic agglomeration level must be reasonably controlled to produce a favorable effect and a sizable amount of emissions.

It should be noted that although the super-efficiency SBM model and STIRPAT model, which consider undesirable outputs, is used to measure and diagnose CEE in RCEP members, driving variables and rational approaches are still worth examining. Additionally, this study experimentally investigates the impact of drivers on CEE; nevertheless, it is also necessary to consider the regional heterogeneity of the level of effect, as it could serve as a valuable guide for future global sustainability.

Author contribution Caiqing Zhang: conceptualization, methodology, validation, project administration, funding acquisition, and supervision. Zixuan Wang: formal analysis, investigation, data curation, software, validation, writing—original draft, and writing—review and editing. Hongxia Luo: investigation, data curation, resources, and writing—review and editing.

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Data availability All data generated or analyzed during this study are included in this published article.

Declarations

Ethical approval Not applicable.

Consent for participate All the authors equally participated and gave their consent to publish the study in this journal.

Consent for publication All the authors gave their consent to publish the study in this journal.

Conflict of interest The authors declare no competing interests.

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