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Spatiotemporal evolution pattern of carbon emission performance in Asian countries

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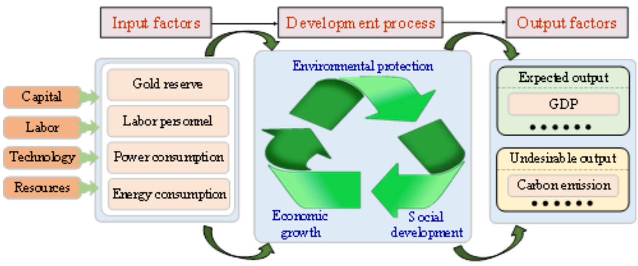
Graphical abstract



Abstract

Due to extensive energy consumption and industrial production activities, Asian countries have become the largest sources of global carbon emissions, with emerging economies like China and India contributing significantly. Against the backdrop of increasing global climate change, carbon emissions have emerged as a focal concern within the international community. To mitigate these emissions, enhancing carbon performance is identified as a crucial endeavor. This study employs the Super-efficiency Slack-Based Measure (SBM) model to comprehensively evaluate the carbon performance of major Asian countries and delves into the carbon performance's influencing factors through factor analysis. Additionally, we utilize geographical methodologies to explore the spatiotemporal evolution characteristics of carbon performance in these countries. Preliminary results indicate that spatial centroid has gradually shifted towards the northeast, which could potentially reflect a geographic concentration change in some form of economic or industrial activity. Moreover, the elliptical parameters for carbon emission efficiency did not exhibit any discernible trend, maintaining a relatively stable overall pattern and distribution. The findings of this study hold significant implications for understanding the spatial heterogeneity and dynamic characteristics of carbon emission efficiency in Asia, offering valuable insights for future policy-making.

Keywords: Carbon emission, Super-efficiency slack-based measure, asian countries, factor analysis, policy

1. Introduction

In the current global context, climate change and its impacts have become one of the most pressing environmental issues (Khalid *et al.* 2021). According to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the ongoing rise in global temperature is well-documented, with anthropogenic activities and large-scale greenhouse gas emissions identified as the main factors (Zhai *et al.* 2018). In the long term, greenhouse gas emissions are expected to continue increasing., thereby exacerbating a multitude of climate issues—including but not limited to global warming, glacial melting, sea-level rise, and the increased frequency of extreme weather events. In the absence of effective emission reduction measures, global temperatures by 2100 are projected to be 4°C higher than pre-industrial levels (Patricia 2021). This point is further emphasized in the IPCC's Sixth Assessment Report, deepening the global understanding of the severity of climate issues. In 2015, the United Nations Framework Convention on Climate Change (UNFCCC) convened in Paris, where over 200 countries signed the Paris Agreement aimed at keeping global warming below 2°C (Unfccc 2015). However, for most countries, particularly developing ones, achieving this target is especially challenging. China pledged in the 2014 'U.S.-China Joint Statement on Climate Change' that its carbon emissions would peak by 2030 and further committed to reducing its carbon emissions per unit of GDP by 60-65% based on 2005 levels. Similarly, at the 26th Conference of the Parties (COP26) in Glasgow, the Prime Minister of India announced ambitious emission reduction targets, aiming to achieve carbon neutrality by 2070 (Satish Kumar *et al.* 2023). In the context of carbon emissions, economic and production activities are widely considered to be the primary sources of emissions, especially when reliant on fossil fuels (Chang *et al.* 2022). To address this challenge, policymakers and environmental management experts are actively working to introduce new production technologies to improve energy efficiency, with the goal of reducing carbon emissions (Sun *et al.* 2017). In this endeavor, assessing the carbon emissions efficiency of various countries has become a top priority.

Research on carbon emission performance is generally classified into two major categories: single-factor and multi-factor measurements. In the single-factor category, the carbon index, defined as the amount of carbon emissions per unit of energy consumption, assesses the carbon emission performance of developing countries (Mielnik and Goldemberg 1999). Similar research includes CO_2 emission intensity (Yu *et al.* 2023), per capita CO_2 emissions (Parker and Bhatti 2020), and energy intensity (Huang *et al.* 2023), among others. The advantages of these single-factor indicators lie in their ease of understanding and application, but they also have certain limitations. These limitations mainly manifest in the fact that carbon emission performance is intrinsically a measure of input-output efficiency during economic activities. This efficiency should not solely rely on energy input but is the result of the combined effects of multiple economic input factors such as capital and labor (Teng *et al.* 2021). Therefore, it is essential to emphasize the 'multi-factor' nature of the measurement during the performance evaluation process and consider the substitution effects of other input elements in the economic production process. Based on the concept of multi-factors and factor substitution, energy consumption, capital investment, and labor are integrated as input variables, yielding both the desired GDP output and undesired CO2 emissions (Xiao *et al.* 2023). This approach enables a more accurate and reasonable measurement of carbon emission performance.

