

Article

Carbon Emission Efficiency Differences Between Coastal and Inland Cities in China: Insights from Climate Cost Analysis

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Abstract

Global environmental issues are becoming increasingly severe, with climate change imposing varying degrees of economic impact on different cities. It is crucial for cities to pursue efficient, low-carbon, and sustainable development pathways to cope with climate change. Carbon emission efficiency (CEE) is an essential indicator for assessing their performance and progress toward low-carbon growth. However, traditional CEE assessments have yet to integrate regional differences in the socioeconomic costs of climate change. To fill this gap, we have built a combined efficient frontier Data Envelopment Analysis (DEA) model based on the weighted carbon emissions of each city's climate costs to evaluate the CEEs of 252 cities in China from 2006 to 2021. Meanwhile, city classification and spatial Markov chains are used for spatio-temporal heterogeneity analysis, and finally, the efficiency is decomposed to determine the impact of different factors on carbon efficiency. The results indicate that the average CEE of coastal cities (0.57) is lower than that of inland cities (0.63), mainly due to higher climate costs and unbalanced development. In contrast, megacities and super-large cities in coastal areas have the highest CEE levels because of economies of scale and technological advantages. Efficiency decomposition shows that pure technical efficiency (PTE) is the primary driver of CEE differences, contributing 33.37% to inefficiency differences. Our findings emphasize the need for targeted, differentiated policies to address unique urban challenges. Green technology investments should be prioritized in areas with high emission reduction potential, while cross-regional technology diffusion mechanisms should be established in areas with medium reduction potential to foster innovation. Overall, this study could offer valuable insights into the sustainable and low-carbon transition of urban development.

Keywords: carbon emission efficiency; DEA; climate costs; spatio-temporal heterogeneous

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1. Introduction

Since 1750, greenhouse gas emissions caused by human activities have increased significantly [1], leading to a series of global issues such as global warming, biodiversity loss, and frequent extreme weather events. The emission reduction progress of China is crucial for achieving the temperature control target of the Paris Agreement [2]. The “carbon peaking by 2030 and carbon neutrality by 2060” goals proposed by China indicate that a sustainable low-carbon economy has become the core of the national development strategy [3,4]. Cities are central to the economic decarbonization process [5], contributing

85% of China's carbon emissions [6]. However, disparities across cities in economic development, technological capabilities, and industrial structures further increase the complexity of developing a low-carbon economy [7]. Therefore, given the characteristics of China's unbalanced regional development, conducting low-carbon assessments for cities is essential to achieving sustainable development.

CEE is a key indicator for assessing the progress of low-carbon economic development, widely applied to evaluate the economic efficiency of urban carbon emissions [8–10]. The concept was first introduced by Yamaji et al. (1993) [11] to help quantify the degree to which regional economic growth has decoupled from carbon emissions. CEE provides a useful tool for cities to coordinate development between the economy, resources, and the environment by establishing a production ratio relationship that minimizes carbon emissions while maximizing economic output [12]. After more than two decades of development, CEE is now mainly measured using a total-factor approach that includes all inputs, such as labor, capital, and energy [13], enabling a more accurate and comprehensive reflection of emission efficiency than single-factor analysis [14]. Current studies primarily employ DEA and Stochastic Frontier Analysis (SFA) [15] for CEE measurement. Compared to SFA, DEA does not require a pre-specified production function [16] and offers advantages in handling decision-making units with multiple inputs and outputs. However, traditional DEA models neglect the influence of slack variables, and have consequently been extended to more advanced forms such as the Slack-Based Measure (SBM) and super-SBM models [10]. These models are widely applied in CEE research across different fields, such as the construction industry [17], manufacturing [18], transportation [19], and agriculture [20]. As research advances, scholars have introduced methodological innovations, such as integrating DEA with the Directional Distance Function (DDF), enabling the handling of desirable and undesirable outputs at the same time [9,21]. Furthermore, some studies have introduced the non-radial DDF model [22] or the slack-based measure based on directional distance function (SBM-DDF) [23]. These models allow inputs and outputs to be adjusted in different proportions, effectively addressing the slack measurement in traditional DDF models [9]. Although methodologies have evolved, most studies assessing carbon efficiency overlook regional disparities in urban development. They typically assume that all cities share a unified efficiency frontier, implying that they operate at the same technological level and development stage. In fact, cities in different regions exhibit significant technological heterogeneity and should structurally belong to different frontiers. Oh (2010) first introduced metafrontier analysis into environmental efficiency research, constructing a unified technical frontier that envelops the boundaries of all characteristic groups, thereby reflecting the objective differences in the actual technical features of different regions [24]. Based on this, studies such as Li et al. (2020) [25] and Bian and Meng (2023) [26] further integrated DDF with metafrontier analysis to address the issue of technological heterogeneity in efficiency evaluation.

The existing literature has made significant progress, yet gaps still remain. Most studies have treated labor, capital, and energy consumption as input factors in constructing input–output indicator systems [27–29], with GDP as the desired output and carbon emissions as the undesirable output of economic activities. Although this approach aligns with the intuitive logic of the production process, it implicitly assumes that “the loss associated with each unit of carbon emission is the same across different cities”, often overlooking regional differences in the socio-economic costs of carbon reduction. Specifically, variations in climate risks across cities lead to significant differences in the actual costs of improving efficiency. The differences in climate costs between coastal and inland cities are particularly significant. The high population density in coastal areas increases the pressure from human activities on the environment, thereby exacerbating the risks and social losses from

extreme weather events, such as floods and hurricanes [30,31]. In other words, the higher the population in high-risk areas, the greater the exposure to these risks [30]. In contrast, although inland cities may face different climate stresses (e.g., high temperatures), they are generally less exposed to extreme climate conditions. Ignoring this climate-related cost heterogeneity may introduce bias into comparisons of CEE across different areas, such as underestimating the urgency of decarbonization in coastal areas, leading to unreasonable carbon reduction targets and further exacerbating regional development imbalances.

To address this limitation, this article introduces a weighted carbon emission approach and a “combined efficient frontier” for coastal and inland cities. By developing a DEA model that incorporates climate costs to evaluate CEE more equitably, providing valuable insights for low-carbon sustainable development in urban clusters across various areas. First, we conduct a long-term CEE assessment of 252 Chinese cities from 2006 to 2021. Then, the spatial Markov transition matrix is introduced to explore the spatiotemporal evolution of CEE. Finally, efficiency decomposition methods are used to examine how factors like industrial and energy structures influence carbon efficiency, thereby enabling the design of fair and effective carbon reduction policies for cities.

Compared with the existing literature, this study contributes by identifying regional heterogeneity and developing a differentiated policy pathway framework. First, it extends the CEE evaluation framework by incorporating climate cost-weighted emissions to identify the impact of climate risk disparities between coastal and inland regions, thereby addressing the research gap in assessments that account for regional climate heterogeneity. Moreover, it establishes differentiated pathways for efficiency optimization. Current emission reduction policies in China generally impose homogeneous constraints, neglecting climate, development, and scale differences among cities. This framework identifies differentiated factors influencing CEE, providing a foundation for more equitable and differentiated city-level carbon reduction targets.

2. Methods

This study incorporates climate costs into a DEA model to evaluate the CEE of cities from 2006 to 2021. A total of 252 cities were selected and categorized into coastal and inland groups based on their proximity to the ocean. First, to estimate total economic losses from climate change, we calculated regional climate costs based on four damages: sea-level rise, building energy, temperature-related mortality, and agriculture. These costs were then used to derive climate damage weights and calculate weighted CO₂ emissions. Next, a combined efficiency frontier DEA model was constructed to evaluate regional CEE, utilizing capital, labor force, energy, and weighted CO₂ emissions as inputs and GDP as the output. Second, cities were classified into five categories based on permanent population to explore CEE heterogeneity across city sizes. Third, to measure the influence of neighboring cities, a Markov transition probability matrix was constructed to analyze the dynamic evolution and spatial patterns of CEE. Finally, we used efficiency decomposition to investigate the causes of CEE inefficiency across three dimensions: technical, scale, and mix efficiency. Finally, we used efficiency decomposition to investigate the sources of CEE loss. The research approach, illustrating specific research steps, is shown in Figure 1.

2.1. Climate Cost Module

This article draws on the concept of social cost of carbon (SCC) from the climate economics theory in the Dynamic Integrated Climate–Economy (DICE) model [32]. We adopt the damage function [33] to calculate the total climate change-related economic damages (climate cost per unit of carbon emission) in different areas from 2006 to 2021. All these damages are converted to the 2005 price level using the GDP deflator. The function

covers sea-level rise damages, building energy damages, temperature-related mortality damages, and agricultural damages, shown in Equations (1)–(9). Among these damages, the factor of sea-level rise damage is not considered in inland areas, so its coefficient is set to 0. The provincial-level carbon climate cost is used to represent the climate cost of its subordinate prefecture-level cities. Based on the principle of marginal analysis, we use a simplified evaluation model. In this model, climate cost is characterized as the marginal climate loss caused by an additional unit of carbon emission.

