Industrial Carbon Emission Efficiency in Chinese Cities: Spatial Correlation Networks, Regional Differences and Driving Factors

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Abstract. Green and sustainable development of industry has gradually become an essential factor for economic development, effective improvement of industrial carbon emission efficiency (ICEE) has a contributing role in realizing industrial carbon emission reduction and sustainable economic development. According to this study, the spatial correlation characteristics and driving factors of ICEE in the Yangtze River Delta (YRD) urban agglomeration are analyzed by using social network analysis and the QAP model. Empirical results show that (1) the spatial variation of ICEE in YRD urban agglomeration is large, showing a decreasing trend from the southeastern cities to the northwestern cities. (2) The spatial correlation network presents a pattern of development from core cities to edge cities, with Suzhou, Changzhou, Hangzhou, etc. as the center to the south and west cities of YRD urban agglomeration. (3) The ICEE substructures in YRD urban agglomeration have four plates, namely "inflow plate", "outflow plate", "bidirectional outflow plate" and "agent plate". (4) The spatial correlation network of ICEE is significantly influenced by the matrix of differences in research and development capabilities, environmental regulation, and rate of foreign investment.

Keywords: Industry carbon emission efficiency; The YRD urban agglomeration; Super-SBM model; Social network analysis; Block model; QAP model

Introduction and literature review

Protecting the environment is an imperative means and method of achieving harmonious development between human society and the natural environment. Global warming is an issue that countries around the world should pay attention to, which is closely related to both socioeconomic growth and natural environmental processes (Freeman et al, 2018). China is the largest developing and manufacturing country; it has emerged as one of the leading contributors to carbon emissions. The Chinese central government has pledged to overcome the contradiction between economic expansion and environmental conservation by establishing a goal of attaining a "carbon peak" in response to the global climate change challenge, and its core is to ensure that carbon dioxide emissions start to gradually reduce after peaking in the future, and aim to reach the maximum level of carbon dioxide emissions by about 2030 (Chen et al., 2020). The YRD urban agglomeration is not only one of the districts that has the greatest amount of urbanization, but it is also a highly active zone in China's economic and social advancement. It is known for its highly intensive industrial system and strong economic strength. However, the industrial industry, as the main consumption industry of fossil resources, has made a huge contribution not only to GDP but also to carbon emissions (Yang et al., 2021). Consequently, ICEE can be improved by decreasing industrial energy consumption during the industrial production process; this is critical for China and the entire world to reach its carbon peak objective.

Currently, the idea of carbon emission efficiency primarily focuses on two key factors: single factor emission efficiency and total factor emission efficiency. This highlights the pressing need for researchers to thoroughly assess and enhance the efficiency of energy use within the framework of carbon emission reduction and sustainable development advancement. The carbon emission efficiency defined by the single-factor concept was proposed in 1993 (Kaya and Yokobori, 1993), who believed that the ratio of carbon emissions and GDP during a given period was carbon emission efficiency, also known as carbon productivity. Some scholars have also chosen carbon emissions for each energy unit used as a measurement indicator and compared it with developed countries to study the contributions of developing countries to the world's carbon reduction and sustainable development (Mielnik and Goldember, 1999). Although single-factor emission efficiency indicators are easier to measure, the diversity of measurement indicators tends to lead to disputes over different issues. Zhou et al. (2009) argued that the single factor method to assessing carbon emission efficiency is limited in its ability to capture all elements of carbon emission efficiency. Consequently, they introduced the notion of considering all components in evaluating carbon emission efficiency.

Ramanathan (2002) believed that to guarantee the rationality of carbon emission efficiency calculation, the calculation elements need to include key factors such as economic development, population size, resource availability, carbon emissions, and energy consumption. Currently, in the academic community, DEA and SFA are widely recognized calculation methods for total factor carbon emission efficiency. SFA is a highly subjective non-parametric method, and the form of production function needs to be set before calculation (Sun and Huang, 2020). The advantage of SFA is that it is stochastic in nature, and the efficiency value is more accurate when considering random error calculation (Sun et al., 2020). Herrala and Goel (2012) assessed the carbon emission efficiency of 170 countries worldwide using the SFA method. However, SFA still has limitations, specific production functions need to be established when using model to calculate to realize the measurement (Zeng et al., 2019). DEA models have two methods, radial distance function and non-radial function, including models such as SBM, CCR, BCC, etc (Wang et al., 2019a). Marklund and Samakovlis (2007) used a DEA model to develop a radial distance function in order to assess the cost of reducing carbon emissions in EU nations. Xue et al (2021) used an EBM model including Hybrid distance to measure the city-level carbon emission efficiency and its spatial and temporal evolution in the BTH region of China. Liu et al (2023) used the Undesirable-SBM model to calculate the carbon emission efficiency and spatial correlation of China's provincial thermal power sector. Yuan et al (2024) measured the carbon emission efficiency of the construction industry in various provinces of China using the super-Slacks-Based Measure model. Wu et al (2024) measured the spatial differences and influencing factors of carbon emission efficiency of three major urban agglomerations in China using the super-SBM model.

Research on carbon emission efficiency in China's industrial sector mostly focuses on two key areas, with one being the regional level. Huang et al. (2023) examined the influence of industrial intelligence on the Industrial Comprehensive Energy Efficiency (ICEE) in 11 provinces located in Yangtze River Economic Belt in China. Lin et al. (2023) examined the level of carbon emission efficiency in 282 cities in China's industrial sector and assessed the influence of environmental regulations on these cities. Xie and Zhang (2022) studied the impact of digital economy growth on ICEE using Chinese province data from 2003 to 2018. The second is the study of industries that have a significant energy consumption and contribute to high levels of pollution. Zhu et al. (2021) studied the spatial and temporal patterns and determinants of carbon emission efficiency in energy-intensive industries, including chemical manufacturing, and nonferrous metal manufacturing and processing at the province level in China. Zhang et al (2023) investigated how the imbalance in labor and energy allocation affects the carbon emission efficiency of 32 industrial sectors in China. Hu et al (2024) measured the carbon emission efficiency of 27 manufacturing industries in China and analyzed the causes of inefficiency.

Social network analysis is an effective approach for studying the intricate structure of networks connecting individual nodes. It is extensively used in several research fields such as social sciences, energy, and environment (Zhang et al, 2021). Spatial Correlation Network is an approach derived from social network analysis to describe the complex network formed by elements in geographic space. The spatial correlation network of carbon emission efficiency is to investigate the structure of the network of carbon-related factors in geographic space by taking the interaction of factors affecting carbon emission as the research object. Zhang et al (2022) studied the spatial attributes of carbon emission efficiency and the intricate network structure of the China's Yangtze River Economic Belt between 2008 and 2020. Some other scholars used social network analysis to explore the spatial correlation network structure and determining variables of carbon emission efficiency in the provincial transportation industry, construction industry and railroad transportation industry in China (Zhang et al., 2022; Gao et al., 2023; Zhang et al., 2023).

Prior research has examined carbon emission efficiency to a certain degree, uncovering spatial variations and factors influencing carbon emission efficiency. The YRD urban agglomeration, which is the most expansive industrial urban agglomeration in China, has yet to be the subject of spatial correlation structure research pertaining to its ICEE. Hence, drawing from prior research, this paper employs social network analysis to construct a comprehensive picture of the spatial network attributes of ICEE in the YRD urban agglomeration. Additionally, it examines the spatial variations and prospective durability of carbon emission efficiency. A proposal is presented to facilitate coordinated carbon emission reduction in urban agglomerations. This proposal seeks to reveal the interrelated network structure of carbon emission efficiency across regions and its impact for collaborative carbon emission reduction. The research findings can serve as a reference for decision-makers as they strive to achieve regional collaborative targets for carbon emission reduction and develop policies that align with those aims.

2. Materials and methods

2.1 Study

The YRD urban agglomeration comprises the provinces of Jiangsu, Zhejiang, Anhui, and the municipality of Shanghai, which is directly governed by the central government. Jiangsu has nine cities: Nanjing, Suzhou, Changzhou, Wuxi, Nantong, Yancheng, Zhenjiang, Yangzhou, and Taizhou. Zhejiang has nine cities: Hangzhou, Ningbo, Jiaxing, Wenzhou, Shaoxing, Huzhou, Jinhua, Taizhou, and Zhoushan. Anhui has eight cities: Hefei, Maanshan, Wuhu, Chuzhou, Tongling, Chizhou, Anqing and Xuancheng. The total economic volume is 29 trillion, accounting for 24.1% of China, and the total population of 2.4 billion people accounts for 17% of China's population. In China, the urban agglomeration known as YRD is the most developed and the biggest of all urban agglomerations at the moment. Figure 1 is the map of the distribution of YRD region and YRD urban agglomeration.