Carbon emission efficiency has been widely scrutinized at various scales including global, national, and urban levels. However, there is a noticeable void in studies focusing on continental dimensions. Traditional approaches to evaluating carbon emission efficiency predominantly consist of the economic environmental comparison method (Parker and Bhatti 2020), indicator system method (Bronts *et al.* 2023), and data envelopment analysis (DEA) (Chen *et al.* 2023). Among these, the Input-Output Model distinguishes itself by providing an in-depth characterization of the interdependent relationships between production elements and outputs across economic sectors (Ruojue *et al.* 2021). This model is also capable of comprehensively assessing the direct and indirect impacts of policy decisions on the economies of specific regions. Due to these inherent advantages, the approach is increasingly being applied to environmental issue-related research. More specifically, as an extension of the DEA model, the Super-Slack-Based Measure (Super-SBM) shows marked advantages in handling undesirable outputs, such as carbon emissions, and has started to be employed in the quantitative assessment of carbon emission efficiency (Du *et al.* 2021). Carbon sequestration in afforestation is introduced as an exogenous variable into a SBM to explore the trends in energy usage and carbon emissions efficiency in China (Teng *et al.* 2021); A quantification of the total-factor carbon emissions efficiency in the construction sector from 2003-2016 is performed by using the Super-SBM DEA method (Zhou *et al.* 2019); Incorporating the Malmquist productivity index, a dynamic measurement of low-carbon economic efficiency across 30 provinces in mainland China from 2005-2012 is calculated using a Super-SBM model that accounts for undesired outputs (Zhang *et al.* 2017); A novel evaluation model based on Slack-Based Measure and Data Envelopment Analysis (SBM-DEA) is proposed for analyzing and optimizing the energy structure of various countries and regions globally (Lin *et al.* 2020); Unlike previous research, this study for the first time comprehensively considers the impacts of pollution technology and mixed integer data on environmental efficiency, and employs a Directional DEA model to generate a standardized environmental efficiency index (Taleb 2023); This study employs the SBM model to conduct an in-depth analysis of temporal and spatial variations in the utilization efficiency of industrial land in the central region from 2003 to 2012 (Jiang 2021). After synthesizing existing literature, current research on carbon emission efficiency in Asia exhibits several notable characteristics and shortcomings that merit further exploration. First, from the perspective of research scope, most studies on carbon emission efficiency are overly focused on the analysis of single variables. This methodological bias tends to overlook the multifaceted intrinsic mechanisms of carbon emissions, thus limiting our comprehensive understanding of carbon emission phenomena at the national level. Second, when constructing indicators for carbon emission efficiency, existing studies often employ overly simplified methods. This could not only result in biased efficiency assessments but also potentially lead to misleading conclusions. Particularly when studies fail to fully consider multi-dimensional factors such as population, society, technology, and resources, any evaluations regarding carbon emission efficiency may be incomplete or one-sided. Lastly, current research frameworks generally lack consideration for regional heterogeneity and its influence factors. This flaw is especially significant because different geographical, cultural, and technological conditions may lead to divergent carbon emission characteristics across various regions.

In the realm of cross-sectional and panel data analysis, Fixed Effects Models (FEM) hold significant advantages, particularly when the research aim involves investigating inherent heterogeneity within the data. For example, Fixed Effects Panel Threshold model was employed to examine the impact of innovation on carbon emissions in 29 selected European Union countries from 2000 to 2019 (Ostadzad 2022). In a framework to account for spatial interactive effects is incorporated by (Venkadavarahan *et al.* 2022), which employs spatial econometrics for the estimation of shared bicycle travel activity. A true FEM is rigorously employed by (Jarboui 2021) for the study of operational and environmental efficiency measures across 45 American oil and natural gas companies during the period from 2000 to 2008. Furthermore, an extension of the FEM to the Stochastic Frontier Model is carried out by (Greene 2005). Through Monte Carlo simulations, it is identified that incidental parameters in Fixed Effects Stochastic Frontier Models behave differently in terms of coefficient estimation compared to other common outcomes. Time Fixed Effects (TFE) Models are primarily used for controlling the heterogeneity that does not change over time. Although FEM are efficient in addressing heterogeneity, they often require extensive data and are not suitable when explanatory variables are time-invariant. In Huang *et al.* 2023, 53 coastal cities in China are selected as the research sample, and land-use remote sensing monitoring data, along with spatial econometrics, are employed to uncover the impact of urbanization on the availability of urban ecological space. Moreover, Spatio-Temporal Fixed Effects (STFE) models combine both aspects, aiming to simultaneously control cross-sectional and time-series heterogeneity to acquire more precise and robust estimation results. This model is particularly useful in panel data analyses as it can reveal causal relationships between variables more accurately. STFE models overcome the limitations of the above two models by simultaneously controlling for both time and individual fixed effects. The utility of these modeling techniques is particularly relevant when addressing the complexity and multi-dimensionality inherent in various socio-economic factors, as evidenced in the doctoral research framework focusing on spatial heterogeneity and scenario simulation based on nighttime light data.