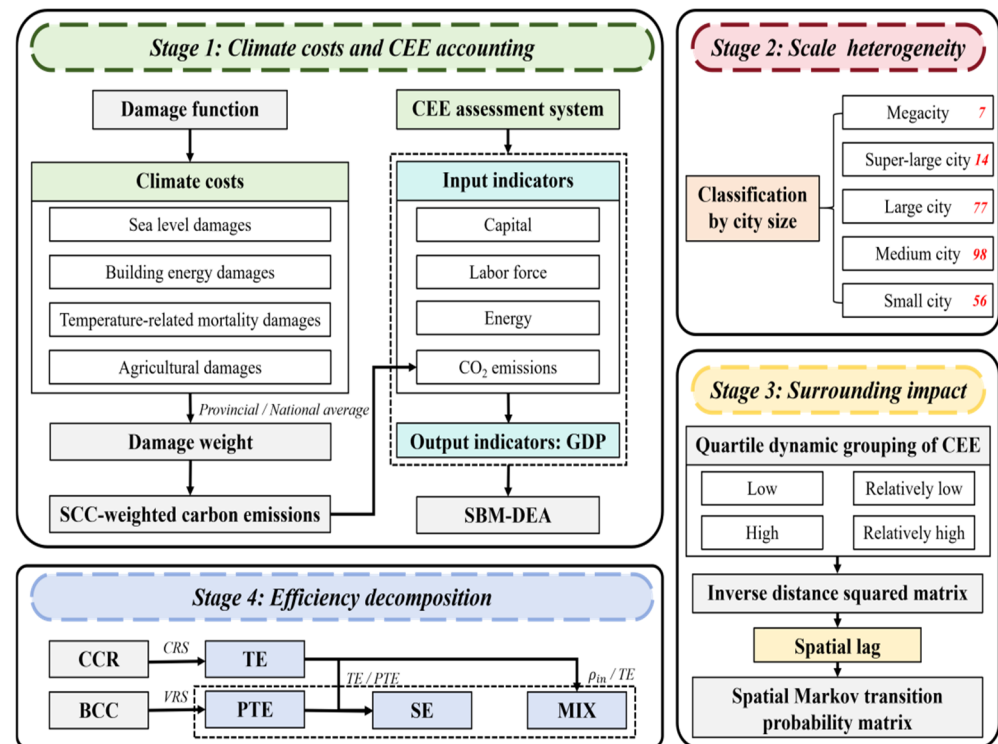


Figure 1. Specific research steps for CEE evaluation incorporating climate costs.

Sea-level rise damages:

$$D_S(t) = \beta_i^S(t) \times Q(t) \quad (1)$$

where $D_S(t)$ represents sea-level rise damages, $\beta_i^S(t)$ represents the damage coefficient in China [34], $Q(t)$ represents the total annual GDP of an area.

Building energy damages:

$$D_E(t) = \beta_i^E(t) \times T_{AT}(t) \times Q(t) \quad (2)$$

where $D_E(t)$ represents building energy damages, $T_{AT}(t)$ represents the average increase surface temperature of a city compared to the pre-industrial level, $\beta_i^E(t) \times T_{AT}(t)$ represents the proportion of energy damages in the regional GDP [33].

Temperature-related mortality damages:

$$D_M(t) = VSL_i(t) \times \beta_i^M(t) \times T_{AT}(t) \times BM_i(t) \quad (3)$$

$$BM_i(t) = Population_i(t) \times BMR_i \quad (4)$$

$$VSL_i(t) = VSL_{US,2020}^{base} \times \left(\frac{GDP \text{ per capita}_{i,t}}{GDP \text{ per capita}_{US,2020}} \right)^\varepsilon \quad (5)$$

where $D_M(t)$ represents temperature-related mortality damages, $VSL_i(t)$ represents the value of a statistical life in different areas. It is derived based on the 2020 baseline VSL value in the U.S. [33] and converted using the ratio of per capita GDP, $\beta_i^M(t)$ is the temperature rise response coefficient for each area, $BM_i(t)$ represents the baseline mortality rate, which is calculated by multiplying the population size $Population_i(t)$ by the baseline mortality rate BMR_i , and ε represents the income elasticity of VSL, which is used to adjust the U.S. VSL to match the income levels of various areas in China.

Agricultural damages:

$$D_A(t) = SGA_i(t) \times f[T_{AT}(t)] \times Q(t) \quad (6)$$

$$SGA_i(t) = SGA_{i,1990} \times \left(\frac{GDP \text{ per capita}_{i,t}}{GDP \text{ per capita}_{i,1990}} \right)^{-\varepsilon} \quad (7)$$

where $D_A(t)$ represents agricultural damages, $f[T_{AT}(t)]$ represents the piecewise function for losses in China [35], the values of the linear function at four points 0 °C, 1 °C, 2 °C, and 3 °C are 0, 0.01532, −3.43637, and −4.21163, respectively. $SGA_i(t)$ represents the share of agriculture in regional GDP, based on the share of agricultural GDP in 1990 and adjusted using the ratio of per capita GDP [36]. ε represents the income elasticity of the share of agriculture in GDP.

Total economic damages:

$$\Omega(t) = D_S(t) + D_E(t) + D_M(t) + D_A(t) \quad (8)$$

$$Cost(t) = \frac{\partial \Omega(t)}{\partial E(t)} = \frac{\Omega(t) - \Omega(t-1)}{E(t) - E(t-1)} \quad (9)$$

where $Cost(t)$ represents the climate cost per unit of carbon emission, which is expressed in 2005 dollars, $\Omega(t)$ total economic damages, $E(t)$ represents carbon emissions.

2.2. Combined Efficient Frontier DEA Module

The capital, labor force, energy, and carbon emission are selected as input indicators, and GDP is selected as the output indicator to construct an urban CEE evaluation system (Table 1). Although some research treats carbon emissions as an undesirable output in DEA models [10,37], we regard them as a necessary climate cost incurred during urban development. The main purpose of the model is to internalize the environmental costs in order to capture the climate differences faced by different cities, rather than treating them as a regular production factor. Since this approach does not affect relative efficiency evaluations, we classify carbon emissions as an input factor. The specific definitions of all input and output indicators are presented below:

- (1) Labor force input is expressed by the number of employed persons in each city [7,29], which includes individuals aged 16 and above engaging in social labor or business activities for remuneration or income. Missing data are calculated as the product of the urban resident population and the provincial average employment rate.
- (2) Capital input is represented by capital stock [7,29], which refers to the total accumulated fixed assets after depreciation within a city for a given year, encompassing physical capital forms such as infrastructure, land assets, and buildings. The capital stock is calculated using the perpetual inventory method (see Equation (10)).

$$K_{i,t} = K_{i,t-1} \times (1 - \delta_t) + \frac{I_{i,t}}{P_{i,t}} \quad (10)$$

where $K_{i,t}$ denotes capital stock. Following Zhang et al. [38], the base year is set as 2006, and the capital stock in the base year is calculated as the fixed capital formation in the initial year of each city divided by 10%. δ_t represents the depreciation rate, which is set to 9.6% [38]. $I_{i,t}$ denotes fixed asset investment, and $P_{i,t}$ represents the price index of fixed asset investment.

- (3) Due to the difficulty in accurately calculating energy consumption across different cities, we use total electricity consumption to represent energy input, which refers to the total amount of electricity consumed by all electricity users in a city within one year.
- (4) Climate input is represented by CO₂ (weighted) emissions, following the definition of the city-level carbon emission accounting scope proposed by the World Resources Institute in the GHG Protocol for Cities [39].
 - CO₂ emissions, which refer to the physical amount of all direct emissions occurring within the administrative boundaries of a city.
 - CO₂ weighted emissions, which refer to carbon emissions weighted by the SCC. We use SCC-weighted emissions to highlight the differences in climate costs among different cities. The damage weight of each province is obtained through the ratio of the provincial climate cost to the national average cost, which is used to calculate the CO₂ weighted emissions of prefecture-level cities within the province (see Equation (11)). This essentially represents a redistribution of carbon emissions. By adopting the national average climate cost, the approach can accommodate the overall development conditions of each period and dynamically adjust the weight proportions across different cities. Areas with climate costs above the national average impose greater economic damage per unit of carbon emissions, and therefore have higher weighted emissions. In contrast, areas with climate costs below the national average cause less economic damage per unit of emissions, resulting in lower weighted emissions.

$$E_{weighted,i,t} = E_{i,t} \times \left(\frac{Climate\ cost_{province}}{Climate\ cost_{China}} \right)^{\epsilon} \quad (11)$$

where $E_{i,t}$ represents CO₂ emissions, $E_{weighted,i,t}$ represents CO₂ weighted emissions, $Climate\ cost_{province}$ represents the climate cost of the province (expressed in 2005 U.S. dollars), and $Climate\ cost_{China}$ represents the average climate cost of China.

- (5) Economic output is represented by the gross domestic product (GDP) of each city. It refers to the final outcomes of production activities within a city over the course of one year, and is mainly used to measure the overall economic scale of an area and the aggregate level of economic activity.

To make full use of all decision-making units (DMUs), we propose a combined efficient frontier for evaluation [40]. This is because substantial differences exist across areas in terms of development stages, resource endowments, and technological foundations [41]. If areas with heterogeneous technological levels are compared on a single undifferentiated frontier, the evaluation results may be biased. By adopting a “combined efficient frontier”, an envelope surface that better matches the actual technological characteristics of each area can be constructed, thereby enabling the estimated CEE to more accurately reflect the objective differences among cities in terms of development levels and climate risks. The specific procedures are as follows: First, conduct SBM-DEA on coastal and inland city groups to obtain their respective efficient DMUs. Although we can directly use these efficient DMUs in each group to compare the efficient frontiers of the two groups, this approach cannot fully utilize most DMUs within each group, and it may reduce the

reliability of subsequent rank-sum tests due to the degrees of freedom. Therefore, we adopt the method proposed by Cooper et al. (2007) [40] to project the inefficient DMUs in both groups onto their respective efficient frontiers to convert all DMUs into efficient ones. This method can use all DMUs in each group to construct a new efficiency frontier, thereby developing a more representative group technology frontier. Then, to quantify and compare the differences between the two frontiers, we combine the two groups of efficient DMUs as the combined efficient frontier and conduct super-efficiency SBM-DEA. Finally, we perform the rank-sum test. The carbon emission efficiency of all prefecture-level cities is evaluated through the generalized SBM model (see Equations (12)–(14)).

$$\min \rho = \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s} \sum_{r=1}^s \frac{s_r^+}{y_{ro}}} \quad (12)$$

$$\begin{cases} x_{io} = \sum_{j \in T} \lambda_j x_{ij} + s_i^- \\ y_{ro} = \sum_{j \in T} \lambda_j y_{ij} - s_i^+ \end{cases} \quad (13)$$

$$\begin{cases} \sum_{j=1}^n \lambda_j = 1, \quad s_i^- \geq 0, \quad s_i^+ \geq 0 \\ i = 1, \dots, m, \quad r = 1, \dots, s, \quad j \in T, \quad i \in V \end{cases} \quad (14)$$

where T represents the combined efficient frontier, and V represents the evaluated urban group.