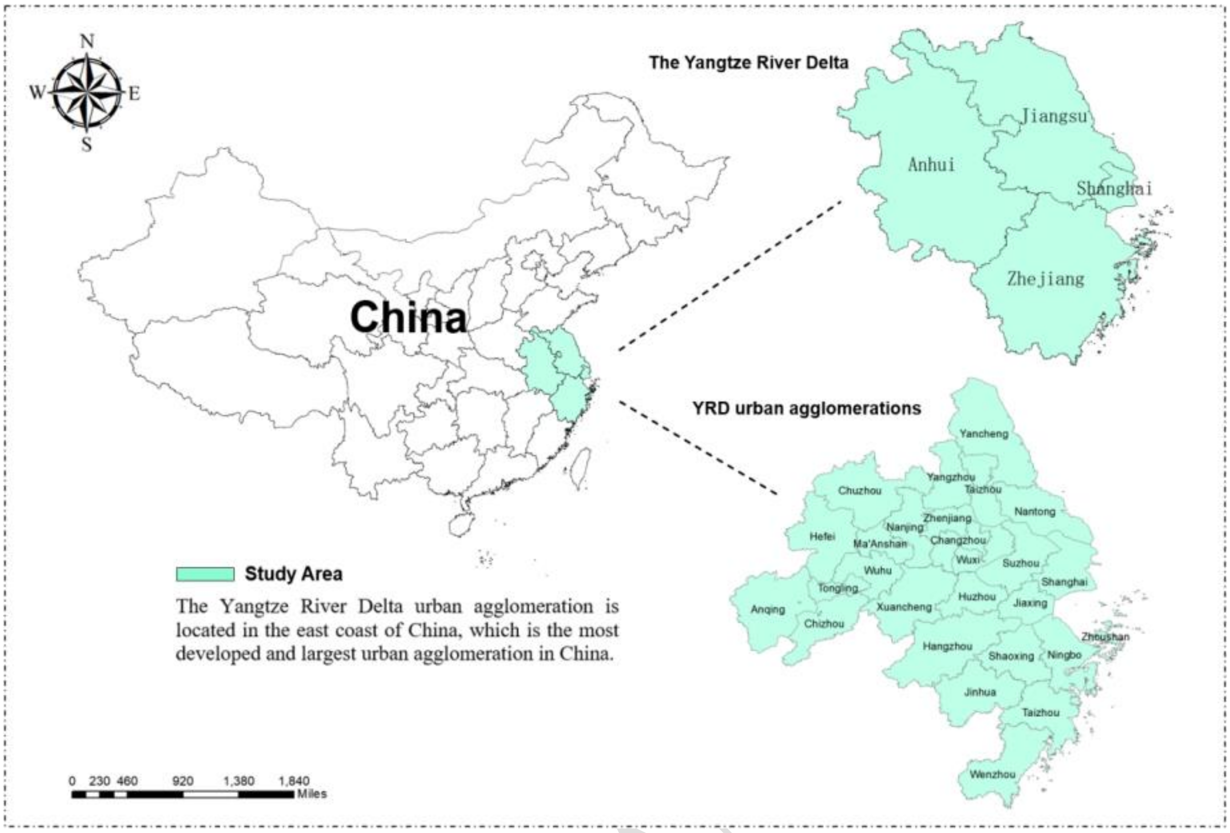

Fig. 1 Map of the distribution of YRD urban agglomeration and YRD region

2.2 ICEE Measurement

The research used the super SBM model to compute the ICEE, using the Max DEA 9 program. Currently, the predominant method for calculating carbon emission efficiency is data envelopment analysis (DEA). It evaluates decision units by considering various input and output indicators in a linear fashion. However, the general DEA model focuses on low input and high output as indicators of high efficiency, overlooking unexpected outputs like CO2 emissions, dust, and other pollutants. To address this limitation, Tone (2001) introduced the SBM model, which incorporates slack variables into the DEA model. Tone argued that economic production often results in significant pollutant emissions, and incorporating unexpected outputs into the SBM model resolves the issues of input slack and inefficiency related to unexpected outputs. However, there are instances in which the efficiency decision-making unit's utmost efficiency value may surpass 100%, or 1. Conventional SBM models are incapable of differentiating these efficient decision-making units with the same degree of effectiveness in this instance. In order to tackle this concern, Andersen and Petersen (1993) introduced a more effective super SBM in which the effective decision-making unit typically possesses a super efficiency value exceeding 1. The equations (1) and (2) present the super SBM model incorporating unexpected outputs.

$$\rho = min \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{io}}}{1+\frac{1}{q+h}(\sum_{r=1}^{q}\frac{S_r^+}{y_{ro}}+\sum_{k=1}^{h}\frac{S_k^-}{b_{ko}})} \tag{1}$$

$$\begin{aligned} &\sum_{j=1}^{n}\lambda_j\chi_{ij} + S_j^- = \chi_{io} \ \ i = 1,2,\dots,m; \\ &\sum_{j=1}^{n}\lambda_j\chi_{rj} - S_r^+ = y_{ro}^{g} \ \ r = 1,2,\dots,q; \\ &\sum_{j=1}^{n}\lambda_j\chi_{kj} + S_k^- = b_{ko}^{b} \ \ k = 1,2,\dots,h; \\ &S_i^- \geq 0, S_r^+ \geq 0, S_k^- \geq 0, \lambda_j \geq 0 \end{aligned} \tag{2}$$

In equation (2): ρ is the ICEE value; S_i^-、S_r^+、S_k^- are slack variables of the input, desired output and unexpected output, respectively; λ is the weight vector.

2.3 ICEE Measurement Indicator System

This study selected 27 cities within the Yangtze River Delta urban agglomeration from 2011 to 2020 as the research objects. The data used includes statistical yearbooks from the official websites of the provincial governments of Jiangsu, Zhejiang, Anhui, and Shanghai, as well as statistical yearbooks and economic development statistical bulletins from various cities. For the indicator selection, this study selects the fixed asset stock of industrial enterprises in the year, the energy consumption of industrial enterprises, and the number of employees of industrial enterprises for input indicators. For output indicators, the value added of industry is chosen as the desired output, and industrial carbon emission is chosen as the non-desired output, and Table 1 displays the detailed indicator system for measuring ICEE.

Table 1 ICEE measurement indicator

Indicator	*Primary indicator*	*Secondary indicator*	*Unit*
Input indicator	Capital	Fixed capital stock	Billion yuan
	Labor force	Year-end employment	Million people
	Energy consumption	Industrial power consumption	kW/h
Output indicator	Expected output	Value added by industry	Billion yuan
	Unexpected output	Industrial CO_2 emissions	Million tons

Regarding the accounting method of carbon emissions, since the IPCC theoretical method is more detailed in classifying fuels for carbon emissions, such a technique offers a globally acknowledged approach to accounting for carbon emissions and has received endorsements from many researchers. (Yang et al., 2021). However, because there is only limited data available on the energy usage of different types of industrial enterprises in prefecture-level cities, the primary factor influencing industrial energy consumption is electricity usage. Therefore, industrial electricity consumption is selected as a substitute indicator for measuring the energy usage of enterprises. The quantification of industrial carbon emissions relies on the carbon emission factor data obtained from China's National Development and Reform Commission (NDRC), which is based on the average emissions of carbon in China's regional power grids. China's power grid locales are categorized into five distinct regions for this purpose, and in this study, the carbon emission factor of the east grid is selected to be multiplied with the industrial electricity consumption, which is to obtain the industrial carbon emissions of the respective cities.

2.4 Decomposition Modeling of Regional Differences in Industrial ICEE

Cities within the YRD exhibit diverse degrees of economic and industrial development across various areas, owing to disparities in geographical position, political status, population size, and resource endowment (Yin et al, 2023). This paper examines the variations in ICEE among different regions within the YRD urban agglomeration. It also offers recommendations for enhancing and modernizing industries in the YRD area, as well as strategies for conserving energy and reducing emissions. The coefficient of variation (CV) is a statistical metric that quantifies the extent of variation across observations from various samples. It is often used to describe the variations in geographic data over space and time, and may indicate the relative level of balance within a dataset. The coefficient of variation is chosen as the analytical technique to compute the regional disparity features of ICEE in the YRD urban agglomeration. The formula used for computation is:

$$CV = \frac{S}{\bar{E}} * 100\% = \frac{1}{\bar{E}}\sqrt{\frac{\sum_{i=1}^{n}(E_i-\bar{E})^2}{n-1}} * 100\% \quad (3)$$

In the above equation: CV represents the coefficient of variation, S represents the standard deviation of ICEE，$\bar{E}$ is ICEE average value，n is the city samples, E_i stands for the value of industrial ICEE of i city. The size of the coefficient of variation value is positively correlated with the variability, and the larger the value, the larger the gap, and vice versa.

2.5 Social Network Analysis

The relationship between ICEE and environmental impact factors in urban agglomeration encompasses not only elements such as sustainable economic growth and carbon emissions, but also the spatial disparities in industrial carbon emissions among various cities and the effectiveness of industrial carbon emissions within cities. A social network is a network of elements interacting with each other, with the flow of elements constituting the connecting lines between nodes, and the city nodes separated within the network acting as nodes. The YRD urban agglomeration has a dense transportation network, including the Shanghai-Nanjing Expressway, Shanghai-Hangzhou Expressway, and railroads. Although multiple modes of transportation have shortened the distance between cities, geographical distance is still a major obstacle to cross-regional economic development. In this study, the traditional gravity model is cited and modified by using the geographic distance between cities combined with economic level and population size as the basis for the social network of ICEE. This modified approach is a research model for measuring the strength of spatial correlation and constructing spatial correlation networks, as modeled below:

$$y_{ij} = \omega * \frac{\sqrt[3]{E_i P_i G_i}\sqrt[3]{E_j P_j G_j}}{D_{ij}^2/(a_i - a_j)^2} \tag{4}$$

$$\omega = \frac{E_i}{E_i + E_j} \tag{5}$$

In the above equation, y_{ij} is the intensity of spatial correlation of industrial ICEE of city i and j, E_i and E_j are ICEE of city i and city j, P_i and P_j are the number of employees in industrial enterprises of city i and city j, G_i and G_j are the GDP of industrial enterprises of city i and j, D_{ij}^2 denotes the geographic distance between city i and city j, a_i and a_j denotes per capita income of industrial enterprises in city i and city j.

