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Spatially Correlated Network Structure and Influencing Factors of Carbon Emission Efficiency in the Power Industry: Evidence from China

Baojun Sun [1,*], Taiwen Feng [2], Mingjing Du [1], Yuqing Liang [1] and Tianbao Feng [1]

[1] School of Computer Information and Management, Inner Mongolia University of Finance and Economics, Hohhot 010070, China
[2] School of Economics and Management, Harbin Institute of Technology (Weihai), Weihai 264209, China
* Correspondence: sunbaojun@126.com

Abstract: As the largest carbon-emitting industry in China, the power industry has huge potential for carbon emission reductions. It is vital to study the spatial correlation of carbon emission efficiency in the power industry (CEEP) from a system perspective to understand the interaction mechanisms of CEEP in different provinces. This study applies the SBM-undesirable model to measure the CEEP in China, and a modified Gravity model and social network analysis (SNA) method are applied to analyze the interaction mechanism of the CEEP from a system perspective. Finally, the influencing factors of the CEEP's spatial correlation are investigated using the quadratic allocation procedure (QAP) method. The results show that (1) the national CEEP is gradually increasing, while the CEEP gap between provinces is widening; (2) the overall network size shows an increasing trend, but the hierarchical structure is somewhat fixed; (3) the central province of a network has a high degree of consistency with the geographically central province, but the spatial spillover effect of the central node provinces on the peripheral provinces is not sufficient; and (4) differences in geographic proximity, energy intensity, and technical level of power generation significantly affect the formation of spatially correlated networks in the CEEP.

Keywords: electric power industry; carbon emission efficiency; spatial correlation; influencing factors; SBM-undesirable model; social network analysis approach

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1. Introduction

As the world's largest consumer of energy and emitter of greenhouse gases, China is committed to achieving carbon neutrality by 2060. Consequently, China is under tremendous pressure to reduce carbon emissions [1–3]. Carbon emission efficiency not only reflects the amount of carbon emissions produced, but also effectively evaluates the quality of regional economic growth, energy efficiency and the degree of technological innovation. Carbon emission efficiency is the focus of much current research on carbon emission-related issues due to its comprehensiveness in assessing carbon emissions [4]. The core objective of carbon emission efficiency is to minimize carbon emissions and other resource inputs while ensuring economic development [5]. Therefore, improving carbon emission efficiency can effectively balance economic development and environmental pollution, significantly increasing the potential for regional carbon emission reduction [6].

China's power industry is a key target for carbon reductions, with carbon emissions produced by this industry exceeding 40% of China's total [7]. Due to the imbalance in the spatial distribution of China's electric power resources and the distribution of load

centers, carbon emissions in the power industry show obvious regional heterogeneity, with complex spatial correlation effects [8]. In addition, with the continuous development of transportation and power networks in China, the frequency of power transactions across regions has increased. Since carbon emissions have significant spatial spillovers, the inter-regional network of carbon emissions produced by the power sector has become more complex [9].

Past research on carbon emission efficiency in the power industry (CEEP) has generally only measured CEEP, and it has not studied CEEP in terms of regional positioning, factor circulation and network transmission mechanisms, even though the spatial spillover of carbon emissions and the complexity of the electricity network have led to varied inter-regional electricity–carbon emission efficiency linkages. To effectively promote synergistic cross-regional emission reductions, it is necessary to study the transmission relationship and influencing factors affecting CEEP from a spatial network perspective.

Against this background, this study analyzes the characteristics of network dynamics in terms of CEEP in thirty provincial and administrative regions in China (due to the availability of data, the regions studied in this paper do not include Tibet, Hong Kong, Macao and Taiwan), analyzing the macro- and micro-characteristics of the networks, as well as the influencing factors, to elucidate the constructive complexity of the CEEP network. The unique contribution of this paper compared to previous studies is threefold: Firstly, by adopting the improved SBM-undesirable model to assess the CEEP, the model is adapted for the calculation of the CEEP, and the accuracy of the assessment is improved. Second, to address the specific nature of the spatial network of the CEEP, this study adapts the modified Gravity model to take into account the heterogeneity of electric power consumption and carbon emission efficiency among regions, making the results of the study closer to the characteristics of the power industry. Finally, the modified Gravity model is applied to calculate the spatial correlation matrix of the CEEP, and the spatial correlation network of the CEEP is mapped via social network analysis (SNA).

The rest of this paper is organized as follows: Section 2 summarizes existing studies of carbon emission efficiency. Section 3 introduces the modified Gravity model, SBM-undesirable model, SNA model and QAP analysis. Section 4 calculates the CEEP, analyzes its spatial correlation and discusses its driving factors. Section 5 puts forward conclusions and policy implications.

2. Literature Review and Hypothesis Development

2.1. Carbon Emission Efficiency

Previous studies mainly measured the carbon emission efficiency through single or multiple elements. In terms of single-factor studies, Sun et al. [10] examined the regional differences in and spatio-temporal characteristics of the carbon intensity of electricity in China. Chen et al. [11] analyzed the impact of renewable energy penetration on reducing regional energy intensity. However, the single-factor measurement method cannot provide a comprehensive measurement of carbon emission efficiency. The multi-factor measurement method, widely used in the measurement of carbon emission efficiency, can more comprehensively assess the complex relationship between production factors and, thus, more accurately measure the carbon emission efficiency [12–14].

Multi-factor measurement methods include the stochastic frontier approach (SFA) and data envelopment approach (DEA), and related studies are shown in Table 1.

Table 1. Multi-factor measurement studies of carbon emission efficiency.

Reference	Methods of Measurement	Influencing Factors	Conclusions
[15]	DEA and SFA	Concentrated PM10, average temperature, average concentrated NO_2, number of days that Ozone Concentration exceeds 120 $\mu g/m^3$ and rainfall.	PM10, the average temperature, the average of NO_2 concentration and rainfall had a significant effect on eco-efficiency.
[16]	DEA and SFA	Gini coefficient, GDP growth, Energy use, Infant mortality, etc.	Results generated from the proposed models interact differently with the socio-economic and business-related variables.
[17]	SFA	Installed capacity, utilized hours, auxiliary power consumption, etc.	The installed capacity, utilized hours, and auxiliary power consumption have positive impacts on the three renewable energy sources.
[18]	DEA	Annual operating rate, capacity utilization ratio, quality of coal and the amount of coal consumption, installed capacity and regional productivity differences	China's coal-fired power plants have huge potential to reduce carbon emissions, annual operation rate and capacity utilization ratio have a significant impact on the technical efficiency of coal-fired power plants.
[19]	DEA	Thermal coal price, age of power units and feed-in tariffs.	Power plants with large installed capacity tend to operate in a stable manner. Higher power coal prices contribute to eco-efficiency, while high power plant ages and feed-in tariffs impair production performance.
[20]	SBM-DEA	The innovation capability, the electricity generation capacity of a province, the investment in the treatment of industrial pollution, etc.	The ability of firms to innovate, the share of electricity generated by coal-fired power plants and the capacity to generate electricity significantly increase environmental efficiency. Waste charges on waste emissions and investment in industrial pollutant treatment reduce environmental efficiency.
[21]	Three-stage DEA with game-crossover methods	Urbanization rate, industrialization rate, energy structure, environmental protection expenditure, upgrading of industrial structure and government intervention	Reducing coal consumption in the central and southwestern regions may help increase carbon emission reduction efficiencies. increasing environmental spending could boost carbon emission reduction efficiencies in the southwest. upgrading industrial structure and government intervention have a positive impact on carbon emission reduction efficiencies in the northwest.

Table 1. *Cont.*

Reference	Methods of Measurement	Influencing Factors	Conclusions
[22]	Meta-frontier DEA	Pure technological change, renewable energy power and CO_2 reduction efficiency, pure technological change and changes in technological efficiency, etc.	Pure technological change is the main factor influencing nuclear power, renewable energy power and CO_2 reduction efficiency, pure technological change and changes in technological efficiency are major contributors to CO_2 reduction efficiency.
[23]	Super SBM-GML	Low-carbon technological progress, energy efficiency, foreign investment and R&D intensity	Low-carbon technological advances, foreign investment and R&D intensity significantly increase carbon total factor productivity in the thermal power sector.

From previous studies, it is known that thermal power generates large amounts of carbon emissions through power generation, and the increase in the proportion of thermal power inhibits the enhancement of the CEEP. In addition, secondary industry, which is mostly composed of heavy industries, consumes large amounts of electricity resources, which in turn generate large amounts of carbon emissions. Due to economic development and technological progress, the proportion of clean energy in the power generation system is gradually increasing, and low-carbon technologies are maturing, further enhancing the CEEP. Therefore, we hypothesize the following:

H1: *Thermal power's share of produced energy (a) has a negative impact on the formation of a CEEP network and industrial structure upgrading (b), while economic development (c) and technological progress (d) have positive impacts on the enhancement of CEEP network formation.*

In terms of carbon emission efficiency measurements, compared with the SFA, the DEA relies less on subjective settings and is more suitable for assessing the efficacy of some inputs within the framework of a multi-input and multi-output production function, and it has, thus, become the dominant methodology for measuring carbon efficiency [24,25].

In recent years, as environmental problems have become more prominent and the cost of pollution control for enterprises has gradually increased, measured carbon emission efficiencies have been very different from reality, as undesired outputs, such as environmental pollutants, have not been taken into account. To calculate the carbon emission efficiency more accurately, many studies have included pollutant emissions as undesired outputs in the measurement [26–28]. However, the results of these studies vary due to their different inputs and outputs.

2.2. Spatial Correlation of Carbon Emission Efficiency

In previous studies, scholars have generally studied the spatial correlation between countries, provinces and cities as spatial elements for determining the efficiency of carbon emissions. The objects of study for determining the spatial correlation of carbon emission efficiency are shown in Table 2.