Table 1. Input and output indicators in data envelopment analysis.

Indicator Type	Indicator	Definition	Unit	Direction	Data Sources *
Input	Labor force input	Total employment	Persons	-	China City Statistical Yearbook [42]; China Labor Statistical Yearbook [43]
	Capital input	Capital stock	10 k CNY	-	China Fixed Asset Investment Yearbook [44]; China Statistical Yearbook [45]
	Energy input	Total electricity consumption	10 k kWh	-	-
	Climate input	CO ₂ emissions (All direct emissions within city administrative boundary)/Weighted emissions	10 k tons	-	CEADs and MEIC v2.0 model [46]
Output	Economic output	GDP	100 M CNY	+	-

* All indicator data also use the statistical yearbooks at the provincial and prefecture-level city levels.

2.3. City Classification Module

To analyze the differences in CEE across cities of different sizes, we follow the Notice of the State Council of China on Adjusting the Standards for City Size Classification issued in 2014, according to which the 252 prefecture-level cities are divided into 5 categories based on the permanent population of their urban areas [47]: “megacities”, “super-large cities”, “large cities”, “medium cities” and “small cities” (Table 2).

Table 2. Classification based on city size.

City Size	Classification Criteria (Permanent Urban Population)	Number
Megacity	>10 million	7 (5 coastal, 2 inland)
Super-large city	5–10 million	14 (8 coastal, 6 inland)
Large city	1–5 million	77 (43 coastal, 34 inland)
Medium city	0.5–1 million	98 (38 coastal, 60 inland)
Small city	<0.5 million	56 (12 coastal, 44 inland)

2.4. Spatial Markov Transition Probability Matrix Module

To reveal the dynamic evolution law of urban CEE, a Markov transition probability matrix is used to analyze the transition between city groups with different CEE levels [48]. We adopt the quartile dynamic grouping method to classify the CEEs of all cities each year into four states [8]: low efficiency, relatively low efficiency, relatively high efficiency, and high efficiency. An inverse distance squared matrix is used to introduce the spatial lag state. Based on the longitude and latitude data of all cities, the inverse distance squared matrix for all cities within the research scope is calculated through Equations (15)–(17). The matrix product of the state vector and the inverse distance squared matrix is used to calculate the lag vector of all cities, as shown in Equation (18). According to the quartiles of the CEEs of all cities each year, the category of the spatial lag state for each city is determined, and then the spatial Markov transition probability matrix is calculated.

$$d_{ij} = 2R \arcsin \left(\sqrt{\sin^2 \left(\frac{lat_i - lat_j}{2} \right) + \cos(lat_i) \cos(lat_j) \sin^2 \left(\frac{lon_i - lon_j}{2} \right)} \right) \quad (15)$$

$$\omega_{ij} = \frac{1}{d_{ij}^2} \quad (16)$$

$$\omega_{ij}^{norm} = \frac{\omega_{ij}}{\sum_{j=1}^n \omega_{ij}} \quad (17)$$

$$y_i^* = \sum_{j=1}^n \omega_{ij}^{norm} y_j \quad (18)$$

where lat_i and lat_j represent the latitudes of cities, while lon_i and lon_j represent their longitudes. d_{ij} represents the geographical distance between two cities, ω_{ij} represents the inverse distance squared, and ω_{ij}^{norm} represents the normalized element of the inverse distance squared matrix.

2.5. Efficiency Decomposition Module

The specific sources of carbon emission efficiency loss vary across different cities. Therefore, the obtained SBM efficiency is decomposed into mixed efficiency (MIX), pure technical efficiency (PTE), and scale efficiency (SE). Under the condition of constant returns to scale (CRS), the relative efficiency evaluated by the Charnes, Cooper, and Rhodes (CCR) model [49] is referred to as total technical efficiency (TE). Under the condition of variable returns to scale (VRS), the relative efficiency evaluated by the Banker, Charnes, and Cooper (BCC) model is PTE. It represents the production efficiency of a DMU under optimal scale and optimal allocation, reflecting the current low-carbon development technology level of a city. SE can be obtained by the ratio of CCR relative efficiency to BCC relative efficiency (see Equation (19)) [50–52]. It indicates the rationality of the production scale of a DMU, reflecting the impact of urban scale on low-carbon development. MIX represents the

rationality of the input combination of a DMU under optimal scale and optimal technology (see Equation (20)), reflecting a city's resource allocation and management capabilities. ρ_{in} represents the relative efficiency evaluated by the input-oriented SBM-DEA model, which reflects the overall efficiency of a city's low-carbon development (see Equation (21)).

$$SE = \frac{TE}{PTE} \quad (19)$$

$$MIX = \frac{\rho_{in}}{TE} \quad (20)$$

$$\rho_{in} = MIX \times PTE \times SE \quad (21)$$

2.6. K-Means Clustering Module

The K-means clustering algorithm partitions data into multiple distinct clusters by iteratively minimizing the sum of squared distances between data points and their corresponding cluster centers. Based on the selected cluster centers (μ_j), the Euclidean distance from each point to all centers is calculated first, and each point is assigned to the nearest cluster (see Equations (22) and (23)). Then, the center of each cluster is updated according to Equation (24). This iterative process is repeated until the cluster centers no longer change. To provide targeted policy for low-carbon economic development across cities, this study employs pure technical efficiency, mixed efficiency, scale efficiency, and emission reduction potential as clustering indicators in the K-means analysis. Among these factors, emission reduction potential is defined as the proportion of the slack movement in carbon emission input relative to the original carbon emission input for each city, indicating the remaining improvement needed for that city to reach the most efficient frontier in terms of carbon emission input.

$$d(x_i, \mu_j) = \sqrt{\sum_{m=1}^M (x_{i,m} - \mu_{j,m})^2} \quad (22)$$

$$C_j = \left\{ x_i : \arg \min_j d(x_i, \mu_j) \right\} \quad (23)$$

$$\mu_j^{(new)} = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i \quad (24)$$

where μ_j represents j -th cluster center; $d(x_i, \mu_j)$ refers to the Euclidean distance between point x_i and the center of the j -th cluster; C_j represents j -th cluster.

3. Results

3.1. Significant Differences in Climate Costs Among Chinese Cities

The quantitative differences in the average values of the four climate damage types are significant, as shown in Figure 2. Temperature-related mortality damage contributes the most to climate costs, approximately 4.5 billion yuan annually, especially in coastal provinces such as Guangdong and Jiangsu. Agricultural damage averages about 3 billion yuan annually, with relatively small fluctuations. The impacts of sea-level rise damage and building energy damage are slight, and their distributions are relatively concentrated.

According to Table 3, the climate cost per unit of carbon emissions shows the characteristic of regional heterogeneity. The climate costs in the eastern coastal areas are the highest, with Shanghai having the highest at 55.46 \$/tC. This reflects the negative effects brought by the aggregation of population, technology and industries in coastal cities. In the southwest, Chongqing and Sichuan also have high climate costs, as the core of the economic circle,

reflecting the challenges and pressures faced by inland developed cities in transitioning their economic development toward a low-carbon direction. In the central and northern areas, the climate costs are at moderate levels, averaging around 5 \$/tC. The climate costs are the lowest in the northwest due to its sparse population and low industrialization, with Inner Mongolia having the lowest at 0.35 \$/tC, about 158 times lower than Shanghai. On average, the climate costs in the eastern coastal areas are approximately nine times those of the northwest, reflecting that the climate costs in coastal provinces are significantly higher than those in inland areas [53].

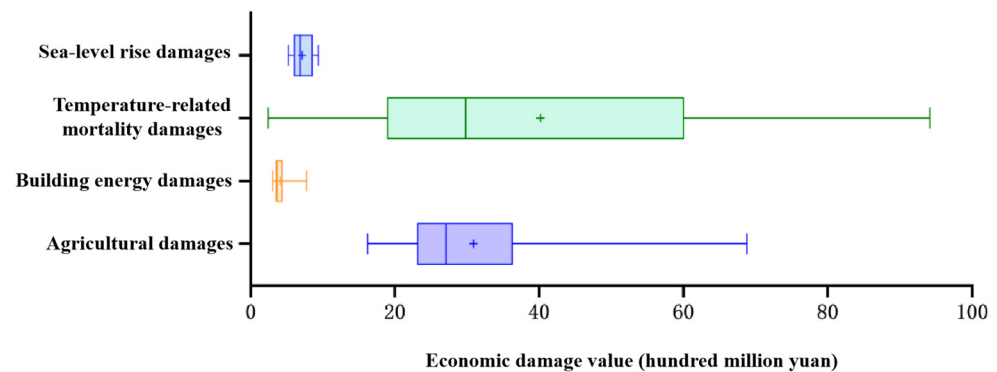


Figure 2. Quantitative values of four temperature-related damages.