To address the gaps in existing literature concerning carbon emission efficiency, Asia, as the largest source of global carbon emissions and an area of high economic activity, occupies a crucial role in global climate change and sustainable development strategies. This study focuses on three core dimensions for in-depth exploration: Firstly, we have developed a carbon emissions input-output model targeting key Asian countries to thoroughly analyze the spatiotemporal evolution characteristics of each country's carbon emission efficiency. Secondly, the study aims to delve into the heterogeneity in carbon emission efficiency across Asian nations, as well as the technological disparities this heterogeneity implies. Lastly, by employing a geospatial ellipse method model, we have conducted a spatiotemporal evolution analysis of the center of gravity for Asian carbon emissions from 2000 to 2015, further investigating its intrinsic correlation with carbon emission efficiency. The findings of this comprehensive study will serve as a robust foundation for policymakers, aiding them in crafting more effective strategies to combat climate change.

The organization of this paper is delineated as follows: Section 2 elaborates on the research methodology employed and provides an overview of the data sources utilized for the study. In Section 3, we present our findings on carbon emission efficiency, coupled with an in-depth analysis of its spatiotemporal evolution patterns. Section 4 engages in a substantive discussion of the research outcomes and puts forth policy recommendations. Concluding remarks, encapsulating the key conclusions and their policy implications, are presented in Section 5.

2. Methodology and data

2.1. Study area

Carbon emissions have garnered widespread attention globally, particularly in the context of an intensifying global climate crisis. In-depth exploration of carbon emissions efficiency holds significant implications not only in the realm of environmental science but also extends far-reaching impacts across economics, energy policy, and international cooperation. As shown in Figure 1, the role of Asian countries is notably prominent, as multiple nations have become major sources of global carbon emissions due to their rapid economic growth and strong reliance on fossil fuels. As a leading economy in both Asia and the world, China's carbon emissions are primarily concentrated in its vast industrial and energy sectors. This is not only a direct outcome of the country's rapid industrialization but also exposes shortcomings in its energy structure. These deficiencies require special attention and improvements within the broader context of global carbon reduction efforts. Meanwhile, countries like India, South Korea, and Japan demonstrate more dispersed sources of carbon emissions; their industrial, transportation, and energy sectors collectively contribute to the growth in their national carbon emissions. Japan's unique situation lies in its relative scarcity of natural resources, particularly in the energy sector. It is highly dependent on external energy supplies, adding complexity to its carbon emissions dilemma and placing it in a particularly sensitive and vulnerable position in global energy supply chains. Additionally, Southeast Asian countries such as Indonesia, Vietnam, and Thailand have their own distinct characteristics in terms of carbon emissions. These countries still exhibit high dependency in their energy structure, particularly on traditional energy sources like wood and coal, inevitably exacerbating their carbon emissions pressure. Addressing the issue of carbon emissions is not just an urgent need for environmental protection but is a multifaceted challenge that spans disciplines, fields, and borders. Therefore, a comprehensive analysis of carbon emission efficiency not only aids in gaining a more accurate understanding of the present climate situation and identifying effective means of reducing carbon emissions, but also furnishes governments with a scientific foundation for shaping more suitable and efficient environmental protection policies.

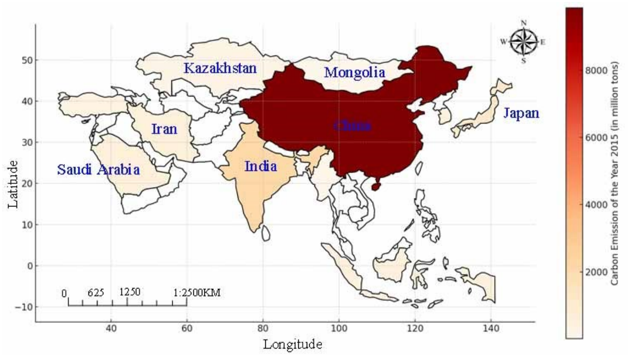


Figure 1. Distribution of the carbon emission in the typical region of Asian

2.2. Data and indicators

Due to the early 21st century, especially the years from 2000 to 2015, was a period of rapid industrialization and economic growth in many Asian countries. This growth phase is critically relevant when studying carbon emissions, as it likely led to a significant increase in emissions due to industrial and energy production activities. And then,This period witnessed several international and national policy developments related to climate change and carbon emissions. For instance, the Kyoto Protocol's first commitment period (2008-2012) falls within this timeframe. Analyzing carbon performance during these years could provide insights into the effectiveness of these policies. Therefore, this study focuses on the period from 2000 to 2015 and employs an input-output framework to quantitatively assess the carbon emission performance of key Asian countries, namely China and India. Due to incomplete data from some countries, the scope of the research is limited to these two nations. Building on this foundation, we explore carbon emission performance and its spatial trends at the national level among major Asian countries. In the literature on carbon emission performance, the core input factors generally include capital, labor, and energy. Expenditures are cash payments for operational activities that provide goods and services to the government.

This study selects macroeconomic data from representative countries in Asia for the period between 2000 and 2015 to conduct an in-depth analysis of core indicators such as Labor (LP), Gross Domestic Product (GDP), Carbon Emissions (CE), Power Consumption (PC), Gold Reserves (GR), and Energy Consumption (EC). The data in this article comes from the world bank database. (https://data.worldbank.org)

This study considers LP, CE, GR and EC; We also treat GDP as the expected output of economic activity, while national CE are considered as the unintended output. Through this set of parameter configurations, we have constructed an input-output indicator system for evaluating the carbon emission performance of key Asian countries (see Table 1). This system not only aids in a more accurate understanding of the relationship between economic activity and carbon emissions, but also helps to reveal performance disparities among countries in reducing carbon emissions.