In this study, the spatial correlation intensity of industrial ICEE in the YRD urban agglomeration, as determined by Equations (4)-(5), serves as the foundation for the individual and overall network structure analyses. Overall network structure is used to describe the overall evolution trend of the spatial network, including Network density, Network efficiency, Network hierarchy, Network connections; Individual network structure describes the significance and location of node cities within the network, and this paper mainly analyzes the network centrality, with indicators including Degree centrality, Closeness centrality, Betweenness centrality.

$$\text{Network Density} = \frac{\alpha}{n(\mathrm{n}-1)} \tag{6}$$

a is the number of connections, n is the total nodes of the network

$$\text{Network Efficiency} = \frac{1-P}{max\,P} \tag{7}$$

P and *max P* denote the number of connections between nodes and the maximum possible number of connections, respectively

$$\text{Network Connections} = 1 - \frac{N}{n \times (n-1)/2} \tag{8}$$

n is the nodes, N is the inaccessible node pairs

$$\text{Network Hierarchy} = \frac{1-C}{max\,C} \tag{9}$$

C and *max c* denote the symmetric accessible pairs and the maximum symmetric reachable pairs

$$\text{Degree centrality} = o/(n-1) \tag{10}$$

o denotes the quantity of nodes inside the network that are linked to a certain node

$$\text{Closeness centrality} = \left(\sum_{j=1}^{o} d_{ij}\right)/(n-1) \tag{11}$$

d_{ij} is the minimum distance of city *i* and *j*

$$\text{Betweenness centrality} = \frac{2\sum_{j=1}^{n}\sum_{i=1}^{n}[g_{ij}(k)/g_{ij}]}{(n-1)(n-2)} \tag{12}$$

$i \neq j \neq k$ and $j < k$, g_{ij} is the quantity of relations between city *i* and *j*, $g_{ij}(k)$ is the quantity of cities that traverse the relational path between cities *i* and *j*.

2.6 Evaluation of ICEE's influence factors

Due to the potential presence of multicollinearity in the variable data utilized in this research, employing the QAP (Quadratic Assignment Procedure) model for correlation and regression analysis is more reliable. The correlation analysis of QAP relies on the substitution of matrix data, whereby the components of two matrices are compared to compute the correlation coefficients between them. On the other hand, the regression analysis of QAP aims to examine the regression connection between a single matrix and numerous matrices. Referring to the existing research results (Shi & Xu, 2022; Wang et al., 2022; Jiang et al., 2022; Lin et al., 2023; Wang et al., 2021b), this study selects the following possible influencing factors: industrial structure, environmental regulation, rate of foreign investment, productivity level, research and development, and energy consumption intensity. In Table 2, the definitions of each variable are listed.

Table 2 Definitions of variables

Variables	*Variable names*	*Variable Descriptions*
IS	Industrial structure	Industrial GDP/Total GDP
ER	Environmental regulation	Investment in environmental control/Total GDP
FIR	Rate of foreign investment	Foreign Industrial Direct Investment/Total Industrial Investment
PL	Productivity level	Industrial added value/Number of employees in industrial enterprises
RD	Research and development	Industrial enterprises' R&D investment/Total industrial GDP
ECI	Energy consumption intensity	Industrial enterprises' energy consumption /Total industrial GDP

In this study, 2011-2020 is selected as the observation year, the mean value of the dependent variable (ICEE) from 2011 to 2020 is taken to build the mean matrix, and the mean value of each independent variable is taken to build the absolute difference to build the difference matrix, and the constructed QAP model is as follows:

$$Q = f(IS, ER, PL, RD, FIR, ECI) \tag{13}$$

In Equation (13), Q is the spatial network relationship of industrial ICEE in YRD urban agglomeration, IS denotes the industrial structure, ER denotes the environmental regulation, FIR denotes the rate of foreign investment, PL denotes the productivity level, RD denotes the research and development, and ECI denotes the energy consumption intensity.

3. Results and analysis

3.1 Measurement of ICEE

The ICEE of the YRD urban agglomeration is calculated through MaxDEAUltra software and super-SBM formulae (1) and (2), which take non-desired outputs into account. Table 3 displays the mean yearly growth rate of the index of ICEE for the 27 cities within the YRD urban agglomeration from 2011 to 2020, which stands at 1.12%, showing a stable growth trend, but the level of the ICEE varies significantly from city to city. This indicates that industries in the YRD urban agglomeration are gradually realizing sustainable development, and the differences among cities might be due to political status, geographic location differences, and natural and human resources. Shanghai has the highest average annual ICEE and Chizhou has the lowest, with a difference of 113.8% between the two cities. The reason is that Shanghai, as the economic center of China, not only has advanced industrial chain and senior technicians, but also the government's strict environmental protection policy makes its industrial enterprises have excellent environmental protection treatment equipment, so that its industrial industry can maintain high speed and green development. The mean yearly growth rate of ICEE of Suzhou is 13.08%, which is 17.49% higher than that of the last place, Tongling (-4.41%). This is because Suzhou is geographically close to Shanghai, and the economic development of Shanghai and Suzhou has formed a linkage. Among them, industrial development is rapid, and the input of Shanghai's high-tech resources has enabled Suzhou to maintain high-speed and high-quality economic development.

Table 3 YRD urban agglomeration ICEE from 2011 to 2020

City	*2011*	*2013*	*2015*	*2017*	*2020*	*Average*	*Rank*	*Annual change*
Shanghai	1.27	1.33	1.32	1.18	1.36	1.303	1	0.76%
Suzhou	0.41	0.47	0.72	0.81	1.24	0.759	6	13.08%
Nanjing	0.95	1.06	1.05	1.03	1.15	1.075	2	2.15%
Wuxi	0.74	0.79	0.62	0.64	1.09	0.767	5	4.40%
Nantong	0.24	0.31	0.29	0.23	0.31	0.277	17	2.88%
Changzhou	0.35	0.34	0.32	0.38	0.36	0.358	14	0.31%
Yangzhou	0.26	0.24	0.24	0.17	0.21	0.217	24	-2.35%
Yancheng	0.18	0.17	0.2	0.23	0.26	0.206	25	4.17%
Zhenjiang	0.27	0.24	0.23	0.2	0.28	0.243	21	0.40%
Taizhou	0.25	0.22	0.27	0.24	0.29	0.257	18	1.66%
Hangzhou	1	0.98	0.86	1.12	1.38	1.073	3	3.64%
Shaoxing	0.72	0.66	0.62	0.65	0.67	0.655	10	-0.80%
Ningbo	0.67	0.64	0.64	0.85	0.86	0.726	7	2.81%
Wenzhou	0.79	0.74	0.67	0.74	0.76	0.725	8	-0.43%
Huzhou	0.43	0.51	0.54	0.52	0.58	0.519	13	3.38%
Jiaxing	0.65	0.52	0.52	0.58	0.62	0.562	12	-0.52%
Jinhua	0.68	0.73	0.68	0.62	0.75	0.688	9	1.09%
Zhoushan	0.91	1.01	0.91	0.84	0.83	0.936	4	-1.02%
Taizhou	0.54	0.68	0.59	0.6	0.62	0.624	11	1.55%
Hefei	0.26	0.28	0.29	0.27	0.31	0.287	16	1.97%
Wuhu	0.3	0.28	0.27	0.2	0.21	0.256	19	-3.89%
Ma'Anshan	0.32	0.31	0.3	0.27	0.25	0.292	15	-2.71%
Tongling	0.3	0.26	0.25	0.22	0.2	0.242	22	-4.41%
Anqing	0.21	0.18	0.18	0.17	0.21	0.189	26	0.00%
Chuzhou	0.26	0.24	0.22	0.2	0.26	0.234	23	0.00%
Chizhou	0.18	0.15	0.15	0.14	0.2	0.165	27	1.18%
Xuancheng	0.22	0.21	0.27	0.25	0.24	0.244	20	0.97%
Average	0.49	0.50	0.49	0.49	0.57	0.51	/	1.12%

The temporal and spatial variation of ICEE in the urban agglomeration of YRD between 2011 and 2020 is compared in Figure 2. The value of ICEE is represented by the depth of the color, which can be seen that the spatial differentiation characteristics of the 27 cities are obvious. In general, the ICEE decreases in a gradient from the cities in the southeast to the cities in the northwest of the YRD, and this difference tends to widen when comparing 2011 and 2020. In 2011, the northern and western portions of the YRD urban agglomeration showed a concentration of cities with low ICEE values. Cities with medium efficiency were found in the southern part, while Shanghai, Nanjing, and Hangzhou comprised the majority of high-efficiency cities. The ICEE values for cities in the northern portions of the YRD urban agglomeration, as well as the majority of cities in the western portions, remain mostly at low levels in 2020. The reason for this is that these cities have a slower economic development, and they continue to depend on an economic development framework characterized by substantial resource use, excessive consumption, and significant emissions throughout the progression in advancing industrialization and urbanization. The ICEE in Shanghai, Suzhou, Nanjing and Hangzhou increase dramatically in 2020. The environmental Kuznets curve demonstrates that as economic development progresses, the environmental quality first deteriorates but eventually improves beyond a certain threshold of economic growth. Although these cities have the fastest industrial development, they have many universities and research institutes, well-developed emerging technology industries, and high resource utilization efficiency, leading to high ICEE, which ensures high-quality industrial development. A pattern has emerged in the YRD urban agglomeration, wherein the high-value core comprises Shanghai, Suzhou, Nanjing, and Hangzhou, while the ICEE progressively declines in the surrounding areas.