Table 3. Average climate cost per unit of carbon emission from 2006 to 2021.

Province/City	Climate Cost (\$/tC)	Province/City	Climate Cost (\$/tC)
Eastern coastal area		Southwest area	
Shanghai	55.46	Guangxi	19.16
Beijing	25.61	Chongqing	16.64
Fujian	22.94	Sichuan	13.60
Guangdong	22.14	Yunnan	5.78
Hebei	19.06	Guizhou	2.37
Tianjin	17.07	Xizang	1.39
Jiangsu	10.62	Northwest area	
Zhejiang	6.86	Gansu	5.49
Anhui	5.91	Qinghai	2.32
Shandong	3.88	Shanxi	1.78
Hainan	3.49	Xinjiang	1.00
Central area		Ningxia	0.98
Hubei	7.86	Inner Mongolia	0.35
Jiangxi	5.84	Northeast area	
Henan	5.44	Heilongjiang	7.71
Hunan	3.98	Jilin	4.61
Shanxi	1.52	Liaoning	1.49

3.2. Spatio-Temporal Evolution Characteristics of CEE Considering Climate Costs

We evaluate the CEE of 252 prefecture-level cities in China from 2006 to 2021 using the combined efficient frontier DEA model. The results are shown in Figure 3. Within the figure, (A), (B), (C), and (D) display the distribution of average urban CEE every four years in chronological order. Overall, China's CEE decreased from 2006 to 2009 and then increased from 2010 to 2021. This shift was closely related to policies implemented between 2010 and 2013, such as low-carbon city pilots and carbon emission trading systems [54,55]. Especially from 2014 to 2021, the national average CEE increased by 14.03%.

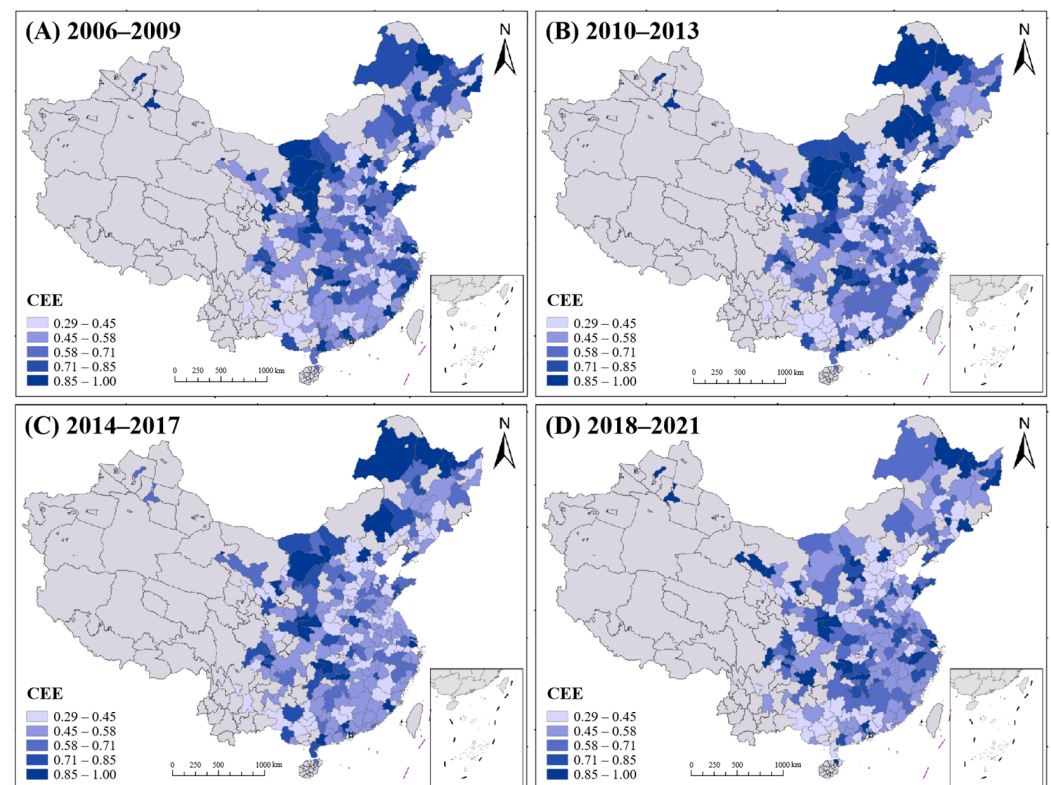


Figure 3. Urban CEE of different cities in China from 2006 to 2021.

Regionally, the CEE in the eastern and southern coastal areas steadily increased, driven by the combined effects of factor agglomeration and enhanced coordination between ecological protection and economic development. Specifically, these regions benefitted from stronger technological innovation, more advanced industrial structures, and more efficient energy utilization, which together support higher economic output. Meanwhile, the balance between ecological and economic development mitigated environmental pressures caused by high-density economic activities. This growth pattern gradually spread to the inland provinces of the middle Yangtze River, forming a high-efficiency CEE cluster in the southeastern area. This finding is consistent with the conclusion made by Jin et al. (2024) that the CEE levels in the Yangtze River Delta area are significantly higher [41]. In contrast, the CEE in the northern coastal areas has declined overall, with a low-efficiency clustering phenomenon around the high-efficiency city of Beijing in most years. The CEE of inland Northeast China and inland areas in the middle reaches of the Yellow River also decreased gradually [41], while Urumqi and Karamay in Xinjiang maintained a high CEE level for a long time. Compared to traditional coal-resource-based cities, cities such as Karamay are characterized by capital and technology-intensive oil and gas industries. Therefore, they generate higher economic outputs with equal inputs and exhibit lower carbon emission intensity for the same level of output. In contrast, Wang and Li (2023) pointed out that some inland western cities, such as Enshi and Xiangxi, exhibit relatively high CEE levels due to the rich ecological assets, low degrees of industrialization and ecological protection [56]. In general, the center of gravity of China's overall carbon emission efficiency is gradually shifting to the southeastern area. Coastal developed cities drove the development of surrounding inland areas through the spatial spillover effects of population, economy, and technology factors [56]. In addition, the strong transportation capacity of the Yangtze River waterway promoted the diffusion process.

Differences exist in efficiency between CO₂ emission-based and CO₂ weighted emission-based assessments for the same city. This also reflects that the impact of cli-

mate costs on CEE cannot be ignored. The results are shown in Figure 4. Coastal and inland areas show different characteristics in CEE changes. When climate costs are incorporated, 63.81% of coastal cities have efficiency losses. Among these, 21.90% of coastal cities suffer severe efficiency losses ($-0.20 \leq \Delta\text{CEE} \leq -0.10$). These cities are concentrated along the coastline, mainly including developed coastal cities such as Beijing and Shanghai. Meanwhile, the southern coastal area suffers the most severe efficiency losses, which may be related to higher temperatures and greater climate damage in the southern area. In contrast, 40.13% of inland cities achieve efficiency improvements. Among these, 12.93% of inland cities improve efficiency significantly ($0.21 < \Delta\text{CEE} \leq 0.44$), which are mainly small and medium cities. The climate risks in these underdeveloped cities are significantly lower than those in large coastal cities, leading to their weighted carbon emissions being much lower than their physical carbon emissions, leading to a large increase in their relative efficiency. At the same time, several prefecture-level cities in Sichuan also have efficiency losses, which are associated with compounded climate risks in Sichuan and Chongqing, including high temperatures and extreme precipitation, thereby intensifying the economic impacts of carbon emissions.

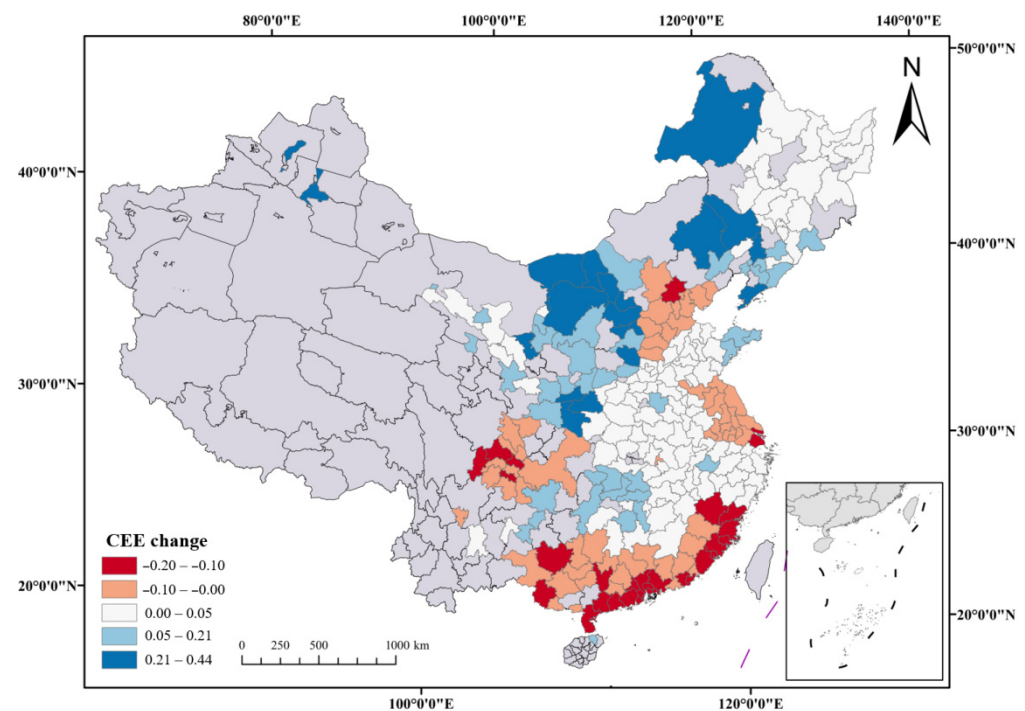


Figure 4. CEE changes in different cities under the CO₂ emission-based and CO₂ weighted emission-based evaluation approaches. Red represents the degree of decrease in a city's CEE, blue represents the degree of increase, and white represents that there is little or no change.