Table 1. The input-output index of country

Indicator	Variable	Unit	Average	Max	Min
Input	GR	Billion USD	3900.04	0.202	378.9
	LP	Million	780.71	0.96	148.1
	PC	Billion kWh	5593.19	2.526	598.9
	EC	Billion Ton	3.097	0.0024	0.4025
Expected output	GDP	Billion USD	11061.6	1.136	1387.84
Undesirable output	CE	Million tons	10.02	0.0073	1.14

2.3. Methodology

2.3.1. SBM-Undesirable model

In a production system with *n* decision units, each unit is characterized by three input-output vectors: input, expected output, and unexpected output. The expected output of S1 and the unexpected output of S2 are produced using m input units. These three input-output vectors can be represented as $x \in R^m, y^g \in R^{S_1}, y^b \in R^{S_2}$. The definitions of matrices *X*, *Y*g, and *Y*b are as follows: $X = [x_1, x_2, \cdots, x_n] \in R^{m \times n}$, $Y^g = [y^g_1, \cdots, y^g_n] \in R^{S_1 \times n}$, $Y^b = [y^b_1, \cdots, y^b_n] \in R^{S_2 \times n}$. Assuming X > 0,Yg > 0,Yb > 0, the production possibility set can be defined as

$$P = \{(x, y^g, y^b) \mid x \ge X\theta, y^g \ge Y^g\theta, y^b \le Y^b\theta, \theta \ge 0\} \tag{1}$$

In the equation, the real expected output falls below the ideal frontier expected output level, while the actual unexpected output surpasses the frontier non-expected output level. Guided by the production possibility set and Tone's SBM model, we proceed to formulate the SBM model for evaluating decision units (x_0, y^g_0, y^b_0) is

$$\rho = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}}}{1 + \frac{1}{S_1 + S_2}\left(\sum_{r=1}^{S_1}\frac{S_r^g}{y^g_{r0}} + \sum_{r=1}^{S_2}\frac{S_r^b}{y^b_{r0}}\right)} \tag{2}$$

$$s.t.\begin{cases} x_0 = X\theta + S^- \\ y^g_0 = Y^g\theta + S^g \\ y^b_0 = Y^b\theta + S^b \\ S^- \ge 0, S^g \ge 0, S^b \ge 0, \theta \ge 0 \end{cases} \tag{3}$$

where $S = (S^-, S^g, S^b)$ represents the relaxation of input, expected output, and non-expected output. The objective function value of ρ is the efficiency value of the decision-making unit, which ranges from 0 to 1. For a given decision-making unit (x_0, y^g_0, y^b_0) , if and only if $\rho = 1$, that is, $S^- = S^g = S^b = 0$, the decision-making unit is effective. If $0 \le \rho < 1$, the evaluated unit is inefficient, and the input and output need improvement. Due to the fact that the above model is a nonlinear model, it is not conducive to the calculation of computational efficiency. By using the Charnes Cooper transformation, the nonlinear equation is transformed into a linear model, with its equivalent form as follows:

$$\tau = \min t - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}} \tag{4}$$

$$s.t.\begin{cases} 1 = t + \frac{1}{S_1 + S_2}\left(\sum_{r=1}^{S_1}\frac{S_r^g}{y^g_{r0}} + \sum_{r=1}^{S_2}\frac{S_r^b}{y^b_{r0}}\right) \\ x_0 t = X\mu + S^- \\ y^g_0 t = Y^g\mu - S^g \\ y^b_0 t = Y^b\mu - S^b \\ S^- \ge 0, S^g \ge 0, S^b \ge 0, \theta \ge 0 \end{cases} \tag{5}$$

In most efficiency evaluation studies, there is a common phenomenon that multiple decision-making units have a 100% "efficiency state". Hence, it holds paramount significance to differentiate between these efficient decision-making units and the factors that exert influence while ranking their efficiency. To yield more rational efficiency assessment values through the efficiency analysis, this study integrates Tone's findings and opts for the super efficiency SBM model in its calculations, represented as follows

$$\ln Y_{it} = \beta_0 + \sum_{t=1}^{n} \beta_k \ln x_{it} + \varepsilon_{it} \tag{6}$$

$$s.t.\begin{cases} \bar{x}_0 \ge \sum_{j=1,\ne k}^{n} \theta_j x_j \\ \bar{y}^g \le \sum_{j=1,\ne k}^{n} \theta_j y_j^g \\ \bar{y}^b \ge \sum_{j=1,\ne k}^{n} \theta_j y_j^b \\ \bar{x} \ge x_0, \bar{y}^g \ge y_0^g, \bar{y}^b \ge y_0^b, \bar{y}^g \ge 0, \theta \ge 0 \end{cases} \tag{7}$$

In the equation, the objective function value of ρ^* is the efficiency value of the decision-making unit, and the value can exceed 1. Other variables are defined in a manner akin to formula (4), and the aforementioned models operate under the premise of a constant scale.