Table 2. Carbon emission efficiency spatial correlation research objects.

Research Area	Research Object	Reference
Nation	15 RCEP countries	[29]
	95 countries	[30]
	Poland	[31]
Province	Thermal power industry	[32,33]
	transportation sector	[34]
	logistics sector	[35,36]
	marine fisheries	[37]
	agriculture	[38]
	manufacturing industry	[39]
Urban agglomeration	Beijing-Tianjin-Hebei	[40]
	Yangtze River Basin	[41]
	Yellow River Basin	[42]
	Pearl River Basin	[43]
City	278 cities in China	[44]
	262 cities in China	[45]
	New energy demonstration cities	[46]
	Low-carbon pilot cities	[47]

We found that no matter what kind of location–division perspective is used to study carbon emission efficiency, it has a general spatial distribution pattern and interaction. With the deepening and refinement of research, the level of location division has gradually transitioned from countries and provinces to cities; however, based on the availability of industry data and the reasonableness of the calculation results, some research on the carbon emission efficiency of some industries remains at the provincial level. Therefore, we hypothesize the following:

H2: *Spatial relationships (a) have implications for the formation of CEEP networks.*

2.3. Spatially Correlated Influencing Factors Affecting Carbon Emission Efficiency

Among the many influencing factors, on the one hand, scholars often choose a single factor that has a greater impact on carbon emission efficiency for research; on the other hand, scholars sometimes choose a variety of factors for more comprehensive research. In single-influencing-factor studies, scholars have examined the relationships between financial development [48], labor transfer [49], cost structure [26], green finance [50,51], income inequality [52] and carbon emission efficiency, respectively. Li et al. [53] and Fang et al. [54] analyzed the reasons for the differences in national- and city-level carbon emission efficiency, respectively, in studies on multiple influencing factors, while Liu and Gong [55] applied a comprehensive analytical methodology to analyze the formation mechanism of provincial carbon emission efficiency networks.

In the power industry, fossil energy consumption in power generation is the main cause of carbon emissions, so energy intensity (fossil energy consumption per unit of power generation) is an important indicator affecting the CEEP. In addition, an increase in demand for electricity leads to an increase in power generation, which in turn increases carbon emissions. Therefore, we hypothesize the following:

H3: *Energy intensity (a) and electricity consumption (b) have negative impacts on the formation of CEEP networks.*

To summarize, scholars have previously conducted in-depth discussions on carbon emission efficiency, and the distribution patterns of the CEEP have been adequately studied, but there has not been any research on the locational qualities, transmission relationship and role positioning of the CEEP from the perspective of an inter-regional spatial correlation network; therefore, past research cannot provide strong support for the efficiency improvement of the overall spatial network. Based on this, to provide a comprehensive depiction of the spatial relationship of the CEEP, this paper, based on the reasonable measurement of the CEEP in 30 regions in China, combines the modified Gravity model and social network analysis (SNA) with the characteristics of the power industry, creates the network of the CEEP, and calculates the overall, individual and clustering characteristics of the network. In addition, to further promote regional synergistic emission reduction, this paper comprehensively analyzes the factors affecting the CEEP network.

3. Methodology and Data

The research framework of this paper is shown in Figure 1.

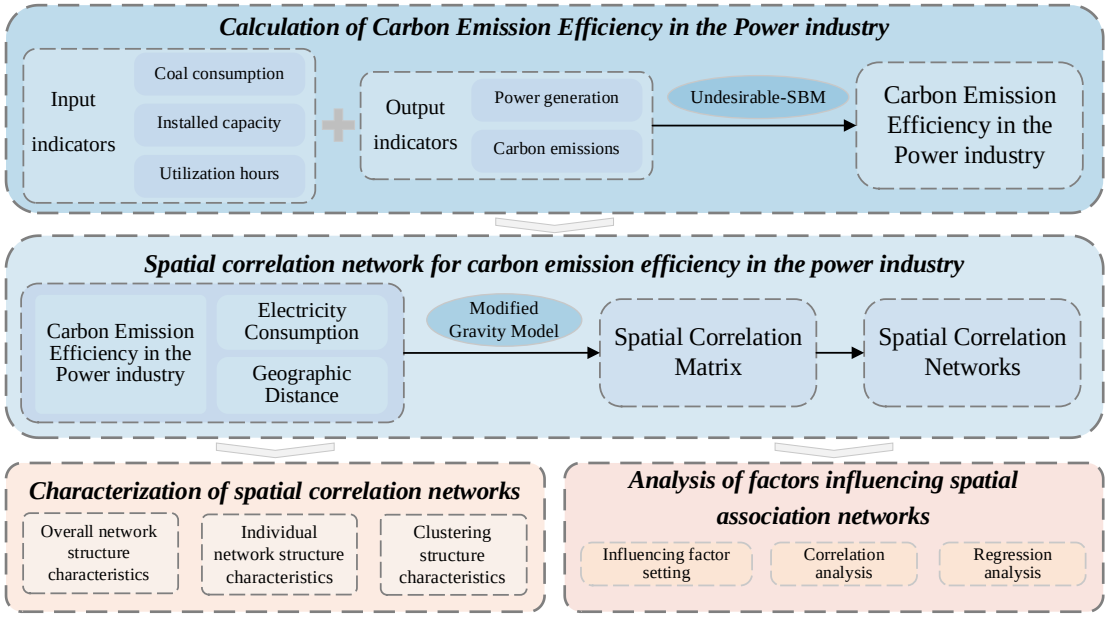


Figure 1. Research framework.

3.1. Data Sources

In this paper, data on coal consumption for power generation, installed power generation capacity, the average utilization hours of power generation equipment, and total power generation and electricity consumption of power plants of 6000 kW and above in each province were sourced from the China Electric Power Statistical Yearbook. Fossil energy consumption data were sourced from the China Energy Statistics Yearbook, and data for the total GDP of each region were sourced from the China Statistical Yearbook. The total annual fossil energy consumption of thermal power generation in each region was expressed in millions of tons of standard coal, and the corresponding conversion coefficients from physical quantity to standard quantity were sourced from the China Energy Statistical Yearbook 2013.

3.2. Calculation of Carbon Emission Efficiency in the Power Industry

3.2.1. Calculation of Carbon Emissions in the Power Industry

In this paper, the IPCC calculation was used to calculate carbon emissions in the power sector with the following formula:

$$C^i = \sum_{m=1} E_m^i \times NCV_m^i \times CEF_m^i \times COF_m^i \times \left(\frac{44}{12}\right), \tag{1}$$

3.2.2. SBM-Undesirable Model

Traditional DEA models are radial-efficiency measures; their disadvantages include overestimating efficiency values and providing only one efficiency value, which need to be corrected for the inclusion of undesired outputs. Therefore, Tone [56] proposed the non-radial efficiency model SBM (Tone, 2001) in 2001 to overcome the shortcomings of the traditional DEA model and further incorporated non-expected outputs into the SBM model. The SBM-undesirable model corrects the calculation bias of the traditional DEA model caused by radial defects by introducing the non-expected output indicators; therefore, it can measure the efficiency value more accurately [57].

Suppose the number of decision making units (DMUs) is n, and each DMU has m inputs x, S_1 desired outputs y^g, and S_2 undesired outputs y^b. The vector is denoted as $x \in R^m$, $y^g \in R^{s_1}$, $y^b \in R^{s_2}$. The formula for the SBM-undesirable model is as follows.

$$\rho^* = \min \frac{1 - \frac{1}{a}\sum_{i=1}^{a} \frac{b_i^-}{X_{i0}}}{1 + \frac{1}{b_1+b_2}\left(\sum_{r=1}^{b_1} \frac{b_r^g}{y_{r0}^g} + \sum_{r=1}^{b_2} \frac{b_r^b}{y_{r0}^b}\right)}$$
$$s.t. \begin{cases} x_0 = X\lambda + b^- \\ y_0^g = Y^g\lambda - b^g \\ y_0^b = Y^b\lambda + b^b \\ b^- \geq 0, b^g \geq 0, b^b \geq 0, \lambda \geq 0 \end{cases} \tag{2}$$

In the above equation, S^-, S^g, S^b are the slack variables of input variables, desired outputs and undesired outputs, respectively, and the objective function $\rho^*(0 \leq \rho^* \leq 1)$ is strictly decreasing concerning S^-, S^g and S^b, and the DMU is valid when $S^- = S^g = S^b = 0$, that is, $\rho^* = 1$; the DMU is invalid when one of S^-, S^g, and S^b is not equal to zero, that is, $0 \leq \rho^* < 1$.

Considering the comprehensiveness and rationality of this assessment system, this study selected indicators in line with the inputs and outputs of the electric power system according to its characteristics. The indicators are shown in Table 3.

Table 3. Selection of input-output indicators.

Indicators	Primary Indicators	Secondary Indicators	Unit
Input indicators	Energy input	Coal consumption for power generation in power plants of 6000 kW and above	10^4 tons of standard coal
	Installation input	Total installed capacity	10^4 kW
	Time input	Average utilization hours of power generation facilities	Hours
Output indicators	Expected output	Power generation	Billion kWh
	Undesirable outputs	Carbon emissions	Million tons

The reasons for selecting these indicators are set out below:

Coal consumption for power generation in power plants of 6000 kW and above: The operation data of large power plants represent the overall situation of regional power generation, and these data are relatively standardized and complete. The installed capacity and power generation of power plants of 6000 kW and above generally account for more than 90% of the total in a province (as shown in Appendix A). Coal is also the primary source of thermal power; thus, coal consumption-related power generation in power plants of 6000 kW and above was chosen as the energy input for CEEP measurement.

Total installed capacity: Total installed capacity encompasses all types of power generation and is indicative of a region's generating capacity, and in this study, it served as a standardized unit of measure for comparisons between regions.