3.3. CEE Varies with City Size: Lowest in Medium and Large Inland Cities and Small and Medium Coastal Cities

In Figure 5, from the perspective of the 16-year average level, the CEE of inland city clusters (CEE = 0.63) is generally better than that of coastal city clusters (CEE = 0.57), and the CEE of coastal areas shows a decreasing trend. The CEEs of coastal and inland cities of different sizes show significant differences in their interannual changes: among small and medium cities, inland cities have better CEEs than coastal cities in all years. The average CEEs of inland small cities reaches 0.7. This higher efficiency primarily results from lower climate damages and simpler industrial structures, which reduce input redundancy and enhance relative efficiency. However, the CEEs of coastal small and medium cities are the lowest among all coastal cities. Their quantity accounts for 47.62%, which is one of

the main reasons for the low overall CEEs of coastal areas. Among large cities, the CEEs of coastal and inland areas are close. But after 2010, the CEEs of coastal areas have been lower than those of inland areas due to the increase in climate costs. Improvements in pure technical efficiency or industrial upgrading in large cities cannot fully offset the damages caused by rising climate costs. Among megacities, the average CEEs of coastal cities are higher than those of inland cities, but this gap is gradually narrowing. This change reflects that the absolute location advantage of large coastal cities built on maritime transportation is gradually fading [52]. Although coastal megacities such as Shenzhen, Guangzhou and Shanghai bear higher climate costs, they still have much higher CEEs than the Chengdu-Chongqing area in inland areas. It suggests that agglomeration effects and the maturity of resource factors in coastal megacities have reached a high level. Consequently, further enhancements can offset the negative impact of climate costs on CEE. This finding aligns with Qiao et al. (2025), who noted that improving resource efficiency in developed coastal cities mitigates the negative environmental effects of scale expansion [57]. The average CEE of inland megacities is 0.76, which has little difference from that of small cities. Overall, the CEEs of inland areas show a “U-shaped” distribution with changes in city size, and the low-carbon economic development level of medium and large inland cities is relatively weak. The CEEs of coastal areas increase with increases in city size, and their main weakness is concentrated in small- and medium-sized coastal cities. Regarding this pattern, Zhang et al. (2021) argue that the high efficiency of inland small and medium cities may represents a kind of “low-level high efficiency,” which is distinct from the “agglomeration-based high efficiency” of coastal super-large cities [52].



Figure 5. Changes in coastal and inland CEE under five city sizes (2006–2021).

3.4. The Impact of Surrounding Cities

We use spatial lags to measure the impact of surrounding cities’ status on CEE. Spatial lags refer to the impact that the status of surrounding cities has on the target city. A city’s CEE is not only influenced by its own factors but also by the CEE of surrounding cities. Cities with high spatial lag are more likely to benefit from the technology spillover of high-CEE city clusters, but those with a low spatial lag tend to be constrained by low-efficiency aggregation. The results show that, the probabilities of cities being in the low-efficiency and lower-efficiency states decrease as the spatial lag level increases, while the higher-efficiency and high-efficiency states gradually increase (Appendix A). Under the high spatial lag state, the total upward transition probability of low-efficiency and lower-efficiency cities increases by 5.84%, while that of high-efficiency and higher-efficiency cities decreases by 8.19%. This indicates that a high spatial lag state has a greater impact on high-efficiency

cities in maintaining their current state. The transition probabilities of lower-efficiency and higher-efficiency cities do not show obvious spatial correlation. The results show that the phenomenon of “fluctuating in the middle efficiency range” is common among these cities, and they are less affected by surrounding areas.

Both coastal and inland cities show a trend where the upward transition probability increases as spatial lag rises, but the spatial spillover effect is more significant in coastal areas. Inland cities exhibit a phenomenon of polarization, with the efficiency of middle-efficiency cities fluctuating. In contrast, middle-efficiency cities in coastal areas show a downward transition trend. This phenomenon can be explained by the “siphoning effect” proposed by Lu and Gong (2025) [58]: highly efficient cities within coastal clusters may siphon human capital and industrial momentum from neighboring medium-efficiency cities, thereby reducing their CEE. Compared with inland cities, coastal cities in the high spatial lag state have a larger overall upward transition amplitude. Meanwhile, coastal cities in the low and lower spatial lag states have a larger overall downward transition amplitude. This indicates that the low-efficiency and high-efficiency aggregation effects of coastal city clusters are more significant. The low-efficiency aggregation of coastal clusters also includes middle-efficiency cities in the lower-efficiency state. However, the high-efficiency aggregation is limited to some cities in the northern Beijing–Tianjin–Hebei economic zone, the eastern Jiangsu–Zhejiang–Shanghai economic zone, and the southern economic zone. This spatial distribution pattern is similar to the findings of Ma et al. (2026) [27], indicating that such high-efficiency agglomeration in downstream coastal areas is persistently observed.

3.5. Decomposed Efficiency Variations Across City Sizes and Their Impact on CEE Differences

The decomposition results of CEE are shown in Figure 6. The average PTE of the 252 cities is 0.74, indicating an overall low level of low-carbon technology. As city size increases, the pure technical efficiency of inland cities shows a “U-shaped” trend, while that of coastal cities shows a continuous upward trend. Coastal areas exhibit a phenomenon where technology spreads gradually from cities with high pure technical efficiency to surrounding cities. The trend is consistent with the change trend of CEE. The average SE of the 252 cities is 0.89, indicating that most cities are at a relatively reasonable scale level. 39.68% of the cities have high scale efficiency, and these cities are mainly concentrated in the central and northern areas. Both coastal and inland cities show an “inverted U-shaped” relationship between scale efficiency and city size: large cities have the optimal scale efficiency, while excessively large or small scales will lead to lower efficiency. The continued expansion of the scale of such agglomeration exerts an inhibitory effect on CEE, which is supported by the findings of Pang et al. (2026) [59]. The overall scale efficiency of coastal areas is higher than that of inland areas. However, inland small cities have large differences in scale efficiency, mainly because their economic output capacity is limited by city size. Megacities and super-large cities have lower scale efficiency than large cities, which is due to agglomeration conflicts and climate damage.

The average value of MIX is only 0.76, and 73.41% of the cities have low mixed efficiency. This indicates that most cities have significant deficiencies in resource allocation capacity. The larger the city size, the more balanced the distribution of its mixed efficiency. Due to the lower climate costs, some small inland cities have better resource allocation combinations than large-scale inland cities. Compared with inland cities, the mixed efficiency of coastal cities increases with the growth of city size, and its distribution is more uniform. However, some super-large coastal cities still have unreasonable resource allocation problems. The average contribution of the three types of efficiency to the inefficiency degree of all cities is as follows: PTE accounts for 33.37%, SE for 24.28%, and MIX for 42.35%. PTE is the main cause of differences in CEE. This finding aligns with Xia et al. (2025) [60],

indicating that green technological innovation is a key factor for cities to achieve high quality and low carbon transformation. Both coastal and inland urban agglomerations have relatively reasonable urban production scales, and need to focus on optimizing resource allocation. Small and medium cities, especially coastal ones, urgently need to advance their pure technical capabilities to address the pressure of high climate costs.