2.3.2. Panel regression model

In the present study, a dynamic panel regression model is employed to systematically investigate the determinants influencing carbon emissions across nations in Asia. Below is the specified model formulation:

$$\ln Y_{it} = \beta_0 + \sum_{t=1}^{n} \beta_k \ln x_{it} + \varepsilon_{it} \tag{8}$$

where Y_{it} serves as the dependent variable, capturing the carbon emissions for each country. Meanwhile, x_{it} represents the independent variables that are theorized to influence carbon emissions. The intercept of the model is denoted by β_0, β_k signifies the set of regression coefficients corresponding to each independent variable, indicating the magnitude and direction of the impact that these variables have on carbon emissions. Finally, ε_{it} stands for the stochastic error term, accounting for unobserved heterogeneity and random disturbances affecting the dependent variable. Existing research has shown that gold reserve, labor personnel, power consumption, energy consumption can influence carbon emission. we selected the variables that characterize influencing factors of the Table 1.

2.3.3. Standard deviation ellipse

The Standard Deviational Ellipse (SDE) serves as a robust tool for the quantitative assessment of inherent spatial characteristics within a set of point elements (Zhang *et al.* 2022), which excels in encapsulating the multidimensional spatial attributes of the focus area under examination. SDE consists of three core elements: the major axis, the minor axis, and the azimuth angle, which collectively provide a comprehensive depiction of both the trend and the dispersion extent of the data. Specifically, the major and minor axes offer insights into the range and orientation of the data, while the azimuth angle emphasizes the primary direction of the tendency. Additionally, the mean center serves as a representation of the data's central point and is indicative of the overall trajectory of its evolution. Along with the mean center, we employed the SDE to illustrate the spatial evolutionary trajectory, which can be articulated as follows:

$$\tilde{X} = \frac{\sum_{i=1}^{n} \omega_i X_i}{\sum_{i=1}^{n} \omega_i}; \tilde{Y} = \frac{\sum_{i=1}^{n} \omega_i Y_i}{\sum_{i=1}^{n} \omega_i} \tag{9}$$

$$\sigma_x^2 = \frac{\sum_{i=1}^{n}\left(\omega_i \tilde{X}_i \cos\theta - \omega_i \tilde{Y}_i \sin\theta\right)^2}{\sum_{i=1}^{n} \omega_i^2}; \ \sigma_y^2 = \frac{\sum_{i=1}^{n}\left(\omega_i \tilde{X}_i \sin\theta - \omega_i \tilde{Y}_i \cos\theta\right)^2}{\sum_{i=1}^{n} \omega_i^2} \tag{10}$$

$$\tan\theta = \frac{\left(\sum_{i=1}^{n} \omega_i^2 \tilde{X}_i^2 - \sum_{i=1}^{n} \omega_i^2 \tilde{Y}_i^2\right) + \sqrt{\left(\sum_{i=1}^{n} \omega_i^2 \tilde{X}_i^2 - \sum_{i=1}^{n} \omega_i^2 \tilde{Y}_i^2\right)^2 - 4\sum_{i=1}^{n} \omega_i^2 \tilde{X}_i^2 \tilde{Y}_i^2}}{2\sum_{i=1}^{n} \omega_i^2 \tilde{X}_i \tilde{Y}_i} \tag{11}$$

3. Results

3.1. Changes of input and output variables of SBM from 2000 to 2015

This investigation conducts a comprehensive and meticulous analysis of key economic indicators by leveraging macroeconomic data from representative Asian countries spanning the years 2000 to 2015. Specifically, LP is broadly acknowledged as a key variable for measuring the economic activity of a nation or region. Statistical data indicate that developing countries manifest an increasing trend in this indicator, whereas developed nations generally exhibit relative stability or slight declines. This observation resonates well with the "Population-Economic Development" model prevalent in development economics, underscoring the importance of other variables like labor quality and productivity. Carbon Emissions serve as a pivotal measure of a nation's environmental governance and sustainability efforts.

Notably, despite continuous GDP growth in most countries, carbon emissions have not increased proportionally, implying the implementation of a series of environmental protection measures. Electricity and energy consumption are closely associated with a nation's industrialization level and quality of life. Figure 2 shows that developed countries have higher per capita energy consumption, but also higher energy use efficiency. In sum, through a comprehensive and nuanced analysis of this dataset, we can not only accurately grasp the evolving patterns of each indicator but also elucidate the intricate interplay and influence mechanisms among these variables. Within the scope of Asia, countries exhibit a wide variety of performances on these core indicators, reflecting the complexities and diversities in their economic, social, and environmental statuses. These variations are influenced not only by unique policy directions, cultural backgrounds, and historical developments of each country but are also closely tied to global economic and political situations. Consequently, a profound examination of these disparities, and their integration into an all-encompassing policy and strategic framework, is crucial for promoting sustainable development.