Average utilization hours of power generation facilities: The average utilization hours reflect the actual utilization efficiency of power plant equipment, which is very important for measuring the CEEP.

Desired output is set as power generation: Electricity generation is the main output of the regional power industry, reflecting the overall power production capacity of the region. Setting generation as the desired output is a comprehensive and effective measure of the CEEP. The undesired output is often set as carbon emissions. Reducing carbon emissions is the main environmental goal of the power industry, and carbon emissions are also an important reference for measuring the energy transition process of the power industry, so carbon emissions were set as the non-desired output for measuring the CEEP in this study.

3.3. Modified Gravity Model

Gravity modeling depicts the spatial interaction of elements. The model not only assesses the overall degree of spatial connectedness within a region, but also reveals the specific spatial pathways of influence between members in the region [58], providing a more accurate measure of the spatial correlation of the CEEP. However, the classical Gravity model does not adequately consider the inter-relationships between the CEEP and the two-way interactions and asymmetries of electricity consumption within regions. Therefore, this study referred to Zhang et al.'s research [41] and improved the traditional Gravity model by replacing economic indicators with electricity indicators, as shown in the following equations:

$$y_{i,j}^{*} = k_{i,j}\frac{E_i \times E_j}{{D_{i,j}}^2} \tag{3}$$

$$k_{i,j} = \frac{C_i}{C_i + C_j} \tag{4}$$

The spatial correlation matrix was calculated, and then the matrix was binarized to result in a 0–1 asymmetric matrix for the spatial correlation of the CEEP.

3.4. SNA

SNA measures the spatial network relationships of elements. By converting the spatial association matrix into a spatial association network, it clarified the locational qualities, conductive relationships and role positioning of provinces in the CEEP network.

Firstly, the overall structural characteristics of the network had to be measured. The formulas are shown in Equations (5)–(8):

$$N_C = 1 - \frac{V}{x(x-1)/2} \tag{5}$$

$$N_D = \frac{y}{x(x-1)} \tag{6}$$

$$N_H = 1 - \frac{S}{R+S} \tag{7}$$

$$N_E = 1 - \frac{y-(x-1)}{x(x-1)/2-(x-1)} \tag{8}$$

Second, to analyze the positioning and role of each province in the network, we characterized the nodes in the network. The formulas are shown in Equations (9)–(11):

$$C_D(i) = \frac{I(i)}{x-1} \tag{9}$$

$$C_C(i) = \frac{\sum_{j=1}^{x} s_{ij}}{x-1} \tag{10}$$

$$C_B(i) = \frac{2\sum_{j<k} r_{jk}(i)/r_{jk}}{(x-1)(x-2)} \tag{11}$$

Finally, to explore the distribution of clusters formed by provinces in the network, the CONCOR method was used to analyze the clustering of the CEEP network, which was divided into different segments according to the characteristics of each cluster. Using this method, provinces with the same correlation coefficients in the CEEP network were classified into the same plate, and the transfer relationship between the plates was analyzed via clustering.

3.5. QAP Analysis

The QAP tests matrices by analyzing the similarity between them [59]. Compared with other nonparametric tests, QAP models do not require independence between variables, and therefore QAP analysis has been widely used in past studies of factors influencing spatial associations. Based on relevant studies [10] and the characteristics of the electric power industry, the influencing factors of the CEEP network were set as follows:

$$T = f(G_P, E_D, I_S, T_E, P_S, E_I, P_R) \tag{12}$$

This study set the average value of the indicator data from 2015 to 2021, established the difference matrix through the average value, standardized the difference matrix, and compared the CEEP matrix with the difference matrixes of influence factors to analyze the influence factors.

4. Results and Discussion

4.1. The CEEP

We calculated the CEEP in 30 Chinese provinces from 2015 to 2021, and the results of the calculations are shown in Table A3. The average result across seven years was calculated for the distribution of the combined CEEP across the country, as shown in Figure 2.

As can be seen from Figure 2, there is significant spatial heterogeneity in the CEEP, and there are six provinces with an average CEEP value exceeding 0.737, namely Inner Mongolia, Shandong, Jiangsu, Sichuan, Yunnan and Guangdong. The average value of the CEEP in Shandong, Jiangsu and Sichuan exceeds 0.9, and the average value in Sichuan is the highest at 0.952. This is because these six provinces are actively developing renewable energy generation facilities, with Inner Mongolia having the largest installed capacity of wind power in the country, Shandong having the largest installed capacity of solar power, Sichuan having the largest installed capacity of hydropower, and Guangdong having the highest installed capacity of nuclear power. The proportion of renewable energy generation

relative to total generation in each province is shown in Table A4. The adjustment of the power structure has reduced the CEEP in these provinces, while total power generation has increased, resulting in higher carbon emission efficiency in electricity.

There are eight provinces with an average CEEP value below 0.384, namely Beijing, Tianjin, Jilin, Heilongjiang, Shanghai, Hainan, Chongqing and Qinghai; the average CEEP in Hainan is the lowest at only 0.332. This is because of the lower power generation capacity of these regions. Due to the economic positioning and resource endowment of Beijing, Tianjin, Shanghai and Chongqing, a large proportion of the power supply comes from outside these provinces, while Jilin, Heilongjiang, Hainan and Qinghai also generate less power due to their relatively low economic development and low power demand. Overall, provinces with larger generation capacity and a higher share of clean energy have higher average CEEP values, and provinces with less generation capacity and a lower proportion of clean energy relative to total energy have lower average CEEP values.

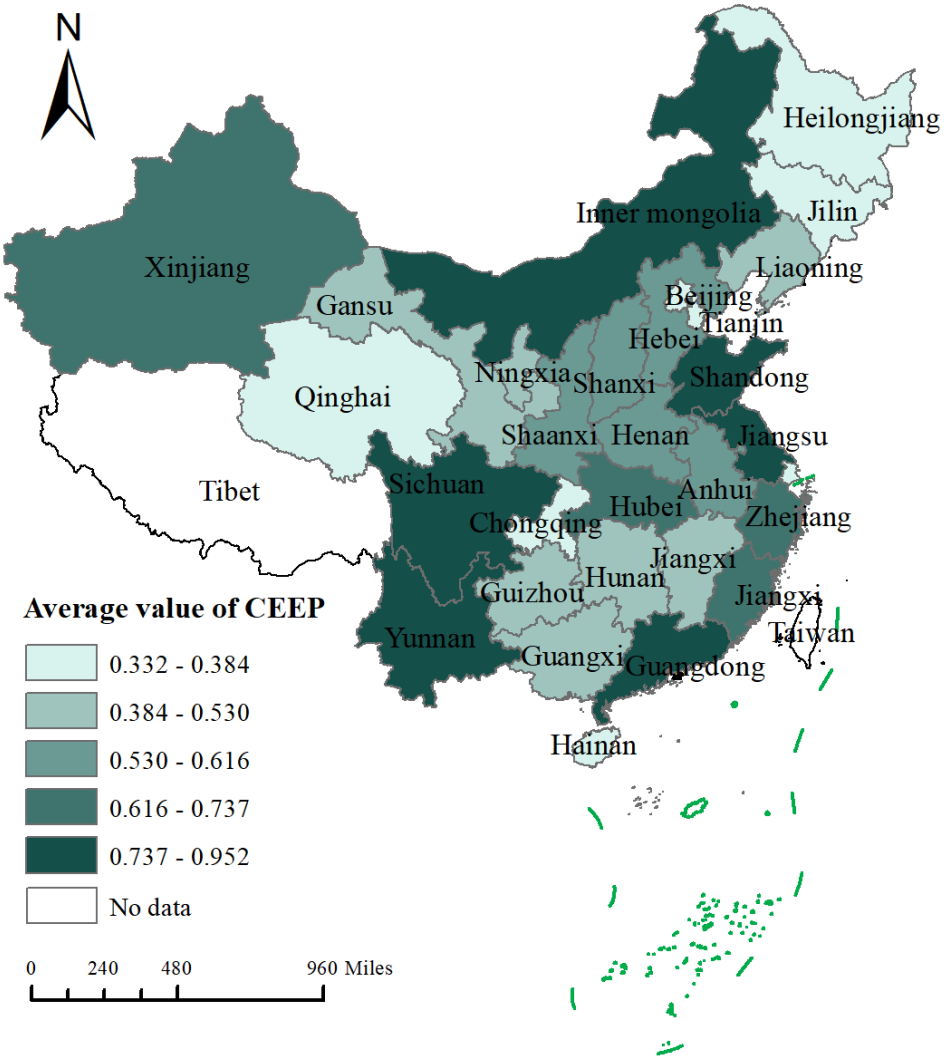


Figure 2. The average value of CEEP distribution.

The trends of CEEP changes at the national and provincial levels from 2015 to 2021 are shown in Figure 3.