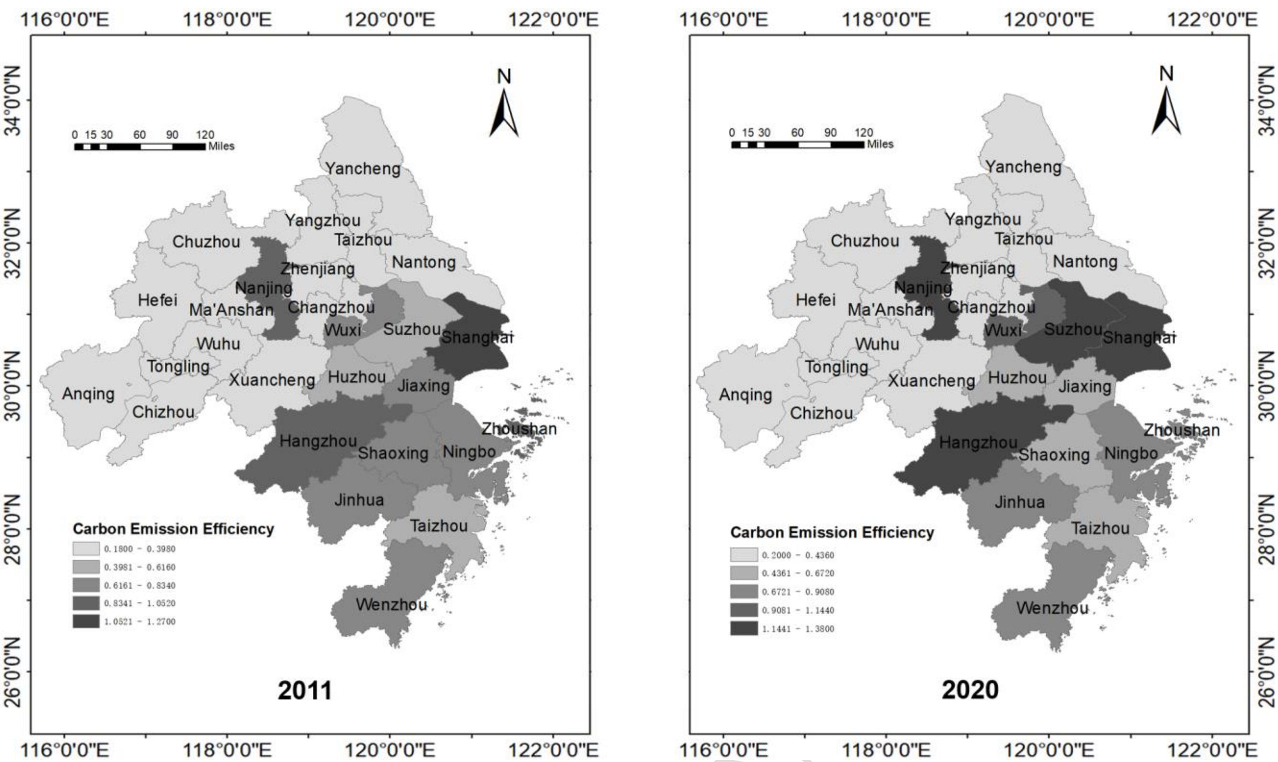

Fig. 2 ICEE spatial distribution of YRD urban agglomeration in 2011 and 2020

3.2 Analysis of spatial variability in ICEE

The coefficient of variation method is able to quantify the variability of ICEE between different regions and time periods by calculating the ratio of the standard deviation to the mean of ICEE data. Through standardization, data from different regions can be compared at the same scale, helping to analyze the unevenness of carbon emissions and thus providing a basis for subsequent model construction and prediction. The formula for calculating the coefficient of variation was combined with ArcGIS software and the natural breakpoint method was used to categorize the coefficient of variation into five classes, as shown in Figure 3, which are, in order, low volatility zone (0.0711-0.1790), lower volatility zone (0.1791-0.3121), medium volatility zone (0.3122-0.5771), higher volatility zone (0.5772-0.8242), and high volatility zone (0.8243-1.0945).

The coefficients of variation of ICEE changes in the YRD urban agglomeration range from 0.0711 to 1.0945, showing a trend of mostly low to medium fluctuations and less high fluctuations, with the degree of equilibrium decreasing from the north to the south, with significant geographical differences.

The high volatility and higher volatility areas are located in urban areas in central Jiangsu

Province and central Anhui Province, accounting for 33.3% of all cities, indicating that the ICEE spatial differences of the cities in this region are significant, which is attributed to the fact that these cities are resource-based cities within the urban agglomeration with rich coal mining resources and well-developed metallurgical industry, and in recent years, the Anhui Province government has implemented several policies pertaining to the metamorphosis of resource-based cities. Each city exhibits significant disparities in technological advancement and environmental restrictions, including the promotion of intelligent manufacturing and the growth of the new energy sector, so the cities have a big gap between the level of industrial development in recent years has led to differences in industrial ICEE.

Cities in the low volatility zone and the lower volatility zone are located in Zhejiang and the south of Jiangsu Provinces, accounting for 51.86% of the urban agglomeration, indicating that the ICEE spatial differences of the cities in this region are not significant since most of these cities are along the coast and have many harbors, and the foreign trade is well developed, and most of the cities are dominated by the manufacturing and processing industry in terms of economic development, and they have been the regions with the largest volume of trade in and out of China. The reason is that most of these cities are coastal and have many ports. Therefore, they have high similarity in industrial structure and technology level, which makes the ICEE between cities have small differences.

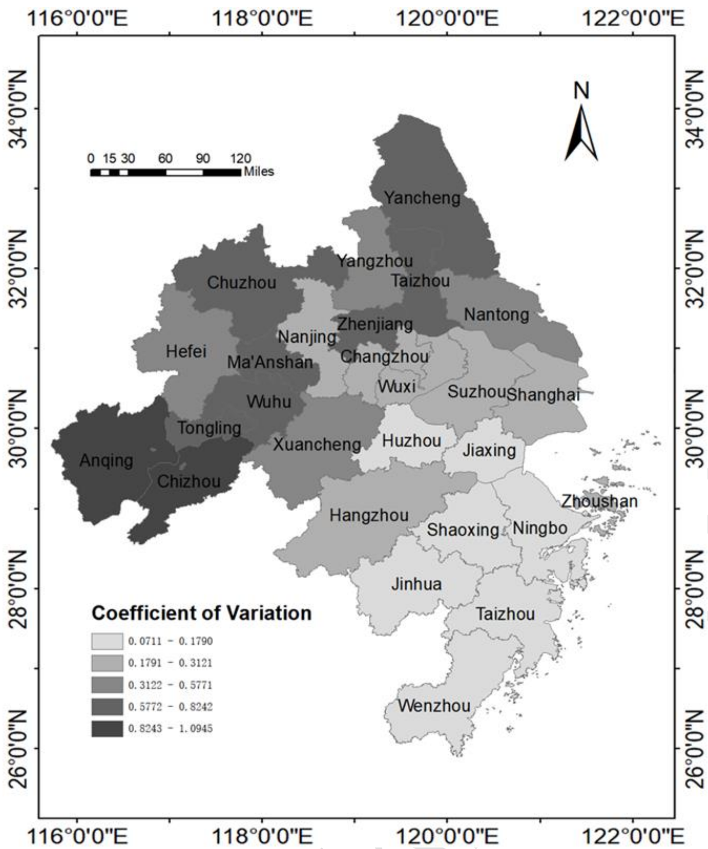

Fig. 3 Variation coefficient of ICEE from 2011 to 2020

3.3 Spatial correlation network structure of ICEE

The gravity matrix of every city in the YRD urban agglomeration is computed in this study utilizing a modified gravity model. The resulting network connection diagrams are then visualized in 2011 and 2020, with a total of 191 connections in 2011, and 196 connections in 2020. According to Figure 4, the YRD urban agglomeration ICEE shows a multilinear and multiflow network structure, in which Suzhou, Changzhou, Hangzhou, and Nanjing are centrally located inside the network and have a significant number of affiliations. These cities are in the center of the YRD urban agglomeration, they have perfect transportation facilities, convenient and fast flow of resources, and strong connections with other cities, while the other edge cities have relatively fewer affiliations and form a spatial network structure of "center-edge" with them.