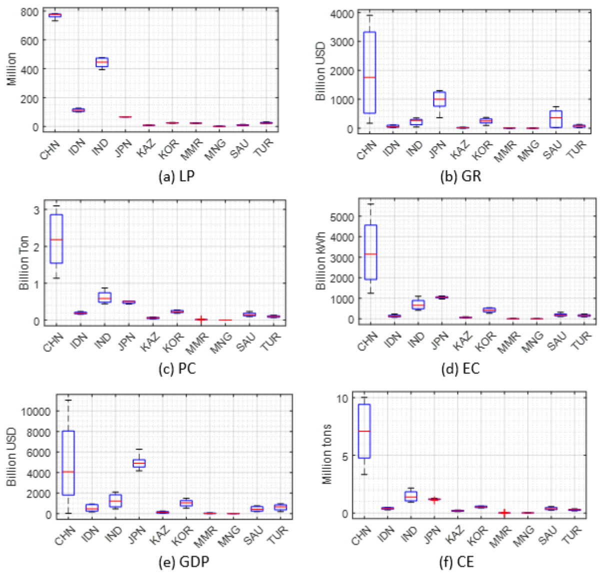


Figure 2. The distribution value of input and output of variables typical Asian countries during 2000–2015.

3.2. Carbon emission performance of SBM from 2000 to 2015

As can be seen in Figure 3, the four geographic heat maps reveal the performance of Asian countries in terms of carbon emission efficiency from 2000 to 2015 in turn. Firstly, significant disparities exist in carbon emission efficiency among different countries and regions. Economies in East Asia and Southeast Asia, such as Japan and Singapore, exhibit higher carbon emission efficiency, likely owing to their advanced industrial technologies and stringent environmental standards. Secondly, over time, some countries have improved their carbon emission efficiency, while others have shown a declining trend. For example, China has notably enhanced its carbon emission efficiency over these 15 years, a development closely tied to its optimized economic structure and strengthened environmental protection measures. In contrast, certain countries in Central Asia and South Asia, such as Kazakhstan and Pakistan, have lagged in improving their efficiency, showing little to no progress. Additionally, the maps illuminate the intricate relationship between environmental issues and socio-economic development. On one hand, high carbon emission efficiency may imply greater production efficiency and economic advancement. On the other hand, without prudent management, it can exacerbate environmental degradation and accelerate climate change. Lastly, it is worth noting that these maps provide only an overarching view of the spatial and temporal trends in carbon emission efficiency and do not delve into the specifics of individual industries or energy structures. Future research will require more detailed data to analyze the particular factors affecting changes in the carbon emission efficiency of different countries, as well as the associated social, economic, and policy implications. Such studies would not only enrich scientists' and policymakers' understanding of the current state of climate change and environmental protection but also offer valuable insights for future sustainable development.

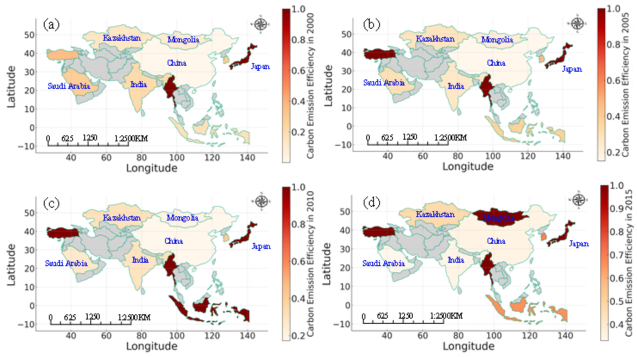


Figure 3. Characteristics of spatiotemporal evolution carbon emission efficiency during 2000–2015.

3.3. The influencing factors of the carbon emission efficiency

The Lagrange Multiplier (LM) test is commonly used for examining whether spatial lag or spatial error is significant in statistical models. It is predominantly utilized to enhance the robustness and precision of these models. One of its key roles is testing specific hypotheses about model parameters, especially in determining their significance (Robert F Engle R. F. 1982 and Baltagi B. H. 2011). This is crucial for evaluating the impact of certain variables and deciding how their inclusion or exclusion affects the model's outcome.

In this study, both the LM-lag and LM-error tests passed at a 1% significance level, indicating that both models are appropriate. In addition to the standard LM test, we also conducted a Robust LM test, which is a more stringent testing method. The results show that in the Robust LM test, both the LM-lag and LM-error tests also passed at a 1% significance level. As shown in Table 2, by synthesizing the above test results, we can confirm that both the Spatial Lag Model (SLM) and the Spatial Error Model (SEM) are applicable to this study. However, the two models may differ in terms of parameter estimation and interpretation, so we will use each of them for further in-depth analysis in the subsequent sections.

After examining three types of fixed-effects models, the spatio-temporal fixed-effects model demonstrated the highest goodness of fit, indicated by the highest R-squared (R^2) value and maximum log-likelihood. These metrics collectively establish the spatio-temporal fixed-effects model as superior in terms of both fitting accuracy and predictive capability. LP exhibited a positive influence across all models examined, most notably achieving the highest coefficient (0.3970) in the time fixed-effects model. Conversely, it was relatively lower in the spatial fixed-effects model (0.146). The impact of GR was also positive, with the highest coefficient observed in the Union OLS model (0.429), and a comparatively lower value in the dual fixed-effects model (0.154). These positive coefficients suggest that both LP and GR may play a constructive role in promoting economic growth or other socio-economic indicators. Both variables displayed negative impacts in all models considered, especially the coefficient of energy consumption in the time fixed-effects model, which was the most significant (-0.4090). This negative relationship may imply that excessive consumption of electricity and energy has detrimental effects on the economy or other socio-economic measures, potentially due to factors such as environmental pollution. In summary, in-depth research could elucidate the underlying mechanisms and influences of these relationships (Table 3).