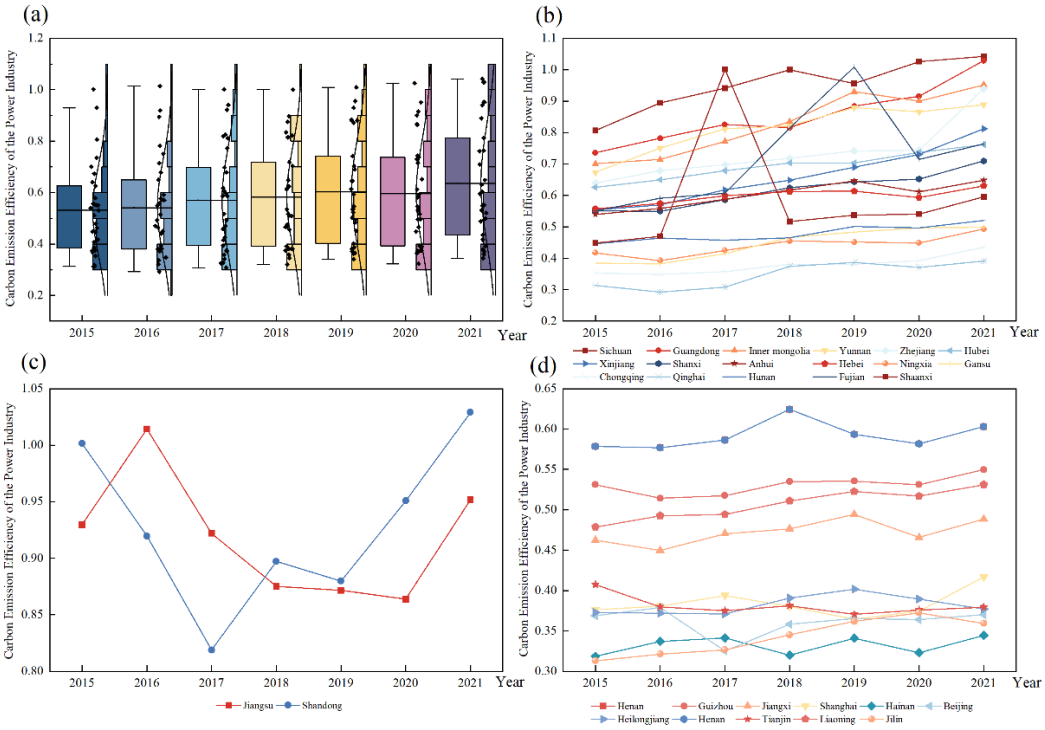


Figure 3. Trends in China's provincial CEEP.

As can be seen in Figure 3a, the CEEP has significant spatial heterogeneity and clustering characteristics. The average CEEP of China's provinces gradually increased from 2015 to 2021, rising from 0.53 to 0.64, with an increase of 19.6%. The length of the boxes in the box line diagram gradually becomes longer, which means that the differences in provincial CEEP become larger, and the provincial CEEP shifts from a centralized distribution pattern to a decentralized pattern due to the different resource endowment levels of provinces and the different degrees of regional clean energy development.

These 30 Chinese provinces are categorized into three groups based on the trend of the CEEP from 2015 to 2021: (1) an increasing trend, (2) a decreasing and then increasing trend, and (3) insignificant changes in efficiency, as shown in Figure 3b–d. (1) There are 17 provinces with an increasing CEEP trend, among which Zhejiang, Guangdong, Xinjiang, Inner Mongolia, Sichuan and Yunnan experienced increases of more than 0.2. This is because these provinces have adjusted their regional energy structures according to regional resource endowment and increased the proportion of clean energy generation. For example, coastal provinces such as Zhejiang and Guangdong have actively promoted the construction of nuclear power plants, and provinces such as Xinjiang and Inner Mongolia have developed wind and photovoltaic power plants. Sichuan, Yunnan and other provinces that are rich in water resources have actively promoted the construction of hydropower facilities, so their regional CEEPs have been significantly improved. (2) CEEP decreased and then increased in Jiangsu and Shandong provinces, which have a greater impact on the overall CEEP of China, as they are provinces with large economies and power generation capacities. Before 2020, the CEEPs of these two provinces fluctuated a lot, and after 2020, the CEEPs of the two provinces gradually increased. These two provinces should actively develop clean energy according to their regional resource endowment to increase the proportion of clean energy in the energy structure. (3) There are 11 provinces with insignificant changes in efficiency, among which Beijing, Tianjin and Shanghai belong to the typical receiving-end city grids, mainly relying on transmission from other provinces due to the scarcity of regional resources. Other provinces have poor regional renewable

energy resources, resulting in slower clean energy development and insignificant regional CEEP changes.

4.2. Spatial Correlation Network of the CEEP

The spatial correlation network based on the spatial correlation matrix for 2015 and 2021 is shown in Figure 4, in which the graphic color reflects the betweenness centrality of the provinces, which indicates the degree of correlation between each province's CEEP and those of other provinces.

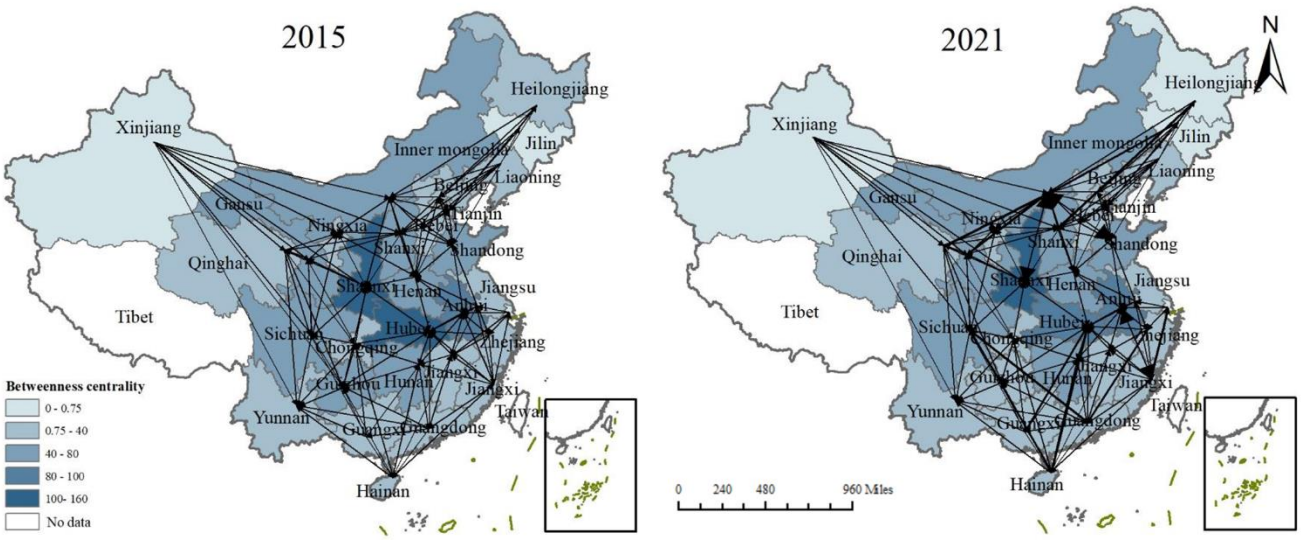


Figure 4. CEEP space-related network diagram.

As shown in Figure 4, the spatial correlations exhibit a typical network structure. In terms of network size, the overall size of the CEEP spatial correlation network in the 30 provinces shows an increasing trend, with the number of correlations increasing from 203 in 2015 to 210 in 2021, and CEEP connections between provinces have become closer.

In terms of network structure, the provinces with the highest overall network betweenness centrality in both 2015 and 2021 are Shaanxi, Hubei and Anhui. The betweenness centrality of Shaanxi decreased from 159 to 125 and that of Hubei decreased from 100 to 95, indicating that the radiation effects of Shaanxi and Hubei on other provinces gradually decreased. However, the betweenness centrality of Anhui increased from 80 to 95, and the radiation effect on other provinces gradually became more significant. The central provinces have more radiant ability in the network and should receive more attention in the overall network. We found that the core of the CEEP network usually covered the provinces in the geographic center of China. Electricity resources in northern and western China need to be transported to the eastern part of the country through the electricity network, reinforcing the relationship between electricity production and consumption between provinces. Provinces at the geographic center play a bridging role in the network and are critical to the effective flow of the CEEP.

4.3. Overall Network Structure Characteristics of the CEEP

The overall network characteristics of the CEEP spatial correlation network are shown in Figure 5, where the network correlation is always 1, indicating that the other provinces are not easily affected by the core provinces; the correlation between provinces is also stronger, so the network correlation is not shown in the figure.

The number of CEEP network connections and the network density in the 30 provinces show an overall increasing trend, indicating that CEEP network connections are more com-

plex. However, the network density was only 0.2414 in 2021, which indicates that although the correlation relationship of the inter-provincial CEEP became closer, there remains much room for improvement. There is still a need to strengthen regional cooperation between provinces and regions, make use of the spatial spillover effect of CEEP and the correlation network, strengthen the spatial optimization of the allocation of electricity resources between provinces and regions, and increase the number of inter-provincial electricity transactions, enabling the rational application of electricity resources.

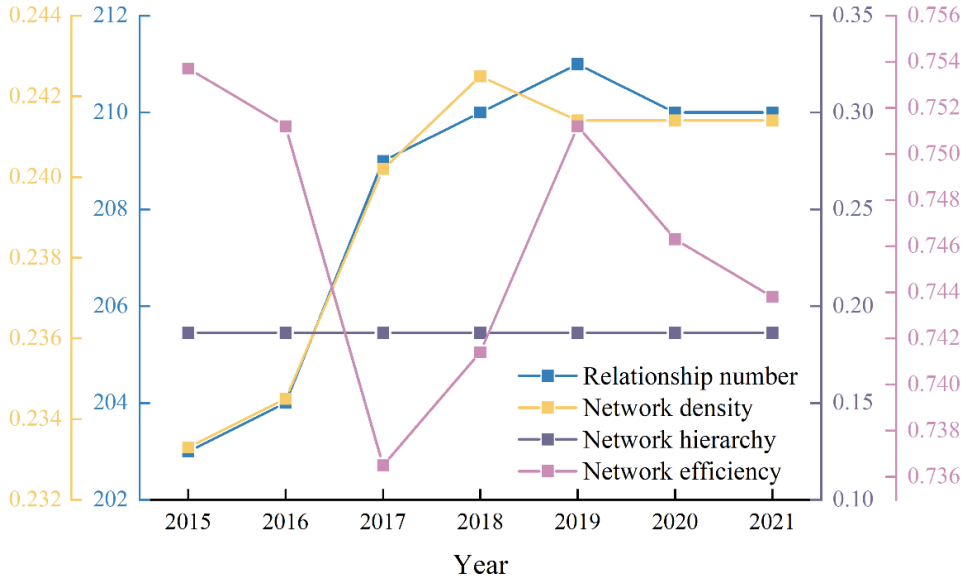


Figure 5. Characteristics of the overall network structure for CEEP spatial correlation.