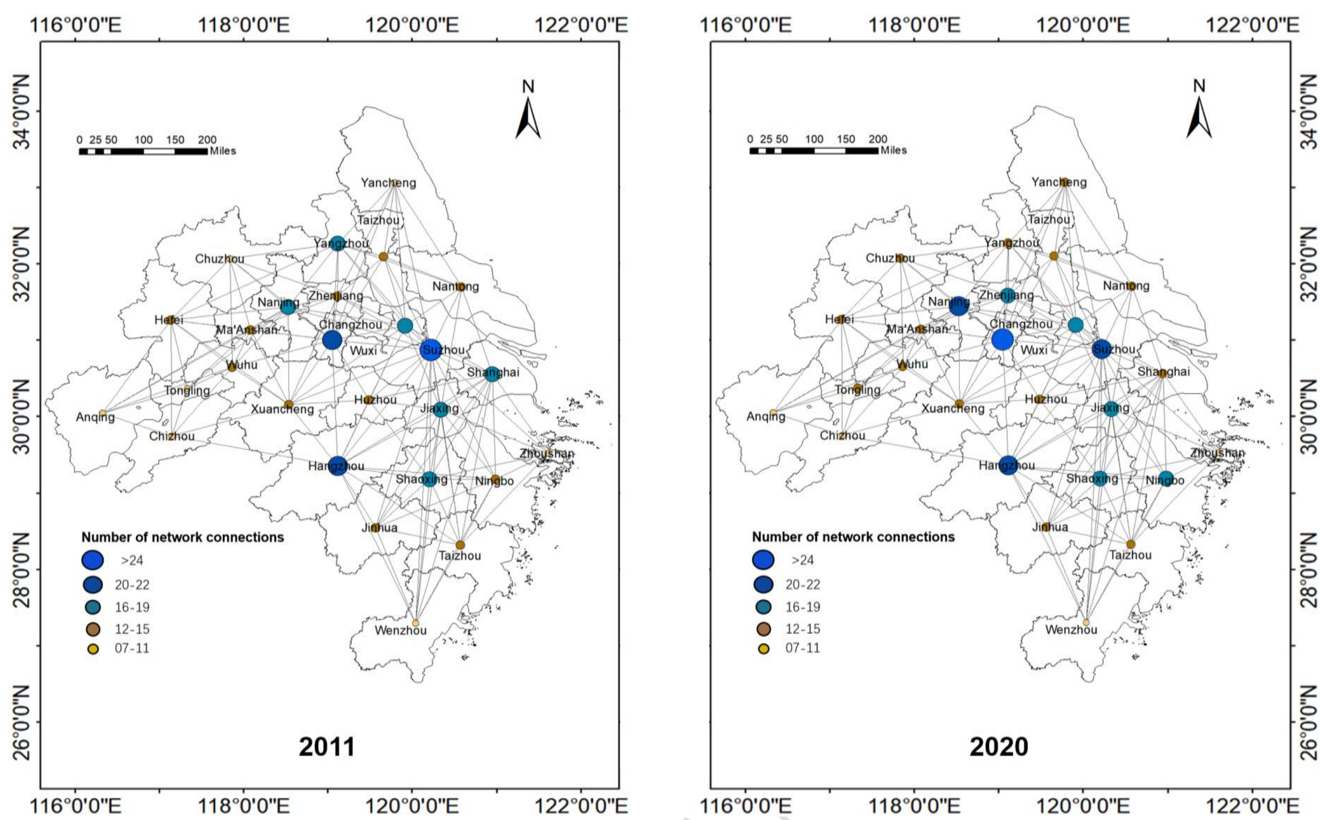

Fig. 4 ICEE spatial network structure in 2011 and 2020 in the YRD urban agglomeration

3.4 Overall Structural Characteristics

The values of the overall structural features' indicators for ICEE social network in the YRD urban agglomeration are computed using the Ucinet 6.0 software. According to Figure 5, there has been an increase in the quantity of spatial correlation network connections and network density of industrial ICEE in the YRD urban agglomeration of year 2011 and 2020. This shows that the spatial interactions of ICEE have strengthened and that the spatial network correlation of ICEE in the YRD urban agglomeration has been enhanced.

The increase of network connections indicates that the spatial correlation between nodes in the network is becoming increasingly close, and the factors such as capital, labor, and economic output will realize the full flow, so that the value of the number of network connections should be as large as possible. Although the number of network connections has increased to 196, there is a big gap of 506 from the total number of 702 relationships, which indicates that there is still significant potential for enhancing the spatial correlation connection of ICEE; if sufficient spatial correlation relationship has been formed among all cities in YRD urban agglomeration, then relying on the convenient flow channels of the factors, such as the developed railroads, high speeds, airlines, and river transportation, the YRD urban agglomeration will realize the optimal allocation of all kinds of factors related to ICEE. In addition, although the increase of network density is conducive to the enhancement of ICEE interactions, the connections exceed the capacity of ICEE spatial correlation network, which will impose constraints on the flow of factors related to ICEE in the YRD urban agglomeration, so the increase of network density should not be over-pursued, and the network density should be systematically raised in accordance with the assurance of a progressive rise in network connections.

The network hierarchy for the ICEE of YRD urban agglomeration has shown a gradual weakening trend from 0.5858 in 2011 to 0.5785 in 2019. This indicates that the hierarchical structure of the network is becoming less rigid, and the nodes that hold a dominant central position are losing their "controlling" role over time. The tendency suggests that the general stability for spatial correlation network of YRD urban agglomeration has been enhanced.

Figure 5 does not depict the spatial correlation network of ICEE within the YRD urban agglomeration due to the network correlation reaching a stable value of one. This indicates that all 27 node cities are located in the overall network for a long period of time, there is no unreachable node in the network, and the correlation network formed by ICEE has a high degree of robustness and a strong spillover effect.

Overall, the network efficiency of ICEE exhibits a marginal decline, with minor fluctuations observed throughout the period. By 2020, the network efficiency will have decreased from 49.45% in 2011 to 47.94%. This study concludes, in conjunction with an examination of the outcomes of high network density, high network correlation, and low network hierarchy, that the spatial correlation for ICEE of YRD urban agglomerations tends to be tighter. Each network node can be connected and thus form spatial correlation and generate spatial spillover. The cross-regional circulation of urban advantageous resources and industrial carbon emission spillover make the spatial correlation structure of ICEE relatively stable and develop in a balanced way.

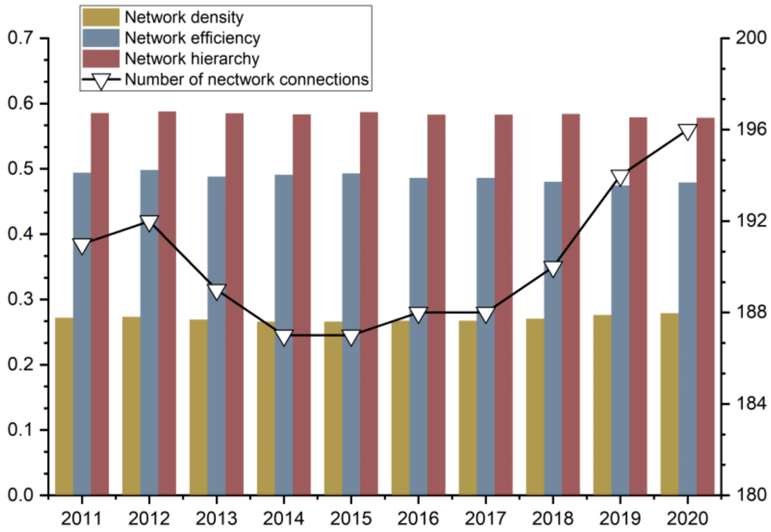

Fig. 5 Results of overall network characteristics indicators from 2011-2010

3.5 Individual network characteristics

In this paper, the individual networks (degree centrality, closeness centrality, betweenness centrality) of the ICEE in YRD urban agglomeration between 2011 and 2020 are measured using Ucinet 6.0 software, which reveals the roles of each city in the social network.

(1) Degree Centrality quantifies the centrality of a node in terms of its ability to hold a place within the network. In Table 4, In-Degree and Out-Degree correspond to accepting relationships and overflow relationships, respectively. The Centrality average value as a whole grows from 36.752 in 2011 to 37.322 in 2020. The cities of Shanghai, Nanjing, Hangzhou, Suzhou, Wuxi, Changzhou and Jiaxing have been at a level higher than the average, they are more connected to other cities and are at the center of the network of ICEE because they are more economically developed and have relatively good transportation facilities. This is due to the fact that these cities have greater economic development, have a superior geographic location, and have sound transportation facilities, which have created a "siphon effect" on neighboring cities. Tongling, Anqing, Chuzhou, and Chizhou are marginalized in the spatial correlation network because their ICEEs are less connected to other cities and their centrality values are lower than the average.

(2) The concept of closeness centrality quantifies the degree to which a node within a network is impacted by other nodes. A relatively insignificant change occurs as the aggregate average value of Closeness centrality rises from 47.04 in 2011 to 47.26 in 2020. Cities such as Nanjing, Wuxi, Changzhou, and Suzhou are larger than the average value, and these cities have the geographical

advantage of having a shorter distance from other cities, so that they can be connected to other cities quickly. The values in Tongling, Anqing, Chuzhou, and Zhoushan are all below the mean. These cities are situated at the periphery of YRD urban agglomeration, which is determined by their geographical location and level of economic development; consequently, their ICEE is less susceptible to the spillover effects of other cities.