Table 2. Spatial econometric model verification results

Standard	Testing method	Statistical	p - value
LM test	LM test no spatial lag	93.3005	0.000**
	LM test no spatial error	65.2148	0.000**
Robust LM test	Robust LM no test spatial lag	783.8614	0.000**
	Robust LM no test spatial error	755.7757	0.000**

Table 3. Regression analysis of influencing factors of carbon emission efficiency of typical Asian countries.

Determinant	Union OLS	SFE	TFE	DFE
LP	0.15	0.146	0.397	0.392
GR	0.429	0.427	0.177	0.154
PC	-0.179	-0.174	-0.013	-0.015
EC	-0.532	-0.526	-0.409	-0.323
σ^2	0.566	0.538	0.3039	0.274
R^2	0.159	0.162	0.0963	0.116
log-likelihood	-111.18	-111.44	-106.87	-106.04
Durbin-Watson	0.523	0.5252	1.0227	1.057

3.4. Spatiotemporal pattern of carbon emission performance

In the scope of Asia, this study employs SDE to quantitatively examine carbon emission efficiency, aiming to clarify spatial heterogeneity and its dynamic evolution over time. We can reveal the spatial distribution patterns of carbon emissions within a specific geographical and temporal framework, thereby accurately identifying regions with high and low carbon emission efficiency. This analysis has profound practical implications for optimizing policy formulation and resource allocation.

The lengths of the major and minor axes of the ellipses in Figure 4 reflect the degree of variance of the carbon emissions data in the corresponding directions, respectively. Specifically, the major axis usually represents the greatest variance in the data, serving as a key dimension for interpreting the spatial heterogeneity of carbon emissions. On the other hand, the minor axis exhibits the least variance, offering auxiliary insights into spatial heterogeneity. The geometric center of the ellipse indicates the average geographic concentration point of carbon emission data within the research area, showing the trends of aggregation or dispersion of carbon emissions. Furthermore, through the use of differently colored elliptical markers, we can make more detailed comparisons and interpretations either temporally or geographically. This multi-dimensional perspective not only enhances our overall understanding of the spatial distribution characteristics of carbon emission efficiency but also provides a more precise and actionable basis for specific policy interventions. The change in the X and Y coordinates of the centroid may reflect a shift in the spatial center of gravity, specifically towards the northeast direction. This can be interpreted as a spatial representation of underlying processes, potentially such as economic growth, urbanization, or other socio-economic transformations. Furthermore, fluctuations in the standard distance and rotational angle may indicate increasing irregularity and complexity in the spatial shape. These parameters' variations could be related to multiple factors like economic development, population distribution, or other socio-economic variables. In summary, SDE serves as a highly accurate and information-intensive method, providing a robust analytical tool for revealing the spatial and temporal heterogeneity of carbon emission efficiency, with significant theoretical and practical implications.

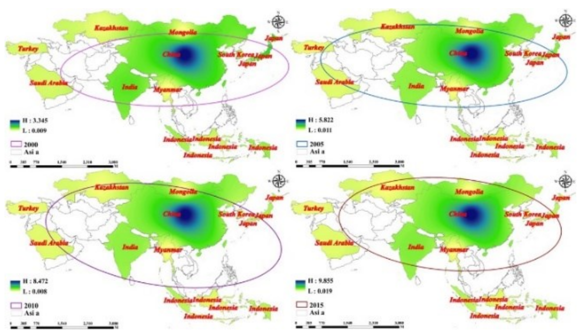


Figure4. Elliptical variance analysis of carbon emission efficiency in Asia. (a) 2000;(b) 2005;(c) 2010;(d)2015.

4. Discussion

4.1. Comparison with previous studies

Climate change and its global repercussions have rapidly escalated into an urgent environmental issue. While a plethora of research has been conducted at global or national scales, specific geographic regions-particularly Asia, known for its high levels of economic activity and carbon emissions-have often been overlooked. This study aims to delineate the key differences between our research and existing literature, and deeply explore the practical implications of these differences. In assessing carbon emission efficiency, most current studies typically rely on single metrics, such as carbon emissions per unit of energy consumption. While these single-factor indicators are easy to understand and implement, they fail to capture the complexity of carbon emissions as a composite result of multiple economic inputs, such as capital and labor. In contrast, this study employs a multifactorial analytical approach, incorporating multiple influencing factors like energy consumption, capital investment, and labor force. This diversified evaluation method not only allows for a more precise reflection of actual carbon emission performance but is also inherently more complex. As for analyzing carbon emission efficiency, the majority of existing research tends to focus excessively on single-variable analyses, thereby ignoring the multifaceted and complex intrinsic structures of carbon emissions. In the diverse environment of Asia, geographical, cultural, and technological differences often result in distinct carbon emission characteristics across various regions. Unlike existing research, which is generally confined to specific time periods or geographic scopes, this study employs a geospatial ellipse method model to perform a comprehensive spatiotemporal evolution analysis on the center of gravity for Asian carbon emissions from 2000 to 2015. Overall, this study exhibits significant differences and advantages in multiple aspects—including research methodology, consideration of regional variations, temporal and spatial scales, and contributions to policy-making—when compared with existing research on carbon emission efficiency. These differences not only elevate the depth and complexity of this study but also enable it to more comprehensively and accurately assess carbon emission efficiency in Asia, thereby providing more robust support and references for related policy formulation.