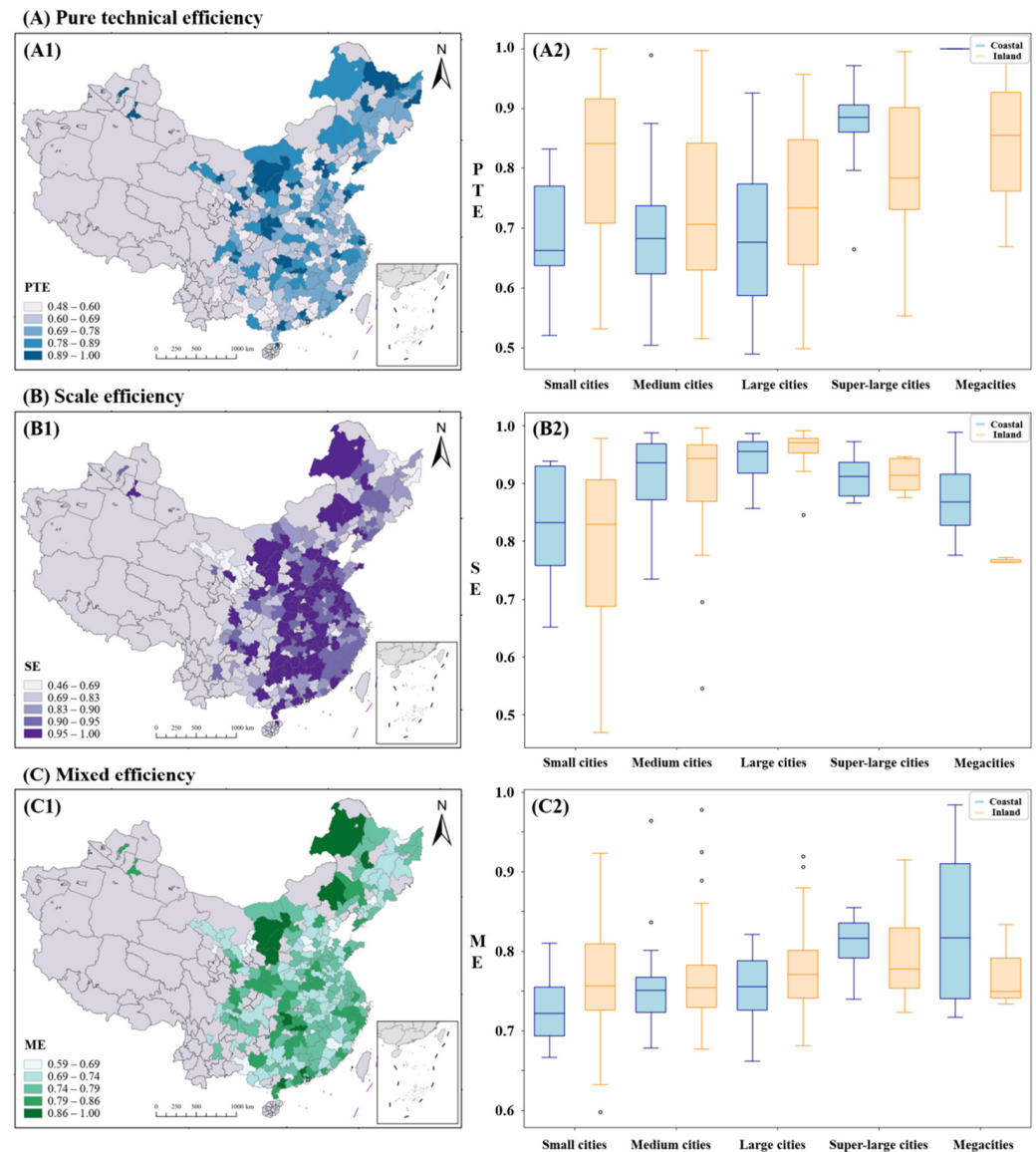


Figure 6. Efficiency decomposition of urban CEE. (A1,B1,C1) display the distribution of three decomposed efficiencies for 252 cities (2006–2021 averages). (A2,B2,C2) compare these efficiencies across five city scales for coastal (blue) and inland (orange) cities.

4. Discussion

4.1. Understanding the CEE Disparity Between Coastal and Inland Cities

By incorporating climate costs into the assessment framework, this study finds that the average CEE of coastal cities is lower than that of inland cities. However, studies that do not consider climate costs generally conclude that CEE in coastal cities is higher than in inland cities [27,29]. In fact, incorporating climate costs fully accounts for regional climate differences and development equity, which may ultimately affect the results. This contradiction in findings can be explained from the following two dimensions.

First, the incorporation of climate costs fundamentally alters the constraints of CEE evaluation. Risks such as sea-level rise, storm surges, and extreme high temperatures are concentrated in coastal areas. As a result, their climate cost per unit of carbon emission is much higher than that of inland provinces, whereas inland areas may generate a “low-cost premium.” By weighting carbon emissions, the high climate costs in coastal areas are converted into higher carbon emission weight coefficients. This does not mean that inland areas are cleaner in terms of production processes, but rather it reveals that after considering the differentiated climate risks, the true costs of economic development are presented more fairly. This conclusion responds to the principle of “common but differentiated responsibility” in global sustainable development discussions.

Second, economic development across coastal cities is uneven. Megacities and super-large cities in coastal areas show the highest CEE levels despite facing higher climate costs. The PTE and MIX of leading cities are extremely high due to knowledge spillovers and strong resource allocation capacity. Our findings align with Wang et al. (2026) [61], showing that as technology, resources, and human capital become more concentrated, the synergistic efficiency among large coastal cities continues to improve. In contrast, a large number of small and medium coastal cities (47.62% of the total coastal cities) have extremely low CEE. These cities are far inferior in green technology, management experience, capital, and talent reserves, making it difficult to cope with the high climate costs. It is precisely the existence of these numerous low-efficiency cities that has lowered the average level of the entire coastal areas. The efficiency differences arising from these relative advantages and disadvantages are consistent with the findings of Jia et al. (2025) [62]. Therefore, the “overall lower” CEE of coastal urban aggregations is essentially a reflection of their unbalanced internal development.

4.2. Exploring the Driving Factors of Efficiency Differences

Significant variations exist in the driving factors across regions. To further characterize the driving factors of the three types of decomposed efficiency, we selected eight indicators from five dimensions: industrial structure, energy structure, technological level, social development, and natural resources as variables for analysis using the multiscale geographically weighted regression model (see Appendices B and C).

Except for energy intensity, the remaining variables have a positive impact on PTE. Factors including industrial structure rationalization, green technology development level, technology investment level, urbanization level and ecological resource level have a significant positive impact. MIX is mainly influenced by green technology development level and clean energy level, while SE shows a significant negative correlation with the industrial structure upgrading and urbanization level. The effect of industrial structure rationalization on PTE shows a pattern of “low in the south, high in the north”, as the higher degree of industrial structure irrationality in northeast areas enables a stronger synergistic effect with technological progress through improved industrial balance compared to the southeastern areas. The negative impact of industrial structure upgrading on SE is particularly significant in northeast areas. The promotion effect of clean energy on MIX is high in the central and east but low in the north and west, a pattern largely attributable to the latter’s heavy reliance on traditional energy. Green technology generally has a positive impact on all efficiencies. Urbanization has a very significant positive effect on the PTE of cities in northern and northeastern China. However, in coastal areas, excessive urbanization leads to increased costs and environmental pressure, which weakens SE [63]. Ecological resources effectively improve PTE in southern coastal areas and northern inland areas through carbon sink effect. This promotion effect is more significant in southern coastal areas, mainly because blue carbon ecosystems have

more advantages than green carbon in terms of carbon sequestration capacity, carbon storage time and carbon storage volume [64].

4.3. Policy Implications

China's emission reduction strategy must proceed from a holistic perspective. By identifying the emission reduction potential of different cities, a collaborative governance system integrating "technology–capital–policy" can be built. Based on efficiency characteristics and regional distribution, cities have different potential for emission reductions, and differentiated emission reduction strategies should be formulated accordingly. Therefore, we applied the k-means clustering method to classify 252 cities into 9 clusters and developed differentiated policy implications based on this classification (Appendix D).

Cities with low emission reduction potential (Clusters 1–3) exhibit pronounced polarization in their internal development levels, and thus require differentiated policy guidance: Cities in Cluster 1 are mainly megacities and super-large cities in both coastal and inland areas, such as Beijing, Shanghai, and Hangzhou. Their efficiencies have reached optimal levels; therefore, they should be encouraged to explore frontier low-carbon technologies, play a leading role and assume international emission reduction responsibilities. Cities in Cluster 2 are all small and medium cities in inland areas, such as Wuhai and Hegang. These cities have weak economic foundations, and economic development should remain their primary policy focus. Cities in Cluster 3 are mainly inland medium and large cities, such as Hefei and Shenyang. Policy for these cities should prioritize improving the rationality of their industrial structure and increasing investment in green technologies, so as to enhance PTE and MIX.

Cities with medium emission reduction potential (Clusters 4–6) mainly include small, medium, and large cities in the eastern coastal and inland areas, and they commonly suffer from low PTE or SE. Cities with medium emission reduction potential (Clusters 4–6) mainly include small, medium, and large cities in the eastern coastal and inland areas, and they commonly suffer from low PTE or SE. Policy should focus on stimulating regional innovation vitality, primarily by promoting the diffusion of advanced technologies to inland areas and accelerating the upgrading of industrial structures and urbanization.

Cities with high emission reduction potential (Clusters 7–9) exhibit low levels of both PTE and MIX and are mainly concentrated in the southern coastal, northern coastal, and northeastern areas. These areas should be the priority targets supported by national emission reduction funding and technology. Policies should focus on the introduction of green technologies and large-scale investment in clean energy infrastructure [65] to improve PTE and MIX at the same time. For cities in the northeastern area (e.g., Benxi and Jilin), carbon emissions can be reduced by leveraging forestry resource endowments. For southern coastal cities (e.g., Jiangmen and Zhanjiang), policies should encourage the utilization of wetland resource advantages to develop blue carbon sink industries and promote nature-based solution (NbS) projects.

5. Conclusions

To systematically evaluate the CEE of 252 prefecture-level cities in China, we built a combined effective frontier DEA model that incorporates climate costs. By accounting for the impacts of climate change on socio-economic systems, this approach extends the CEE evaluation framework. It reveals a new perspective on the comparison of CEE between coastal and inland cities and could provide targeted strategies for sustainable urban development in different cities. Our approach could provide a useful tool for urban low-carbon economic assessment and offers methodological references for similar studies in other cities and regions. The study finds that PTE is the main cause of CEE differences. Inland cities

generally have higher overall CEE due to lighter climate damage, but medium and large cities still face development challenges. Although coastal cities bear higher climate costs and small/medium-sized cities are inefficient, their megacities maintain nationally leading efficiency levels due to technological and managerial advantages, reflecting regional development imbalances.

These findings provide valuable directions for advancing net-zero emissions and sustainable development policies in different cities. China should increase investment in green technologies, supporting the leading role of eastern coastal areas in technologies, while promoting technology diffusion and energy structure adjustment to stimulate regional innovation in inland areas. Furthermore, greater policy guidance should be provided on industrial restructuring of the northeastern areas by promoting the development of clean energy and natural resources. China could also accelerate the establishment of a coordinated emission reduction framework featuring “technology research in the eastern areas, energy transformation in the central and western areas, and industrial transformation in the northeastern areas” to achieve the net-zero goals.