(3) The concept of betweenness centrality is employed to quantify the extent to which a node in a social network exerts influence over other nodes. The overall average of Betweenness centrality ranges from 36.519 in 2011 to 33.037 in 2020. Cities such as Hangzhou, Changzhou, Nanjing, Suzhou, and Xuancheng are larger than the average, which are critical network nodes with substantial influence over the spatial connectivity of other nodes. The cities of Zhoushan, Wenzhou, Yancheng, Anqing, and Taizhou have significantly lower than average betweenness centrality, and have weaker control over the resources of other node cities. These cities are located on the periphery of the YRD urban agglomeration and have a limited economic foundation, which makes them unable to act as "intermediaries" for other node cities.

Table 4 Centrality analysis of social network of ICEE

City	***Degree Centrality***						***Closeness Centrality***		***Betweenness Centrality***	
	In-degree		***Out-degree***		***Centrality***					
Year	2011	2020	2011	2020	2011	2020	2011	2020	2011	2020
Shanghai	12	11	6	6	46.154	42.308	56.52	55.32	44.824	36.449
Suzhou	19	16	5	6	73.077	61.538	78.79	72.22	62.064	51.186
Nanjing	10	10	7	11	46.154	53.846	65.00	68.42	83.583	109.192
Wuxi	13	13	6	6	50.000	50.000	66.67	66.67	34.533	30.632
Nantong	6	7	7	5	26.923	26.923	52.00	50.98	31.204	19.594
Changzhou	14	17	7	8	53.846	65.385	68.42	74.29	85.650	104.678
Yangzhou	8	6	8	8	38.462	34.615	61.91	56.52	32.196	10.882
Yancheng	3	3	7	8	26.923	30.769	54.17	55.32	0.450	12.275
Zhenjiang	9	10	6	6	38.462	42.308	61.91	59.09	16.694	12.200
Taizhou	6	8	7	7	26.923	34.615	54.17	56.52	4.851	12.123
Hangzhou	9	10	11	10	50.000	53.846	66.67	68.42	144.180	150.974
Shaoxing	9	9	8	8	38.462	38.462	54.17	54.17	31.511	25.608
Ningbo	8	8	7	8	34.615	34.615	53.06	53.06	36.050	40.834
Wenzhou	2	2	8	7	30.769	26.923	52.00	47.27	0.000	0.167
Huzhou	5	6	7	7	30.769	30.769	56.52	59.09	32.090	22.371
Jiaxing	11	10	7	8	46.154	46.154	56.52	56.52	45.579	26.461
Jinhua	4	5	8	6	30.769	23.077	52.00	46.43	9.791	21.760

Zhoushan	1	1	6	6	23.077	23.077	49.06	49.06	0.000	0.000
Taizhou	6	5	8	7	34.615	30.769	53.06	48.15	16.993	7.104
Hefei	7	8	8	7	38.462	34.615	52.00	50.00	60.103	52.414
Wuhu	7	8	6	7	34.615	38.462	50.00	50.98	30.511	27.482
Maanshan	7	8	6	6	34.615	34.615	50.00	50.00	27.138	19.793
Tongling	4	4	6	7	23.077	26.923	44.83	48.15	18.028	17.283
Anqing	3	3	6	5	23.077	19.231	44.83	46.43	9.194	7.833
Chuzhou	3	3	7	8	26.923	30.769	49.06	50.00	22.403	2.293
Chizhou	2	2	6	8	23.077	30.769	52.00	56.52	19.160	11.638
Xuancheng	3	3	10	10	42.308	42.308	63.42	63.42	87.220	58.774
Average	7.07	7.26	7.07	7.26	36.752	37.322	56.25	56.04	36.519	33.037

3.6 Analysis of substructures within the YRD urban agglomeration

Based on the ICEE matrix in 2020, Ucinet 6.0 software was used to establish the Block model and use the CONCOR method for cohesive subgroup analysis, to explore the plate correlation relationship of ICEE spatial correlation network. The initial proposition of Block Model analysis was made by White in 1976 (White, 1976). This method enables the examination of the elemental transfer pathway and the placement of individual plates within a matrix network. As shown in Table 5, the matrix of 27 cities in YRD is divided into 4 plates.

There are a total of 196 associative relationships in the social network, of which 117 are In-flow relationships and 79 are Out-flow relationships.

Table 5 Plate correlations in spatial correlation networks of ICEE

Plates	***City***	***In-flow relation***		***Out-flow relation***		***Expected internal relationship***	***Actual internal relationship***
		Inside plate	***Outside plate***	***Inside plate***	***Outside plate***		
Plate I	Anqing, Chizhou, Chuzhou, Hefei, Ma’anshan, Tongling, Wuhu, Xuancheng	33	6	31	25	26.92%	28.21%
Plate II	Changzhou, Nanjing, Taizhou, Wuxi, Yancheng, Yangzhou, Zhenjiang	35	32	35	19	23.08%	29.91%
Plate III	Hangzhou, Jiaxing, Jinhua, Ningbo, Shaoxing, Taizhou, Whenzhou, Zhoushan	40	10	40	20	26.92%	34.19%
Plate IV	Shanghai, Suzhou, Nantong, Huzhou	9	31	9	15	15.38%	7.69%

Plate I contain a total of 33 internal relations, receives 6 relations from outside the plate, and sends out 25 relations. The quantity of relations sent out is greater than the received. The actual proportion of internal relations is 28.21% greater than the expected proportion of 26.92%, so Plate I is an "out-flow Plate".

Plate II has a total of 32 internal relations and receives 19 external relations. It only sends out 32 relations to outside the plate. The proportion of actual relations within the plate is 29.91%, which is higher than the expected proportion of 23.08%. Additionally, the cities within the plate have a higher number of relations both inside and outside the plate. Therefore, Plate II can be classified as a "bidirectional outflow Plate".

Plate III contains a total of 40 internal relations and receives 10 relations from outside the plate. It also sends out 20 relations outside the plate. The proportion of actual internal relations, which is 34.19%, is higher than the expected proportion of 26.92%. Therefore, Plate III is classified as an "agent Plate".

Plate IV has a total of 9 internal relations, 30 relations received from outside the plate, and 15 relations sent outside the plate. Therefore, the number of receiving relationships is significantly greater than the number of overflow relationships. The proportion of actual internal relationships is 7.69%, which is smaller than the expected internal relations of 15.38%. Thus, Plate IV is classified as an "inflow Plate".

Table 6 Density and image matrices for spatial correlation plates of ICEE

Plates	***Density matrix***				***Image matrix***			
	Plate I	***Plate II***	***Plate III***	***Plate IV***	***Plate I***	***Plate II***	***Plate III***	***Plate IV***
Plate I	0.589	0.375	0.031	0.063	1	1	0	0
Plate II	0.089	0.833	0.018	0.464	0	1	0	0
Plate III	0.016	0.054	0.714	0.5	0	0	1	1
Plate IV	0	0.286	0.219	0.75	0	1	0	1

In this paper, to explore the transmission law of the factors of ICEE changes, based on the above Table, the density matrix of four plates is computed and then transformed into the Image matrix. Any value in the density matrix that exceeds the overall density of the network (0.2792) is designated as 1, while all other values are allocated as 0. Further information can be found in Table 6. In the image matrix of the plate I, the value "1" points to plate II and has an internal correlation, which acts as an "outflow" plate and transmits the elements of ICEE growth to plate II. The cities in Plate I are mostly situated in the western region of the YRD urban agglomeration in Anhui province. These cities are considered economically underdeveloped compared to other cities, particularly in terms of industrial sector, while the seven cities in Plate II are in Jiangsu province, which is geographically close to the cities in plate I, and has always been relatively developed in the YRD urban agglomeration in terms of industrial industry, which has a high demand for the resources of cities in plate I. Plate II has an internal correlation, as a developed area of industrial industry, with a high degree of industrial agglomeration and mutual resource spillover between cities. Plate III has an internal correlation and points to plate IV, which regulates its own ICEE through the "outflow" and "inflow" of factors, and becomes the "agent plate" of the four plates. Plate IV, as an "inflow plate", has an internal correlation and points to Plate II, which, as a "bidirectional outflow plate", provides factors of ICEE growth to Plate IV. Being the most economically advanced area in the YRD urban agglomeration and China overall, it serves as the focal point for economic and social progress and exerts a "dominant" influence on the growth of high-efficiency industries. The ICEE of YRD urban agglomeration shows a clear "hierarchical" character.

4. Analysis of driving factors

4.1 QAP analysis

To analyze the driving factors through regression, the QAP model is employed. Prior to commencing the regression analysis, a correlation analysis of the influencing factors is conducted utilizing the QAP model. The presence of multicollinearity among the variables is evident in Table 6. In order to mitigate this issue, the QAP model is employed for the regression analysis. The correlation coefficients of environmental regulation, the rate of foreign investment, and R&D are all positively correlated at a 1% level of significance, as shown in Table 7. This indicates that the variables in question are extremely correlated with the ICEE correlation network. At the 10% significance level, the correlation coefficient of industrial structure is negative, indicating a negative correlation with the spatial correlation network of ICEE. The relationship between energy consumption intensity and productivity level is not influenced by the ICEE spatial correlation network.