Network hierarchy refers to the regional characteristics of individual node behavior in the network and the important relationship between groups. It reflects the connection mode and relationship strength between different nodes in the network, as well as how these nodes are organized into different levels or subgroups. The CEEP network hierarchy was maintained at 0.1862. This shows that the overall network was hierarchical from 2015 to 2021, but the relationship gradient was insignificant. The location and role of the core node provinces in the low-carbon transition of electricity between the 30 Chinese provinces were not significant, the spatial spillover effect of the core node provinces on the peripheral provinces was not sufficient, and the provincial CEEP network hierarchy needed to be further optimized.

The overall efficiency of the CEEP network shows a decreasing trend, indicating that the number of connections between provinces in the network increased, the network transmission efficiency became higher, and the flow of CEEP became more rapid and efficient.

4.4. Individual Network Structure Characteristics of CEEP

The individual network characteristics of the CEEP network are shown in Figure 6.

The individual network characteristics in 2015 and 2021 were compared, as shown in Figure 6a.

In terms of degree centrality, there was a significant increase in provinces of Shanxi, Zhejiang, Hubei, Guangdong, Guangxi, Hainan, Sichuan, Qinghai and especially Inner Mongolia, which had the largest increase. This shows that the spatial spillover effects of these provinces became more pronounced and their role in the network became more important. Degree centrality became significantly lower in Beijing, Jiangxi, Henan, Guizhou, Ningxia and Xinjiang, indicating that these provinces have a progressively lower impact on the CEEP in other provinces.

In terms of closeness centrality, except for Beijing and Xinjiang, where closeness centrality decreased, closeness centrality showed an increasing trend in most provinces. This indicates that the number of direct links between most provinces in the network became larger and the CEEP spread through the network more rapidly.

The betweenness centrality in Inner Mongolia, Anhui, Shandong and Sichuan increased from 2015 to 2021, indicating that these provinces played a more significant, central role in the network. However, the betweenness centrality of Beijing, Shanxi, Henan, Guizhou and Shaanxi became gradually lower, which meant that these provinces were becoming weaker bridges in the network and struggled to control and influence other regions.

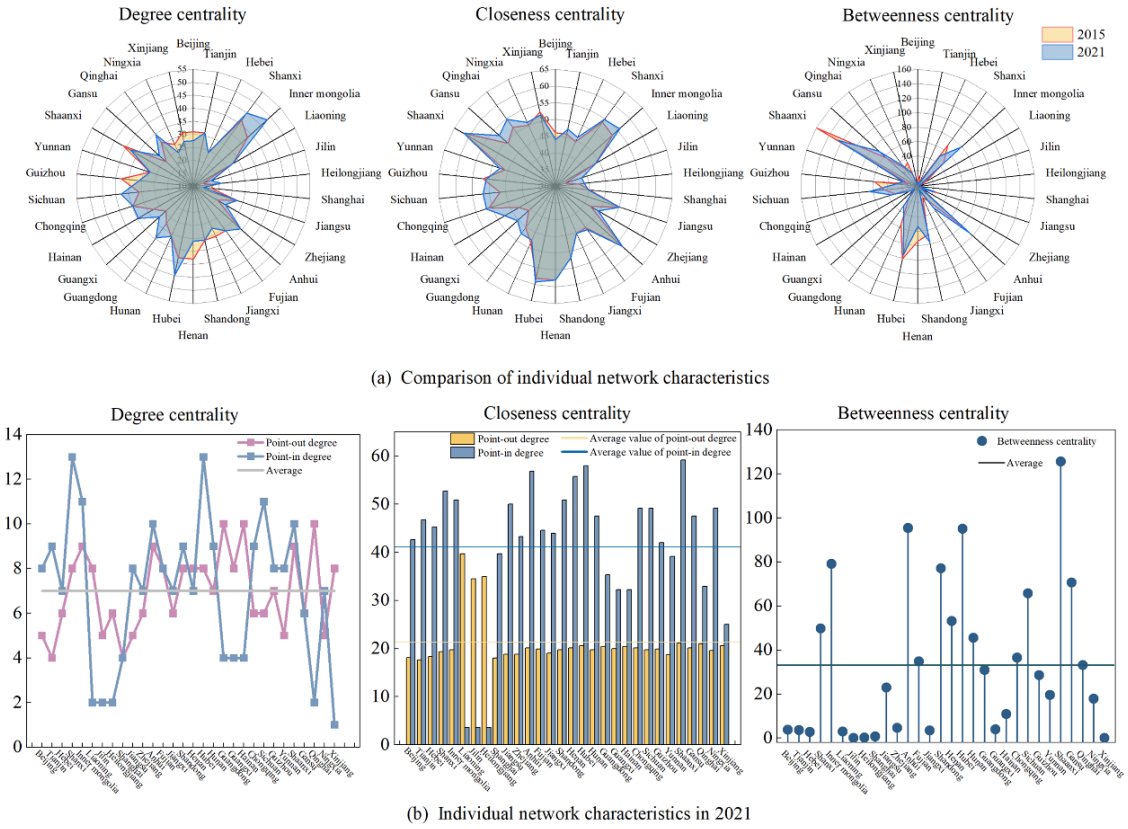


Figure 6. Individual network characteristics in 2015 and 2021.

In addition to analyzing the evolution of the CEEP networks of provinces in 2015–2021, it is also necessary to refine the analysis of individual characteristics based on the latest data. Therefore, in this paper, the data of 2021 are selected, and the degree centrality and closeness centrality are divided into point-out degrees and point-in degrees; the calculation results are shown in Figure 6b.

In terms of degree centrality, the average value of both the point-out degrees and point-in degrees of the network nodes is 7. There are 14 provinces where the point-out degrees are greater than the average value, including Shanxi, Inner Mongolia, Shandong, Guangdong and Xinjiang, which have large amounts of electrical energy, and Anhui, Fujian, Henan, Hubei and Guangxi, which have increased proportions of clean energy sources. The influence of these provinces on other provinces in the spatial network is gradually increasing. In addition, there are 15 provinces with a point-in degree greater than the average value, including Beijing, Tianjin, Jiangsu, Chongqing, etc., indicating that these provinces are vulnerable to fluctuations in CEEP in other provinces.

In terms of closeness centrality, the average value of the network node point-out degree is 21.3033, and the only ones larger than the average value are Heilongjiang, Jilin

and Liaoning, indicating that these three provinces have established direct links with a large number of provinces. This also means that these three provinces have a greater impact on other provinces if they have higher CEEPs. The average value of the point-in degree is 41.0944. Twenty provinces have larger point-in degrees than the average value, including Beijing, Tianjin, Hebei, Jiangsu, Anhui, Chongqing, etc. This indicates that it is easy for the CEEPs of these provinces to be influenced by other provinces. Therefore, these provinces are facing stronger uncertainty.

The average value of betweenness centrality in 30 provinces is 33.9668. The betweenness centralities of 11 provinces are larger than the average value, namely Shaanxi, Anhui, Hubei, Inner Mongolia, Shandong, Gansu, Sichuan, Henan, Shanxi, Hunan and Fujian. This shows that these provinces have a significant impact on the CEEPs of other provinces, acting as bridges in the network, and also have greater control over power resources, technology and labor in other regions. It is worth noting that the betweenness centralities of Heilongjiang, Jilin and Liaoning, which have higher closeness centrality, are almost zero. The reason for this may be that these three provinces can only participate in the network through direct connections instead of being a central node due to their remote location.

4.5. Clustering Structure Characteristics of the CEEP

Taking the 2021 data as an example, CONCOR clustering is applied to analyze the cohesive subgroup clustering of the CEEP network; the clustering results are shown in Figure 7a. The results show that the spatial correlation network of the CEEP forms four cohesive subgroups to analyze the spillover effects of the plates, which are called the Two-way overflow, Broker, Net Benefit and Net overflow plates. The transfer relationship between the plates is shown in Figure 7b.

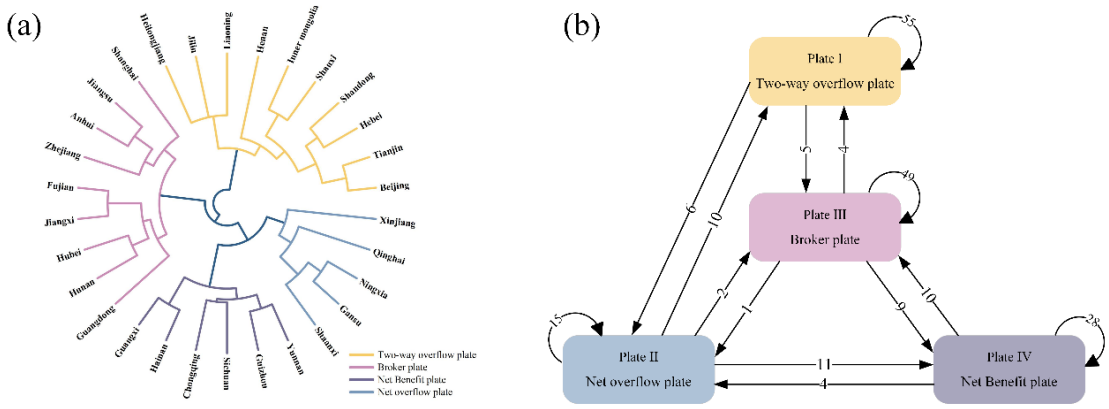


Figure 7. Clustering results of 30 provinces and plate transfer relationship in 2021.