However, the study has certain limitations. Due to data constraints, the sample is limited to 252 cities. Future research could extend the analysis to county-level units and incorporate multi-source data. Furthermore, the impacts of climate change are multidimensional and complex and are not limited to linear damages caused by carbon emissions. Future assessments of climate costs could be extended to biological and ecosystem dimensions and could account for the nonlinear effects. Meanwhile, climate adaptation capacity may vary within the same area. More detailed spatial classifications could be considered in the future.

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Appendix A

Table A1. Results of spatial Markov transition probability matrix for all cities.

Spatial Lag State	State at Time t	State at Time $t + 1$			
		Low	Relatively Low	Relatively High	High
Low	Low	79.70%	17.71%	2.21%	0.37%
	Relatively low	18.38%	60.00%	20.54%	1.08%
	Relatively high	4.46%	18.32%	58.91%	18.32%
	High	1.29%	4.31%	18.10%	76.29%

Table A1. Cont.

Spatial Lag State	State at Time t	State at Time $t + 1$			
		Low	Relatively Low	Relatively High	High
Relatively low	Low	78.17%	19.84%	1.19%	0.79%
	Relatively low	16.08%	60.00%	19.61%	4.31%
	Relatively high	2.24%	17.16%	68.28%	12.31%
	High	0.00%	4.06%	15.74%	80.20%
Relatively high	Low	79.82%	17.04%	3.14%	0.00%
	Relatively low	15.57%	60.66%	21.31%	2.46%
	Relatively high	4.11%	22.83%	58.90%	14.16%
	High	1.00%	2.49%	13.43%	83.08%
High	Low	76.38%	16.58%	4.52%	2.51%
	Relatively low	19.16%	56.70%	22.61%	1.53%
	Relatively high	3.52%	19.53%	59.77%	17.19%
	High	0.32%	3.17%	11.75%	84.76%

Table A2. Results of spatial Markov transition probability matrix for coastal cities.

Spatial Lag State	State at Time t	State at Time $t + 1$			
		Low	Relatively Low	Relatively High	High
Low	Low	84.21%	14.74%	1.05%	0.00%
	Relatively low	13.11%	63.11%	21.31%	2.46%
	Relatively high	4.38%	19.71%	59.12%	16.79%
	High	1.72%	8.62%	13.79%	75.86%
Relatively low	Low	83.46%	15.04%	1.50%	0.00%
	Relatively low	15.53%	54.37%	26.21%	3.88%
	Relatively high	5.10%	21.43%	64.29%	9.18%
	High	0.00%	7.69%	15.38%	76.92%
Relatively high	Low	83.21%	15.33%	0.00%	1.46%
	Relatively low	14.42%	62.50%	22.12%	0.96%
	Relatively high	1.61%	16.13%	65.32%	16.94%
	High	0.94%	4.85%	20.39%	73.82%
High	Low	77.23%	18.67%	2.46%	1.64%
	Relatively low	21.90%	53.25%	22.95%	1.90%
	Relatively high	3.16%	18.99%	57.59%	20.25%
	High	0.33%	1.33%	15.67%	82.67%

Table A3. Results of spatial Markov transition probability matrix for inland cities.

Spatial Lag State	State at Time t	State at Time $t + 1$			
		Low	Relatively Low	Relatively High	High
Low	Low	72.12%	23.08%	3.84%	0.96%
	Relatively low	16.25%	63.75%	17.50%	2.50%
	Relatively high	4.76%	22.22%	60.32%	12.70%
	High	0.70%	3.52%	16.20%	79.58%
Relatively low	Low	77.70%	16.55%	5.04%	0.71%
	Relatively low	22.66%	53.13%	21.09%	3.12%
	Relatively high	1.97%	18.42%	63.16%	16.45%
	High	0.00%	2.75%	13.74%	83.51%
Relatively high	Low	74.42%	19.77%	4.65%	1.16%

Table A3. Cont.

Spatial Lag State	State at Time <i>t</i>	State at Time <i>t</i> + 1			
		Low	Relatively Low	Relatively High	High
Relatively high	Relatively low	18.84%	66.67%	13.04%	1.45%
	Relatively high	3.20%	20.80%	62.40%	13.60%
	High	1.00%	3.01%	10.53%	85.46%
high	Low	77.96%	18.16%	3.10%	0.78%
	Relatively low	15.15%	58.37%	23.45%	3.03%
	Relatively high	5.68%	19.32%	63.64%	11.36%
	High	1.50%	2.00%	12.50%	84.00%

Appendix B

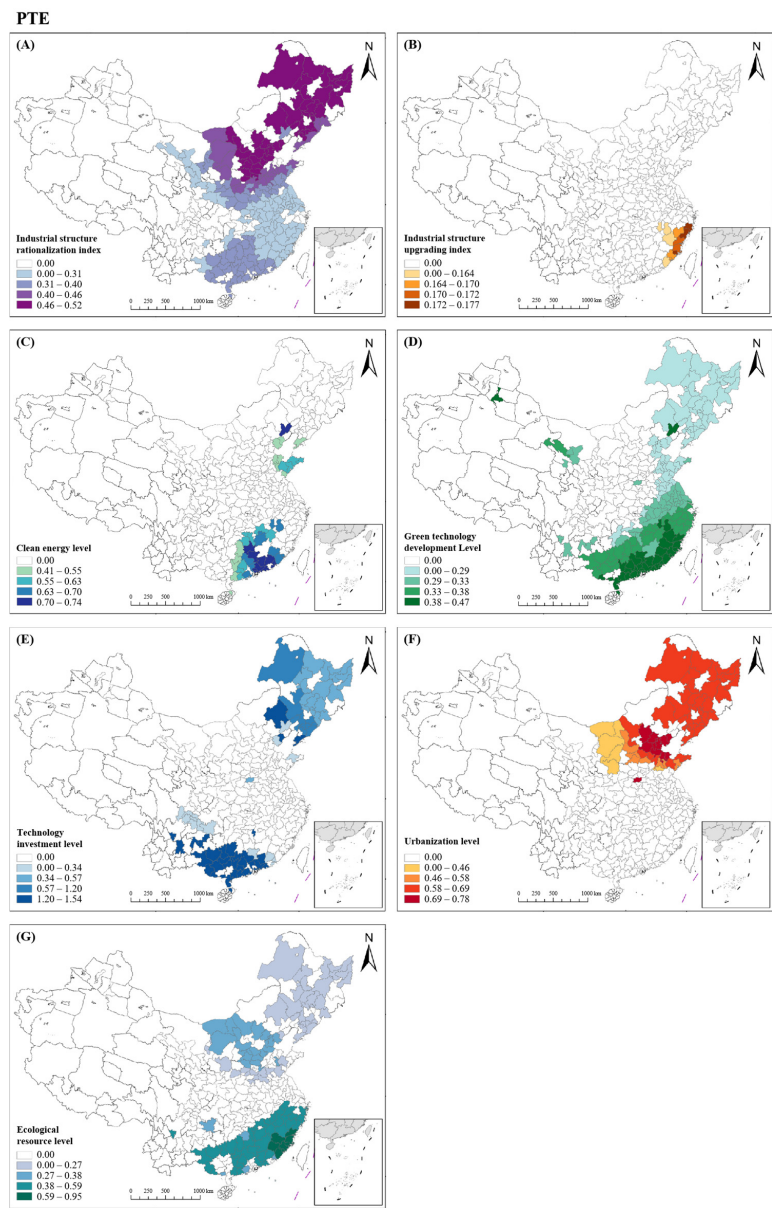


Figure A1. The impact of different factors on pure technical efficiency. (A–G) represent the spatial distribution of the impacts of the industrial structure rationalization, industrial structure upgrading, clean energy, green technology development level, technology investment level, urbanization level, and ecological resource level on PTE, respectively.