Table 7 Correlation matrix between driving factors

Variables	*IS*	*ER*	*FIR*	*PL*	*RD*	*ECI*
IS	*1.000******	*0.846**	*0.544****	*0.241******	*0.058****	*0.174****
ER	*0.846**	*1.000******	*0.142*	*0.037**	*0.257****	*0.018******
FIR	*0.544****	*0.142*	*1.000******	*0.538**	*0.161****	*0.223**
PL	*0.241******	*0.037**	*0.538**	*1.000******	*-0.436**	*0.808******
RD	*0.058****	*0.257****	*0.161****	*-0.436**	*1.000******	*-0.457****
ECI	*0.174****	*0.018******	*0.223**	*0.808******	*-0.457****	*1.000******

Note: * * *, * *, * * are significant levels of 0.01, 0.05, and 0.1

4.2 QAP regression analysis

For the regression analysis on the driving factors of ICEE, 10,000 random permutations of the matrix were utilized. Parameter estimation and testing were then conducted to derive the regression results. The regression equation achieves an overall fit level of 0.507, signifying that six influencing factors account for 50.7% of the variance in the strength of spatial correlation among ICEE in YRD.

Table 8 QAP model analysis results

Variables	*Correlation Analysis*		*Regression Analysis*	
	Coefficient	*p-Value*	*Coefficient*	*p-Value*
IS	*-0.4019**	*0.077*	*-0.3816*	*0.879*
ER	*0.2620****	*0.000*	*0.3481***	*0.041*
FIR	*0.3971****	*0.003*	*0.3022****	*0.002*
PL	*0.0877*	*0.328*	*0.8230*	*0.341*
RD	*0.4450****	*0.000*	*0.4194****	*0.000*
ECI	*-0.3069*	*0.216*	*-0.2627*	*0.372*

Note: * * *, * *, * * respectively represent significant levels of 0.01, 0.05, and 0.1; R^2=0.507

The regression coefficient of the industrial structure matrix differences is negative and it is not significant, the industrial structure differences between cities have no significant effect on the strength of spatial correlation of industrial ICEE, which may be due to the fact that the industrial industry in the YRD urban agglomeration maintains a stable growth rate year-round and the internal industrial structure is fixed. This might be attributed to the consistent yearly growth rate of industrial sectors in the YRD urban agglomeration and the unchanging industrial composition. Matrix of Differences in Environmental Regulation is significantly positive at 5% level of significance, suggesting that variations in environmental regulation influence the spatial correlation of ICEE. This may be attributed to the tendency of industrial enterprises from cities with stringent environmental regulatory policies to relocate to cities with more lenient policies, thereby inducing a degree of carbon transfer. At the 1% significance level, the regression coefficient of the matrix of differences in the rate of foreign investment is substantially positive, showing that an increase in the foreign investment rate differences can strengthen the correlation of ICEE between cities, which may be due to the fact that foreign enterprises have exerted their technological outflow effect and played an exemplary leading role for local enterprises, which improves the correlation of ICEE. The regression coefficient for the Matrix of differences in productivity level is positive, but lacks statistical significance. This suggests that disparities in productivity do not have an impact on the establishment for the ICEE spatial correlation network, which means that different types of industrial industries have different forms and efficiencies of personnel organization and management systems, and specific ICEE correlations cannot be formed among cities. The regression coefficient of the Matrix of differences in R&D capabilities is positive at the 1% level significantly, cities with large differences in R&D promote the formation for spatial correlations of industrial ICEE. This may be due to the fact that in the process of industrial enterprises responding to the low-carbon transition policy, the expanding differences in low-carbon production technologies promote the flow of production technologies and senior technicians between cities, which strengthens the linkage of industrial ICEE. The regression coefficient of the Matrix of differences in energy consumption intensity is negative but lacks statistical significance, suggesting that energy consumption intensity does not have a major impact on the establishment of spatial correlation of ICEE in the YRD urban agglomeration. The reason for this might be attributed to the shift in the industrial chain of the YRD area from rapid expansion to a steadier growth phase. As a consequence, the level of energy consumption has also stabilized, leading to little variations in energy consumption intensity between cities.

5. Conclusions and policy recommendations

The ICEE of YRD urban agglomeration is assessed using the Super-SBM model between 2011 and 2020. The QAP model is then employed to examine the driving factors by analyzing the evolutionary characteristics of the spatial correlation network of ICEE of YRD urban agglomeration via the modified Gravity model and social network analysis. The following are the primary findings of this study: the average ICEE for the YRD urban agglomeration raised from a value of 0.49 in 2011 to 0.57 in 2020, exhibiting a varying upward trend. In general, the spatial differentiation features are clearly evident, with a noticeable overall pattern of a decreasing gradient from the southeastern cities to the northwestern cities. Moreover, the disparities between the cities are progressively growing with each passing year. The coefficient of variation of ICEE changes in the urban agglomeration of the YRD ranges from 0.0711 to 1.0945, showing a trend of predominantly low and medium fluctuations and less high fluctuations, with the degree of equilibrium decreasing from north to south, and there are significant geographical differences. The YRD urban agglomeration's ICEE has a spatial network correlation structure known as "center-edge," where Suzhou, Nanjing, Hangzhou, and Changzhou serve as the central hubs that extend their influence to the surrounding regions. The network density exhibits an increase from 0.2721 to 0.2792, suggesting a reinforcement of the spatial interaction of ICEE inside the YRD urban agglomeration. The network hierarchy exhibits a marginal decline from 0.5858 to 0.5785, indicating an improvement in the general stability of the spatial correlation network of ICEE in the YRD urban agglomeration. The total network efficiency exhibits a gradual decline. The QAP correlation study reveals that the matrix of variations in research and development, environmental regulation, and rate of foreign investment significantly affect the shape of the ICEE spatial correlation network. However, the matrix of variations in industrial structure, productivity level, and energy consumption intensity do not significantly affect the ICEE, and their influence mechanisms need to be further explored.

Given the above conclusions, to promote the smooth promotion of low-carbon development of industrial industries, combined with the obvious spatial correlation and heterogeneity of ICEE in the YRD urban agglomeration, this study proposes the following recommendations:

(1) Due to the high energy consumption of industrial sectors for YRD urban agglomeration and the ICEE spatial correlation, the development of industrial industries among cities not only depends on their energy resources, but also is influenced by the surrounding cities, so the government departments should act as intermediaries to facilitate the connection between industrial enterprises in different cities, and rationally allocate resources between different cities to ensure that the economy of resource-rich regions can continue to develop in a green and sustainable

way, while energy-poor cities can obtain the guarantee of energy supply, so that the cities in the YRD urban agglomeration can form the advantage of resource integration to improve the ICEE of the industry.

(2) Shanghai, Nanjing, Suzhou, and Hangzhou hold prominent positions within the individual social network and possess evident resource advantages. Under the coordination of the government, these cities can provide technical, personnel, and financial support to cities in other regions to ensure the reasonable flow of various resource elements. For cities with different levels of economic development, differentiated emission reduction policies should be implemented, and economically developed regions should take the lead in implementing regulations to reduce industrial carbon emissions to provide reference and experience for surrounding cities.

(3) In promoting the development of the environmental industry and optimizing the energy mix, inter-city collaboration can be promoted by identifying key city nodes, understanding their linkages and resource flows, and accelerating smart transformation and clean energy applications. This will help to optimize resource allocation, promote technology diffusion and assess the differences in carbon emissions between cities so that differentiated policies can be formulated to reduce reliance on traditional energy sources.

The empirical research in this paper has made some progress, but the validity of the results still needs to be further verified due to the limitations of the scope and focus of the study. The social network analysis method and modeling parameters used in this study may have certain errors, and the construction of the network structure and the setting of the node weights may fail to fully reflect the actual situation, resulting in certain bias in the results of the analysis of spatial relationships. This study focuses on the YRD urban agglomeration, and although the region has a high degree of economic activity and carbon emission representation, the findings may not be directly generalizable to other regions. In view of the limitations of this study, it is necessary for scholars in related fields to further deepen the research questions and continue to study them.

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Consent to Publish

All the authors agree to publish this paper in this journal.

References

Andersen, P., & Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science*, *39*(10), 1261–1264. https://doi.org/10.1287/mnsc.39.10.1261

Chen, W., Wang, G., Xu, N., Ji, M., & Zeng, J. (2023). Promoting or inhibiting? New-type urbanization and urban carbon emissions efficiency in China. *Cities*, *140*, 104429. https://doi.org/10.1016/j.cities.2023.104429

Feng, Y., Wang, X., & Liang, Z. (2021). How does environmental information disclosure affect economic development and haze pollution in Chinese cities? The mediating role of green technology innovation. *Science of The Total Environment*, *775*, 145811. https://doi.org/10.1016/j.scitotenv.2021.145811

Freeman, J., Baggio, J. A., Robinson, E., Byers, D. A., Gayo, E., Finley, J. B., Meyer, J. A., Kelly, R. L., & Anderies, J. M. (2018). Synchronization of energy consumption by human societies throughout the Holocene. *Proceedings of the National Academy of Sciences*, *115*(40), 9962–9967. https://doi.org/10.1073/pnas.1802859115

Gao, H., Li, T., Yu, J., Sun, Y., & Xie, S. (2023). Spatial correlation network structure of carbon emission efficiency in China's construction industry and its formation mechanism. *Sustainability*, *15*(6), 5108. https://doi.org/10.3390/su15065108

Herrala, R., & Goel, R. K. (2012). Global CO2 efficiency: Country-wise estimates using a stochastic cost frontier. *Energy Policy*, *45*, 762–770. https://doi.org/10.1016/j.enpol.2012.03.007

Hu, S., Yuan, Z., & Wang, A. (2024). Improving carbon emission efficiency in Chinese manufacturing: A study considering technological heterogeneity and noise. *Energy*, *291*, 130392. https://doi.org/10.1016/j.energy.2024.130392

Huang, Q., Chen, Q., Qin, X., & Zhang, X. (2023b). Study on the influence of industrial intelligence on carbon emission efficiency–empirical analysis of China's Yangtze River Economic Belt. *Environmental Science and Pollution Research*, *30*(34), 82248–82263. https://doi.org/10.1007/s11356-023-28160-1

Jiang, H., Yin, J., Qiu, Y., Zhang, B., Ding, Y., & Xia, R. (2022). Industrial carbon emission efficiency of cities in the Pearl River Basin: Spatiotemporal dynamics and driving forces. *Land*, *11*(8), 1129. https://doi.org/10.3390/land11081129

Kaya, Y., Yokobori, K. (1993) Global Environment, Energy, and Economic Development Held at the United Nations University, Tokyo, 10:25-27.