As can be seen in Figure 7a, the Two-way overflow plate mainly includes the northern provinces of China, and there are both strong internal connections within the plate and more connections with other sections. The Broker plate mainly consists of the central and southeastern provinces of China, which have more connections with the network and have a greater impact on its propagation and evolution. The Net Benefit plate consists mainly of provinces in Southwest China, which have more inflow relationships but fewer outflow relationships. The Net overflow plate mainly includes the northwestern provinces of China, and this module has more outflow relationships but fewer inflow relationships. The clustering results are characterized by significant geographic aggregation.

As can be seen in Figure 7b, the number of network relationships in 2021 is 210, of which the number of relationships within the four plates is 148, or 70.5% of the total, and the number of relationships between less than four plates is 62, or 29.5% of the total. There are significantly more connections within the plates than between the plates. Among them,

the Two-way overflow plate mainly passes the relationship to the Net overflow plate and Broker plate, indicating there is a strong CEEP spillover from the northern part of China to the northwestern and central parts of the country. A greater number of relationships are passed from the Net overflow plate to the Net Benefit plate, indicating that Southwest China primarily receives CEEP spillovers from Northwest China. The number of relationships passed from the Net overflow plate to the Broker plate is 2, which accounts for only 9% of the number of relationships passed from the Net overflow plate outward, indicating that the Northwest region has a smaller impact on the CEEP in the central and Southeast regions.

4.6. Analysis of Factors Influencing the Spatial Correlation of CEEP

To provide strong guidance for cross-regional CEEP improvement, QAP is utilized to study the spillover paths and interaction mechanisms of the CEEP network.

4.6.1. QAP Correlation Analysis

QAP correlation analysis is performed via Ucinet for 20,000 random permutations, and the results of the runs obtained are shown in Table 4.

Table 4. Correlation analysis results of CEEP spatial correlation influencing factors.

	Obs Value	Significant	Average	Std Dev	Maximum	Minimum	$p \geq 0$	$p \leq 0$
I_S	−0.079	0.030	0.000	0.040	−0.199	0.133	0.970	0.030
G_P	0.653	0.000	0.000	0.044	−0.153	0.186	0.000	1.000
P_S	−0.130	0.003	0.000	0.040	−0.205	0.131	0.997	0.003
T_E	−0.127	0.003	0.000	0.039	−0.197	0.119	0.997	0.003
E_I	−0.176	0.000	0.000	0.039	−0.207	0.124	1.000	0.000
E_D	−0.085	0.028	0.000	0.041	−0.172	0.130	0.972	0.028
P_R	−0.040	0.158	0.000	0.040	−0.177	0.143	0.842	0.158

Table 4 show that the correlation coefficient of geographic proximity is significantly positive, indicating that geographic proximity promotes the spatial correlation of CEEP. The correlation coefficients of energy intensity, power structure, power generation technology, economic level and industrial structure are significantly negative, indicating that the inter-provincial differences in these five variables are significantly negatively correlated with spatial association. The result of the correlation coefficient of electricity consumption is not significant, indicating that regional differences in electricity consumption have little effect on the formation of the CEEP network.

We further correlate the seven variables that are significantly correlated with the spatial correlation matrix; the results of the analysis are shown in Table 5. Table 5 show that industrial structure and geographic proximity, geographic proximity and power structure, geographic proximity and power generation technology, geographic proximity and energy intensity, geographic proximity and economic development, power structure and power generation technology, power structure and energy intensity, and power generation technology and energy intensity are all significantly correlated, so it is necessary to perform regression analyses of the influencing factors.

Table 5. QAP correlation analysis results.

	I_S	G_P	P_S	T_E	E_I	E_D	P_R
I_S	1	−0.153 ***	−0.019	−0.057	−0.116 *	0.287 **	−0.094
G_P		1	−0.143 ***	−0.139 ***	−0.172 ***	−0.150 ***	−0.014
P_S			1	0.712 ***	0.772 ***	0.004	−0.153 **
T_E				1	0.881 ***	−0.068	−0.113 *
E_I					1	−0.095	−0.112 *
E_D						1	0.145
P_R							1

Note: *, **, *** represent significant levels at 10%, 5% and 1%, respectively.

4.6.2. QAP Regression Analysis

Since the correlation coefficient of electricity consumption did not pass the significance test, electricity consumption was excluded from the correlation analysis, and regression analyses were performed on six indicators: industrial structure, geographic proximity, power structure, power generation technology, energy intensity and economic development. The results are shown in Table 6.

Table 6. QAP regression results for CEEP spatial correlation influencing factors.

Independent	Unstdized Coefficient	Stdized Coefficient	Significance	Proportion as Large	Proportion as Small
Intercept	0.153	0.000			
I_S	0.009	0.006	0.399	0.399	0.602
G_P	0.766	0.642	0.000	0.000	1.000
P_S	0.031	0.022	0.332	0.332	0.668
T_E	0.122	0.080	0.099	0.099	0.902
E_I	−0.236	−0.151	0.024	0.977	0.024
E_D	0.002	0.001	0.496	0.496	0.505
P_R	0.009	0.006	0.399	0.399	0.602
R^2	0.433		Adj-R^2	0.429	
Probability	0.000		Observations	870	

Table 6 show that geographic proximity significantly contributes to the formation of the electricity carbon emission efficiency network, indicating that geographically neighboring provinces are capable of more effective CEEP transmission due to the more efficient flow of clean energy and low-carbon resources between neighboring provinces and lower flow costs. Therefore, active regional collaboration should be encouraged between neighboring provinces with large differences in CEEP, and the advantage of geographical proximity should be utilized to promote regional CEEP. Thus, Hypothesis H2 is supported.

Increased technological differences in provincial-level power generation can contribute to the formation of CEEP networks. This is because widening differences in power generation technology research and development inputs have exacerbated inter-provincial disparities in resource development levels, human capital, etc., leading to more frequent inter-regional cooperation in power resources and increased spatial correlation. Hypothesis H1, stating that technological progress has a positive impact on the formation of CEEP networks, is, thus, supported.

Increased provincial energy intensity differences can significantly hinder the formation of CEEP networks. This is because different provinces consume different amounts of energy for power generation, with some provinces having a higher share of clean energy, more advanced energy-saving technologies, and smaller energy consumption per kWh. In other provinces, the lack of clean energy alternatives, relatively outdated energy-saving technologies, and high energy consumption per kWh reduce the spatial relevance of CEEP. Hypothesis H3, stating that energy intensity has a negative effect on the formation of CEEP networks, is, thus, supported.

In addition, differences in industrial structure, power structure and economic development do not significantly affect CEEP spatial correlation.

4.7. Study Comparison

Regarding CEEP measurement, compared with the study of provincial thermal power carbon emission efficiency, this paper studies the carbon emission efficiency of the entire power industry per province, including clean energy sources such as photovoltaic, wind and hydropower, so there may be gaps in the measurement of the efficiency value for provinces with large amounts of clean energy generation.

In terms of spatial association research, compared with spatial clustering research on CEEP [32], this paper pays more attention to the CEEP spatial correlation network. Based

on this, we study the positioning and conduction relationships between provinces in the network, allowing us to reveal the linkages and interactions between different regions in terms of the CEEP and identify the key nodes and sub-networks, ensuring that we more accurately understand the interactions and dependencies between regions.

In contrast with past research on CEEP influencing factors [60], this study analyzes the influencing factors of the CEEP network, exploring the complexity of the network structure by analyzing the formation mechanism and spatial correlation complexity of the CEEP network and providing a new perspective for understanding and optimizing the CEEP.

The findings of this paper show that the eastern provinces have higher CEEPs with advanced abatement technologies, consistent with the conclusions of T. Fang et al. [61], although this study analyzes the provincial CEEP at the macro level rather than studying the carbon emission efficiency of regional power plants at the micro level. In addition, the eastern provinces, as intermediate nodes of the CEEP network, greatly impact other regions through network role relationships, consistent with the conclusions of Yan et al. [62]. However, this paper focuses more on analyzing the spatial spillover effects of regional CEEP from the perspective of spatial network relationships rather than from the perspective of spatial clustering characteristics.

4.8. Model Scalability Discussion

This paper analyzes the network relationship of CEEP by combining Gravity model and SNA, and this combination method can be applied to other regions and industries to help them sort out the network effect of industry carbon emission efficiency and formulate emission reduction policies in line with the characteristics of the region and industry.

In the scalability study of industries, scholars have applied the combination method to the fields of agricultural water use efficiency [63], green innovation network [64] and industrial carbon emission [65]. While the study of applying the combination method to the fields of iron and steel, cement and building materials, which have larger carbon emissions, is still comparatively less, scholars can refer to the method of this paper to calculate the carbon emission efficiency of the industry and study its network relationship by setting reasonable input–output indicators.

In regional extensibility studies, scholars have conducted network analyses of China's urban agglomeration tourism economy [66] and urban agglomeration carbon emissions [58], while fewer studies have been conducted in other regions of the world. Thus, the combined methodology can be applied to other countries and regions to support the development of relevant policies in the region.

Based on the accessibility of data, the measurement of CEEP in this paper only stays at the provincial level, with fewer network nodes. Future research can refine the study area to the city and county level, expand the network scale, form a more obvious aggregation effect, and better straighten out the transfer relationship of elements between nodes.

5. Conclusions and Policy Recommendations

5.1. Conclusions

This study delves into the characteristics of network dynamics in terms of CEEP in thirty provincial and administrative regions in China, analyzing the macro- and micro-characteristics of the networks, as well as the influencing factors, to elucidate the constructive complexity of the CEEP network. The conclusions of this paper are as follows.

First, the national CEEP has gradually increased, but the CEEP gap between provinces has become larger. The CEEPs of provinces rich in clean energy resources have increased significantly, while the CEEPs of provinces with poor clean energy resources have barely changed.