4.2. Policy implications

Facing the profound impact of climate change on the global ecological environment, the assessment and improvement of carbon emission efficiency have not only become urgent tasks for governments worldwide but also central focal points for international organizations and research institutes. Particularly in Asia, a major source of global carbon emissions, the design and implementation of effective measures to reduce carbon emissions and improve carbon emission efficiency hold critical geopolitical and environmental significance. To enhance carbon emission efficiency, a diversified, multi-layered, and interdisciplinary comprehensive policy framework is required. Such a framework should encompass multiple dimensions, from technological innovation to regulatory regimes, from public awareness to international collaboration. Only through such a holistic and multifaceted approach can we effectively address the various challenges posed by climate change and advance toward the long-term goals of global sustainable development. In this context, this article specifically proposes a series of policy recommendations tailored to the environmental and economic conditions of Asian countries.

First, in order to promote the research and widespread application of green technologies, governments should make explicit commitments to increase funding support for R&D in relevant fields, including but not limited to offering tax incentives and R&D subsidies. Moreover, a multi-stakeholder collaboration platform should be established to enable domestic and international higher education institutions, research organizations, and industries to jointly advance the development and application of more efficient and environmentally friendly technologies. Secondly, governments should take practical measures to optimize the domestic energy structure. This includes using legislative and other legal means to promote the development and application of renewable energy, such as setting minimum standards for the proportion of renewable energy in total energy consumption. At the same time, stricter restrictions or additional environmental taxes should be imposed on enterprises and industries that rely on coal and other high-carbon, high-pollution energy sources. Lastly, establishing and perfecting a legal and regulatory system related to carbon emissions and environmental protection is an essential step. This not only requires the formulation of comprehensive and strict environmental regulations but also ensures that these regulations are strictly enforced and monitored. This may require the establishment of specialized agencies responsible for environmental protection or strengthening the enforcement capabilities of existing institutions.

On a global scale, we also need to establish extensive cooperative relationships with other countries and international organizations to jointly face the global challenges brought about by climate change. Through such multilateral or bilateral cooperation, we can not only share best practices and technological solutions but also fom a more unified and efficient climate action on a global scale.

4.3. Limitations and future research

While this study presents a comprehensive examination of the spatiotemporal patterns of carbon emission efficiency across Asian countries, it is not without limitations. First, due to data constraints, the study primarily focuses on major Asian economies like China and India, which may limit the generalizability of the findings to smaller or less-developed countries in the region. Second, the study employs a static model for assessing carbon emission efficiency, which does not account for dynamic changes in technology or policy over time. Third, the study assumes a constant scale of efficiency, which may not hold true for all countries or industries involved. Lastly, the current study has not delved into sectoral variations within countries, which could offer more nuanced insights into the sources and solutions of carbon emissions. Future research could focus on developing dynamic models that account for changes in technology, policy, and other variables over time. Additionally, a more granular analysis at the sectoral level within countries could provide valuable insights. Multi-country studies that include a wider range of developing and developed countries would also be beneficial to understand the global dynamics of carbon emission efficiency. Moreover, incorporating more advanced statistical and machine learning techniques could improve the robustness and predictive power of the models used.

5. Conclusion

This research delves into the spatiotemporal evolution of carbon emission efficiency across Asian countries over the period from 2000 to 2015, employing a Super-Slack-Based Measure (Super-SBM) model. The study meticulously evaluates the carbon emission performance of prominent Asian nations, utilizing panel regression models and spatial econometric methods to uncover the driving forces behind these efficiencies. It reveals significant variances in carbon emission efficiency among these countries, highlighting the superior performance of technologically advanced nations like Japan and Singapore. Notably, nations such as China have demonstrated considerable improvements, attributed largely to policy interventions and technological progress.

The study underscores the necessity of a comprehensive, multi-dimensional policy framework that integrates technological, economic, and social aspects to enhance carbon emission efficiency and mitigate the impacts of climate change. Strategies such as investing in green technology research and development, refining energy structures, and implementing rigorous regulatory measures are critical. Moreover, the research stresses the importance of international collaboration as a fundamental component in the global effort to combat climate change.

By addressing gaps in existing literature and offering pragmatic policy recommendations, this research provides a substantial foundation for both policymakers and scholars focused on addressing climate challenges. It emphasizes the need for continual research in identifying and bridging research gaps, strategizing based on current circumstances, and exploring areas for further improvement. This includes a deeper examination of the role of emerging technologies, the interplay of socio-economic factors in policy effectiveness, and the potential for adaptive strategies in different national contexts. The study's findings and suggestions are pivotal not just for Asian countries but also offer valuable insights for global climate initiatives in the 21st century.

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