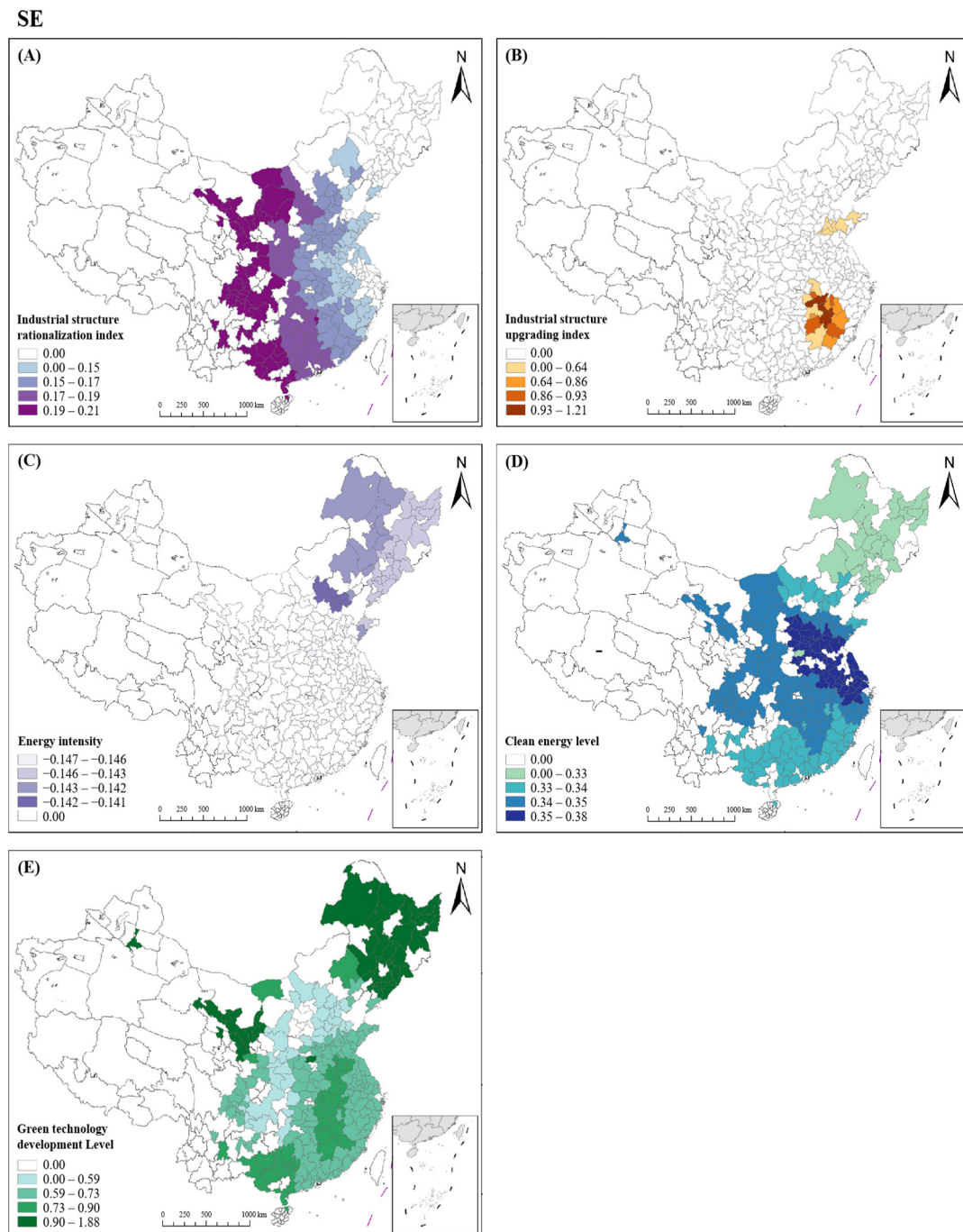


Figure A2. The impact of different factors on scale efficiency. (A–E) represent the spatial distribution of the impacts of the industrial structure rationalization, industrial structure upgrading, energy intensity, clean energy, and green technology development level on SE, respectively.

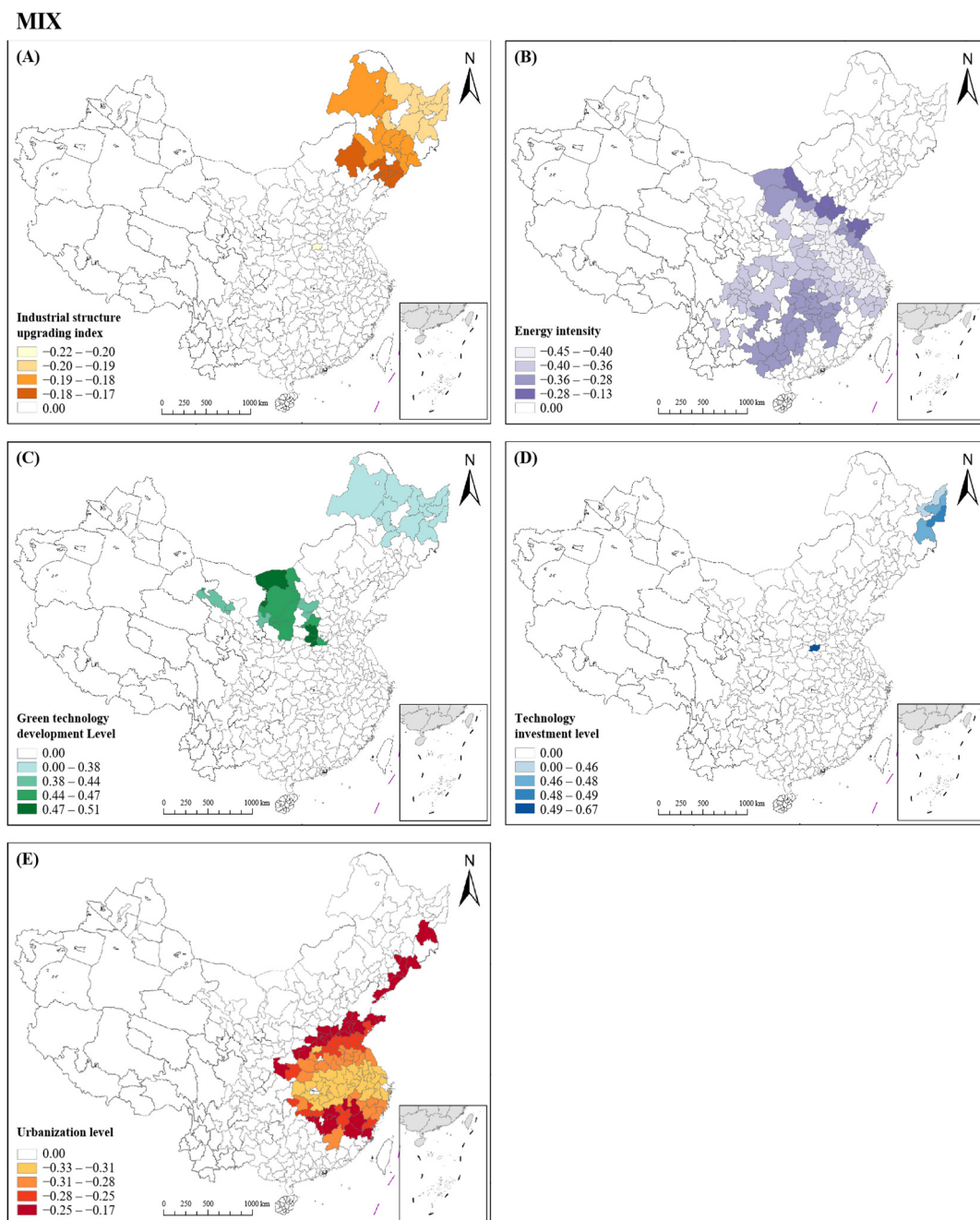


Figure A3. The impact of different factors on mix efficiency. (A–E) represent the spatial distribution of the impacts of the industrial structure upgrading, energy intensity, green technology development level, technology investment level, and urbanization level on MIX, respectively.

Appendix C

Table A4. Correlation results of eight explanatory variables.

Explanatory Variables	Mixed Efficiency		Pure Technical Efficiency		Scale Efficiency	
	<i>p</i>	Correlation	<i>p</i>	Correlation	<i>p</i>	Correlation
Industrial structure rationalization index	0.005	+	0.000	+	0.251	/
Industrial structure upgrading index	0.055	+	0.114	+	0.001	–

Table A4. Cont.

Explanatory Variables	Mixed Efficiency		Pure Technical Efficiency		Scale Efficiency	
	<i>p</i>	Correlation	<i>p</i>	Correlation	<i>p</i>	Correlation
Energy intensity	0.002	—	0.364	/	0.004	—
Clean energy level	0.000	+	0.169	+	0.682	/
Green technology development level	0.000	+	0.000	+	0.083	+
Technology investment level	0.396	/	0.000	+	0.063	+
Urbanization level	0.293	/	0.000	+	0.000	—
Ecological resource level	0.675	/	0.000	+	0.276	/

Note: +, — and / represent positive, negative and no correlation, respectively.

Appendix D

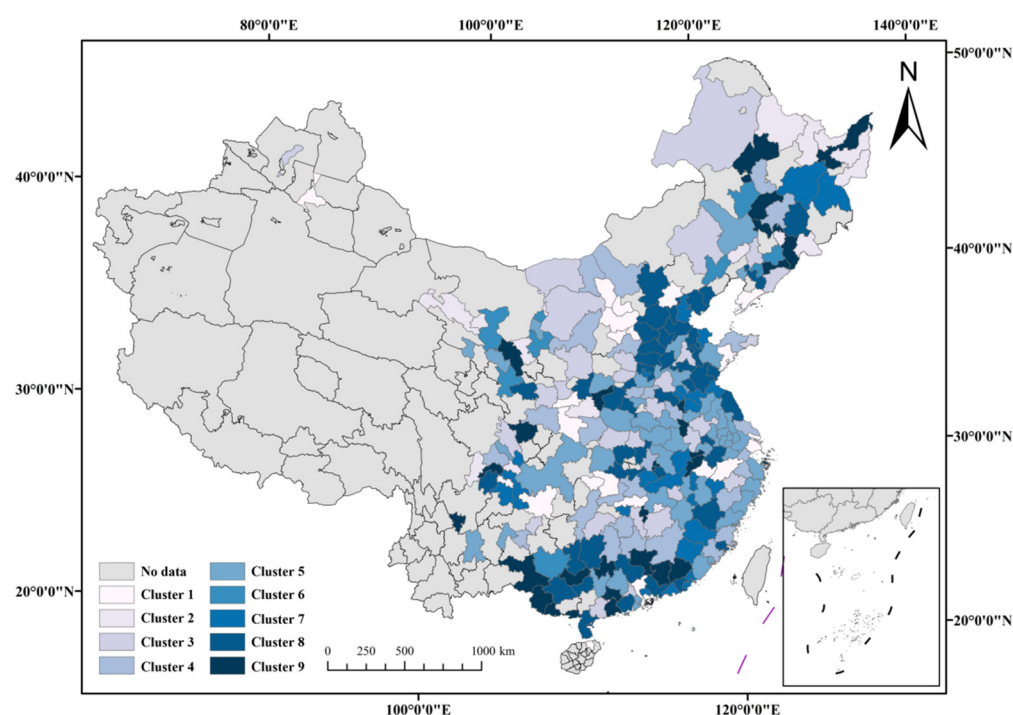


Figure A4. Geographical distribution of clustering results.

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