Second, the overall network size is expanding, and network connections are being strengthened. The association relationship of CEEP has become closer, but there is still much space for improvement. The network hierarchy is somewhat fixed but does not create a significant gradient of relationships. The network center provinces are highly consistent with the geographic center provinces, and the central node provinces do not have sufficient influence on the peripheral provinces.

Third, power-exporting provinces have stronger CEEP spillover effects, while power-importing provinces have stronger CEEP benefiting effects. Transit provinces have higher betweenness centrality and can control and influence other regions to a greater extent.

Fourth, geographic proximity, differences in energy intensity, and the technical level of power generation between provinces have the greatest impact on the formation of CEEP networks, where geographic proximity and the technical level of power generation can significantly enhance the formation of spatial correlation networks. In contrast, exacerbating differences in energy intensity between provinces inhibits the formation of spatial networks.

5.2. Policy Recommendations

Based on these conclusions, this study makes the following recommendations.

First, government should focus on regional CEEP gaps and select appropriate power system development paths according to local conditions such as energy resources, economic positions and power technology. For example, regions rich in clean energy resources such as Inner Mongolia, Xinjiang, Sichuan and Yunnan should enhance provincial and overall CEEP by actively adjusting their power structures.

Second, government should clarify the positions of provinces in the CEEP spatial association network and continue to optimize the hierarchical structure of the CEEP spatial network. Since reducing the level of social networks enhances inter-regional resource flows [67], inter-provincial interactions must be strengthened. The central node provinces (such as Shaanxi, Anhui and Hubei) should actively develop low-carbon technology, invest in talent, and promote the reasonable flow and efficient aggregation of electric power resources by utilizing the spatial spillover effects. Marginal provinces such as Heilongjiang, Jilin and Liaoning should enhance the CEEP spatial correlation with other provinces and increase grid construction and power transactions between marginalized provinces and other provinces.

Third, government should grasp the transmission mechanism and plate structure of the CEEP network to increase the overall efficiency of the network. In the national CEEP network, the Two-way overflow plate (such as Shandong, Shanxi, and Inner Mongolia) and Net overflow plate (such as Shaanxi, Gansu, Ningxia and Qinghai) should actively increase the share of clean energy, formulate more stringent energy-saving and emission reduction measures, and popularize the advantages and experience of thermal power emission reduction, all while guaranteeing the production of electricity. The Broker plate (such as Jiangsu, Jiangxi and Hunan) should act as a network intermediary and maintain a close relationship with other block provinces through electric power technology innovation and electric power talent cultivation, facilitating the dispersion of CEEP enhancement technologies through spatially connected networks. Net Benefit plate (such as Guizhou, Guangxi, Hainan) should strengthen connections with high CEEP provinces (e.g., Sichuan, Guangdong), strengthening inter-regional power grids, increasing the frequency of technical exchanges between plates, and fully absorbing efficient provincial technologies.

Fourth, government should focus on the mechanism of CEEP spatial correlation formation. First, government could actively use spatial, technological and industrial differences for promoting the formation of the CEEP spatial correlation. Second, government could focus on provinces with large gaps in CEEP but spatial proximity to promote interprovincial cooperation and exchanges. Third, through technical communication, electric power resource development, and electric power industry transfers, government could narrow down the differences in technology and innovation in the power industry among provinces in Southwest, northeast and central China to promote cross-regional efficiency in the power industry.

5.3. Limitations and Further Directions

In this paper, the network relationship of CEEP is analyzed by combining the Gravity model and SNA. This method can be applied to other regions and industries to determine the network effect of industry carbon emission efficiency and formulate emission reduction policies in line with the characteristics of a region and industry.

In studies of industry scalability, many scholars have applied the combination method to agriculture [68] and industrial carbon emissions [65], while fewer studies have applied the combination method to iron, steel, cement and building materials, which have larger carbon emissions. Scholars can use the method outlined in this paper to calculate the carbon emission efficiency of an industry and study its network relationship by setting reasonable input–output indicators.

In regional extensibility studies, scholars have conducted network analyses of the tourism economies of China's urban agglomerations [66] and these urban agglomerations' carbon emissions [58], but fewer studies have been conducted in other regions of the world, so the combined methodology should be applied to other countries and regions to support the development of relevant policies in the region.

Based on the accessibility of data, the measurement of the CEEP in this study was only conducted at the provincial level, which has fewer network nodes, so future research should cover the city and county level, expand the network scale, outline the aggregation effect more clearly, and clarify the transfer relationship of elements between nodes.

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Nomenclature

C^i	Carbon emissions in the power industry in province i
m	Type of energy
E_m^i	Energy consumption of province i in thermal power generation
NCV_m^i	Average low level heat generation of energy m in province i in thermal power generation
CEF_m^i	Carbon emission factor for the calorific value equivalent of energy m in thermal power generation in province i
COF_m^i	Carbon oxidation factor of energy m for province i in thermal power generation
44/12	Gasification coefficient of carbon dioxide
n	Number of decision making unit (DMU)
a	Number of DMU inputs
b	Number of DMU outputs
b_1	Number of desired outputs
b_2	Number of undesired outputs
y^g	Desired outputs
y^b	Undesired outputs
b^-	Model input indicator
b^g	Slack variables for the desired outputs
b^b	Slack variables for the undesired outputs
$y_{i,j}^*$	correlation between the CEEP in region i and j
E_i	CEEP of region i
E_j	CEEP of region j
D_{ij}	spherical distance between region i and j
C_i	Electricity consumption of region i
C_j	Electricity consumption of region j
N_C	Network correlation
N_D	Network density
N_H	Network hierarchy
N_E	Network efficiency
C_D	Degree centrality
C_C	Closeness centrality
C_B	Betweenness centrality
x	Number of nodes in the network
V	Number of unreachable pairs in the spatial association network
y	Number of relations that exist between nodes and nodes
S	Number of symmetrically reachable pairs of relations
R	Number of unidirectionally reachable relations
$I(i)$	Actual number of relationships between region i and other regions
s_{ij}	Shortcut distance between region i and j
r_{jk}	Shortcut distance between region j and k
$r_{jk}(i)$	Shortcut distances between region j and k through region i
T	CEEP matrix
G_P	Space adjacency matrix
E_D	Level of economic development, represented by GDP per capita
I_S	Industrial structure, represented by percentage of secondary industry
T_E	Level of power generation technology, represented by carbon emissions per unit of power generation
P_S	Power structure, represented by proportion of thermal power
E_I	Energy intensity, represented by energy consumption per unit of power generation
P_R	Power requirement, represented by electricity consumption

Appendix A

Table A1. Share of installed capacity of power plants of 6000 kW and above.

Province	2015	2016	2017	2018	2019	2020	2021
Beijing	99.36%	99.00%	98.28%	97.34%	96.55%	95.82%	94.48%
Tianjin	99.47%	99.39%	98.93%	98.65%	98.59%	98.28%	98.13%
Hebei	99.41%	98.98%	96.61%	94.61%	93.57%	92.33%	88.39%
Shanxi	99.55%	99.46%	99.00%	97.68%	97.28%	97.09%	96.66%
Inner mongolia	99.89%	99.86%	99.86%	99.83%	99.27%	99.52%	99.46%
Liaoning	99.44%	99.37%	99.08%	98.54%	98.32%	98.10%	97.52%
Jilin	98.93%	98.82%	97.91%	97.74%	97.50%	97.28%	97.39%
Heilongjiang	99.55%	99.43%	98.89%	97.35%	97.26%	97.31%	97.07%
Shanghai	99.23%	98.73%	97.83%	96.91%	96.40%	95.84%	95.08%
Jiangsu	98.45%	98.30%	96.89%	95.43%	94.78%	94.27%	93.63%
Zhejiang	93.88%	95.15%	91.86%	89.53%	88.21%	87.22%	86.20%
Anhui	98.24%	97.65%	94.29%	93.43%	93.31%	92.39%	90.33%
Fujian	91.87%	92.26%	92.26%	91.53%	91.45%	91.65%	91.59%
Jiangxi	90.62%	91.07%	88.29%	87.56%	87.70%	88.89%	88.61%
Shandong	99.40%	98.86%	96.50%	94.77%	93.59%	90.76%	86.54%
Henan	99.35%	99.27%	97.55%	95.29%	94.92%	94.18%	91.44%
Hubei	98.03%	97.91%	96.72%	96.01%	95.92%	95.99%	95.94%
Hunan	91.46%	91.58%	90.69%	89.34%	89.10%	89.79%	90.08%
Guangdong	95.17%	94.99%	94.42%	94.44%	94.28%	94.31%	93.73%
Guangxi	93.75%	94.68%	94.97%	94.81%	95.49%	95.73%	95.83%
Hainan	100.00%	95.44%	94.78%	95.54%	95.53%	95.90%	95.83%
Chongqing	95.07%	94.86%	94.97%	94.51%	94.57%	94.41%	94.29%
Sichuan	94.96%	95.09%	95.30%	95.24%	95.10%	95.30%	95.85%
Guizhou	95.48%	95.68%	95.86%	95.28%	95.68%	95.44%	95.42%
Yunnan	97.45%	95.27%	95.40%	97.56%	97.10%	97.28%	97.32%
Shaanxi	98.58%	98.56%	83.08%	97.69%	96.16%	96.31%	96.63%
Gansu	97.37%	97.47%	97.32%	96.34%	95.79%	95.82%	96.13%
Qinghai	98.79%	97.95%	98.03%	98.57%	99.34%	99.06%	99.08%
Ningxia	99.90%	99.86%	99.76%	99.60%	99.53%	99.56%	99.55%
Xinjiang	99.10%	99.68%	100.00%	100.00%	100.00%	100.00%	99.37%

Table A2. Share of electricity generated by power plants of 6000 kW and above.

Province	2015	2016	2017	2018	2019	2020	2021
Beijing	99.76%	99.77%	99.49%	99.33%	99.13%	98.68%	98.73%
Tianjin	99.83%	99.83%	99.83%	99.70%	99.55%	99.57%	99.61%
Hebei	99.83%	99.76%	99.40%	98.64%	98.03%	97.49%	96.10%
Shanxi	99.72%	99.68%	99.64%	99.38%	99.11%	98.94%	98.80%
Inner mongolia	99.92%	99.95%	99.95%	99.96%	99.91%	99.82%	99.82%
Liaoning	99.81%	99.71%	99.72%	99.48%	99.40%	99.31%	99.21%
Jilin	99.29%	98.92%	98.98%	98.74%	98.70%	98.38%	98.07%
Heilongjiang	99.66%	99.67%	99.69%	99.32%	98.81%	98.83%	98.78%
Shanghai	100.00%	100.00%	99.65%	99.30%	99.16%	98.96%	98.81%
Jiangsu	99.68%	99.68%	99.43%	98.99%	98.74%	98.56%	98.52%
Zhejiang	97.71%	97.46%	97.61%	96.72%	95.91%	96.11%	96.14%
Anhui	98.74%	98.76%	98.50%	98.09%	97.88%	97.49%	97.50%
Fujian	92.57%	90.17%	94.33%	95.65%	94.33%	96.17%	96.69%
Jiangxi	91.75%	92.63%	94.10%	95.23%	93.59%	94.72%	95.20%
Shandong	99.83%	99.71%	99.51%	98.81%	98.43%	97.87%	96.64%
Henan	99.65%	99.61%	99.56%	98.79%	98.40%	97.99%	97.27%
Hubei	98.81%	98.80%	98.53%	98.67%	98.69%	98.29%	98.39%
Hunan	90.82%	91.15%	92.39%	93.51%	92.01%	92.14%	92.51%
Guangdong	96.15%	94.05%	96.67%	96.85%	95.61%	97.15%	97.95%
Guangxi	88.02%	96.47%	96.65%	98.21%	98.58%	98.14%	98.56%
Hainan	100.00%	97.22%	97.38%	98.17%	98.55%	98.28%	98.47%
Chongqing	95.46%	95.17%	95.19%	95.87%	95.94%	95.34%	96.11%
Sichuan	94.98%	94.39%	94.73%	95.64%	95.95%	96.28%	96.81%
Guizhou	93.37%	94.07%	94.23%	93.39%	95.08%	94.63%	95.22%
Yunnan	97.53%	95.32%	96.18%	97.78%	97.28%	97.17%	97.77%
Shaanxi	98.71%	98.98%	80.94%	99.15%	98.43%	98.27%	98.45%
Gansu	95.36%	95.70%	95.23%	95.50%	94.51%	94.57%	94.93%
Qinghai	98.60%	97.65%	98.38%	98.88%	99.66%	99.47%	99.49%
Ningxia	100.00%	100.00%	100.00%	99.94%	99.88%	99.77%	99.80%
Xinjiang	99.15%	99.70%	100.00%	100.00%	100.00%	100.00%	99.59%

Table A3. CEEP in 30 provinces.

Region	Province	2015	2016	2017	2018	2019	2020	2021	Average
North China power grid	Beijing	0.369	0.379	0.325	0.358	0.365	0.364	0.370	0.361
	Tianjin	0.407	0.380	0.375	0.381	0.370	0.376	0.379	0.381
	Hebei	0.557	0.574	0.599	0.612	0.613	0.593	0.630	0.597
	Shanxi	0.550	0.550	0.586	0.625	0.643	0.652	0.710	0.617
	Inner mongolia	0.701	0.714	0.772	0.835	0.930	0.900	0.952	0.829
	Shandong	1.001	0.920	0.819	0.897	0.880	0.951	1.029	0.928
Northeast China Power Grid	Liaoning	0.479	0.493	0.494	0.511	0.523	0.517	0.531	0.507
	Jilin	0.313	0.321	0.327	0.345	0.362	0.373	0.359	0.343
	Heilongjiang	0.373	0.372	0.371	0.391	0.402	0.390	0.377	0.382
East China Power Grid	Shanghai	0.376	0.381	0.394	0.380	0.365	0.375	0.417	0.384
	Jiangsu	0.930	1.014	0.922	0.875	0.872	0.864	0.952	0.918
	Zhejiang	0.640	0.678	0.698	0.718	0.742	0.744	0.940	0.737
	Anhui	0.540	0.558	0.587	0.616	0.646	0.612	0.649	0.601
	Fujian	0.551	0.591	0.607	0.815	1.009	0.715	0.764	0.722
Central China Power Grid	Henan	0.578	0.577	0.586	0.624	0.593	0.582	0.603	0.592
	Hubei	0.625	0.650	0.679	0.703	0.703	0.737	0.762	0.694
	Hunan	0.447	0.464	0.457	0.466	0.502	0.496	0.521	0.479
	Jiangxi	0.462	0.449	0.470	0.476	0.494	0.466	0.488	0.472
	Sichuan	0.806	0.894	0.941	1.000	0.956	1.026	1.042	0.952
	Chongqing	0.353	0.348	0.357	0.381	0.381	0.392	0.435	0.378
Northwest Power Grid	Shaanxi	0.448	0.470	1.001	0.517	0.537	0.541	0.595	0.587
	Gansu	0.385	0.382	0.415	0.467	0.484	0.497	0.499	0.447
	Qinghai	0.313	0.292	0.308	0.374	0.387	0.371	0.392	0.348
	Ningxia	0.417	0.393	0.425	0.455	0.451	0.448	0.493	0.440
	Xinjiang	0.554	0.570	0.618	0.648	0.689	0.73	0.812	0.66
Southern Power Grid	Guangdong	0.735	0.782	0.825	0.815	0.884	0.915	1.029	0.855
	Guangxi	0.511	0.440	0.460	0.509	0.546	0.546	0.551	0.509
	Hainan	0.318	0.337	0.341	0.32	0.341	0.323	0.344	0.332
	Guizhou	0.531	0.514	0.517	0.535	0.535	0.531	0.550	0.530
	Yunnan	0.674	0.751	0.812	0.821	0.879	0.866	0.889	0.813
Average		0.532	0.541	0.570	0.582	0.603	0.596	0.635	0.580

Table A4. Share of renewable energy generation in total generation.

Province	2015	2016	2017	2018	2019	2020	2021	Average
Beijing	2.47%	3.67%	4.06%	3.56%	3.90%	4.61%	5.10%	3.91%
Tianjin	1.13%	1.50%	2.03%	2.42%	3.88%	4.45%	4.92%	2.90%
Hebei	8.47%	11.31%	13.55%	15.29%	17.67%	20.17%	26.48%	16.13%
Shanxi	5.66%	8.00%	9.51%	11.30%	12.33%	13.90%	18.14%	11.26%
Inner mongolia	12.77%	14.53%	15.55%	16.12%	16.27%	17.03%	20.65%	16.13%
Liaoning	17.91%	22.45%	24.73%	28.30%	13.50%	14.81%	16.67%	19.77%
Jilin	16.19%	20.86%	22.61%	23.88%	23.97%	27.17%	29.98%	23.52%
Heilongjiang	10.19%	12.19%	14.57%	16.62%	18.38%	19.44%	20.96%	16.05%
Shanghai	1.34%	1.80%	2.31%	2.80%	2.99%	3.36%	3.28%	2.55%
Jiangsu	6.17%	6.63%	8.25%	11.32%	7.29%	8.44%	10.94%	8.43%
Zhejiang	25.21%	25.80%	24.01%	25.94%	11.54%	10.68%	10.46%	19.09%
Anhui	3.59%	5.24%	6.48%	7.59%	7.74%	9.08%	11.26%	7.28%
Fujian	41.10%	54.31%	47.90%	42.93%	21.18%	16.43%	15.39%	34.18%
Jiangxi	18.74%	21.11%	18.38%	16.06%	19.60%	18.82%	19.69%	18.91%
Shandong	2.92%	3.95%	5.06%	7.57%	7.51%	8.20%	11.80%	6.72%
Henan	4.85%	4.74%	6.44%	9.58%	11.90%	14.01%	19.79%	10.19%
Hubei	56.28%	57.94%	59.33%	55.56%	50.05%	59.07%	55.18%	56.20%
Hunan	43.32%	45.05%	41.34%	35.75%	41.59%	45.30%	41.51%	41.98%
Guangdong	24.71%	29.39%	27.21%	28.20%	10.80%	9.17%	7.52%	19.57%
Guangxi	58.79%	56.19%	57.25%	50.77%	36.56%	38.06%	35.21%	47.55%
Hainan	8.20%	31.94%	36.07%	35.17%	10.43%	10.92%	9.97%	20.39%
Chongqing	33.97%	36.90%	35.79%	31.54%	31.65%	35.72%	31.80%	33.91%
Sichuan	86.60%	89.64%	90.08%	88.43%	87.50%	87.69%	85.48%	87.92%
Guizhou	44.54%	40.05%	39.86%	40.34%	38.41%	41.81%	38.30%	40.47%
Yunnan	89.19%	90.61%	91.89%	91.03%	90.81%	88.73%	87.92%	90.02%
Shaanxi	8.10%	7.99%	10.96%	12.22%	13.77%	14.10%	16.55%	11.95%
Gansu	42.51%	42.18%	47.32%	48.09%	50.75%	49.58%	46.07%	46.64%
Qinghai	79.23%	72.69%	75.16%	85.22%	88.11%	89.45%	85.54%	82.20%
Ningxia	12.01%	16.68%	17.59%	18.84%	18.97%	19.91%	24.35%	18.33%
Xinjiang	16.58%	18.49%	22.48%	22.50%	22.99%	21.20%	22.33%	20.94%

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