Li, S., & Wang, S. (2019). Examining the effects of socioeconomic development on China's carbon productivity: A panel data analysis. *Science of The Total Environment*, *659*, 681–690. https://doi.org/10.1016/j.scitotenv.2018.12.409

Li, Y., & Gao, K. (2022). The impact of green urbanization on carbon emissions: The case of new urbanization in China. *Frontiers in Environmental Science*, *10*. https://doi.org/10.3389/fenvs.2022.1070652

Li, Y., Wang, Y., Li, J., & Huang, Q. (2023). Global value chain embedding mode and carbon emission efficiency: Evidence from China's manufacturing industry. *Technological Forecasting and Social Change*, *194*, 122661. https://doi.org/10.1016/j.techfore.2023.122661

Lin, X., Cui, W., & Wang, D. (2023). The heterogeneous effects of environmental regulation on industrial carbon emission efficiency in China using a panel quantile regression.

Environmental Science and Pollution Research, *30*(19), 55255–55277. https://doi.org/10.1007/s11356-023-26062-w

Liu, Y., Guo, R., & Pan, W. (2023). Evaluation of carbon emission efficiency and spatial relevance in the thermal power industry: Evidence from China. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-023-03573-7

Lloyd, E. H., Hurst, H. E., Black, R. P., & Simaika, Y. M. (1966). Long-Term storage: An experimental study. *Journal of the Royal Statistical Society. Series A (General)*, *129*(4), 591. https://doi.org/10.2307/2982267

Mandelbrot, B. B., & Wallis, J. R. (1969). Robustness of the rescaled range R/S in the measurement of noncyclic long run statistical dependence. *Water Resources Research*, *5*(5), 967–988. https://doi.org/10.1029/wr005i005p00967

Marklund, P.-O., & Samakovlis, E. (2007). What is driving the EU burden-sharing agreement: Efficiency or equity? *Journal of Environmental Management*, *85*(2), 317–329. https://doi.org/10.1016/j.jenvman.2006.09.017

Mielnik, O., & Goldemberg, J. (1999). Communication The evolution of the “carbonization index” in developing countries. *Energy Policy*, *27*(5), 307–308. https://doi.org/10.1016/s0301-4215(99)00018-x

Ramanathan, R. (2002) Combining indicators of energy consumption and CO2 emissions: A cross-country comparison. *International Journal of Global Energy Issues*, 17(3), 214. https://doi.org/10.1504/ijgei.2002.000941

Shao, H., & Wang, Z. (2021). Spatial network structure of transportation carbon emission efficiency in China and its influencing factors. *Chinese Journal of Population, Resources and Environment*, *19*(4), 295–303. https://doi.org/10.1016/j.cjpre.2022.01.002

Shi, X., & Xu, Y. (2022). Evaluation of China’s pilot low-carbon city program: A perspective of industrial carbon emission efficiency. *Atmospheric Pollution Research*, *13*(6), 101446. https://doi.org/10.1016/j.apr.2022.101446

Sun, C., Li, Z., Ma, T., & He, R. (2019). Carbon efficiency and international specialization position: Evidence from global value chain position index of manufacture. *Energy Policy*, *128*, 235–242. https://doi.org/10.1016/j.enpol.2018.12.058

Sun, H., Kporsu, A. K., Taghizadeh-Hesary, F., & Edziah, B. K. (2020). Estimating environmental efficiency and convergence: 1980 to 2016. *Energy*, *208*, 118224. https://doi.org/10.1016/j.energy.2020.118224

Sun, W., & Huang, C. (2020). How does urbanization affect carbon emission efficiency? Evidence from China. *Journal of Cleaner Production*, *272*, 122828. https://doi.org/10.1016/j.jclepro.2020.122828

Wang, J., Sun, K., Ni, J., & Xie, D. (2021a). Evaluation and factor analysis of industrial carbon emission efficiency based on “green-technology efficiency”—the case of Yangtze River basin, China. *Land*, *10*(12), 1408. https://doi.org/10.3390/land10121408

Wang, K., Wu, M., Sun, Y., Shi, X., Sun, A., & Zhang, P. (2019). Resource abundance, industrial structure, and regional carbon emissions efficiency in China. *Resources Policy*, *60*, 203–214. https://doi.org/10.1016/j.resourpol.2019.01.001

Wang, L., Wang, Z., & Ma, Y. (2021b). Heterogeneous environmental regulation and industrial structure upgrading: Evidence from China. *Environmental Science and Pollution Research*, *29*(9), 13369–13385. https://doi.org/10.1007/s11356-021-16591-7

Wang, S., Wang, H., Zhang, L., & Dang, J. (2019). Provincial carbon emissions efficiency and its influencing factors in China. *Sustainability*, 11(8), 2355. https://doi.org/10.3390/su11082355

White, H. C., Boorman, S. A., & Breiger, R. L. (1976). Social structure from multiple networks. I. Blockmodels of roles and positions. *American Journal of Sociology*, *81*(4), 730–780. https://doi.org/10.1086/226141

Wu, D., Mei, X., & Zhou, H. (2024). Measurement and analysis of carbon emission efficiency in the three urban agglomerations of China. *Sustainability*, *16*(20), 9050. https://doi.org/10.3390/su16209050

Xie, N. Y., & Zhang, Y. (2022). The impact of digital economy on industrial carbon emission efficiency: Evidence from Chinese provincial data. *Mathematical Problems in Engineering*, *2022*, 1–12. https://doi.org/10.1155/2022/6583809

Xue, L.M., Zheng, Z.X., Meng, S., Li, M., Li, H., & Chen, J.M. (2021). Carbon emission efficiency and spatio-temporal dynamic evolution of the cities in Beijing-Tianjin-Hebei Region, China. *Environment, Development and Sustainability*, *24*(6), 7640–7664. https://doi.org/10.1007/s10668-021-01751-z

Yan, D., Lei, Y., Li, L., & Song, W. (2017). Carbon emission efficiency and spatial clustering analyses in China’s thermal power industry: Evidence from the provincial level. *Journal of Cleaner Production*, *156*, 518–527. https://doi.org/10.1016/j.jclepro.2017.04.063

Yin, H., Xiao, R., Fei, X., Zhang, Z., Gao, Z., Wan, Y., Tan, W., Jiang, X., Cao, W., & Guo, Y. (2023). Analyzing “economy-society-environment” sustainability from the perspective of urban spatial structure: A case study of the Yangtze River delta urban agglomeration. *Sustainable Cities and Society*, *96*, 104691. https://doi.org/10.1016/j.scs.2023.104691

Yuan, R., Xu, X., Wang, Y., Lu, J., & Long, Y. (2024). Evaluating carbon-emission efficiency in China’s construction industry: An sbm-model analysis of interprovincial building heating. Sustainability, 16(6), 2411. https://doi.org/10.3390/su16062411

Zeng, L., Lu, H., Liu, Y., Zhou, Y., & Hu, H. (2019). Analysis of regional differences and influencing factors on China’s carbon emission efficiency in 2005–2015. *Energies*, 12(16), 3081. https://doi.org/10.3390/en12163081

Zhang, N., Zhang, Y., & Chen, H. (2023). Spatial correlation network structure of carbon emission efficiency of railway transportation in China and its influencing factors. *Sustainability*, *15*(12), 9393. https://doi.org/10.3390/su15129393

Zhang, R., Tai, H., Cheng, K. T., Cao, Z., Dong, H., & Hou, J. (2021). Analysis on evolution characteristics and dynamic mechanism of urban green innovation network: A case study of Yangtze River economic belt. *Sustainability*, *14*(1), 297. https://doi.org/10.3390/su14010297

Zhang, R., Tai, H., Cheng, K., Zhu, Y., & Hou, J. (2022). Carbon emission efficiency network formation mechanism and spatial correlation complexity analysis: Taking the Yangtze River

Economic Belt as an example. *Science of The Total Environment*, *841*, 156719. https://doi.org/10.1016/j.scitotenv.2022.156719

Zhou, P., Ang, B. W., & Han, J. Y. (2010). Total factor carbon emission performance: A Malmquist index analysis. *Energy Economics*, *32*(1), 194–201. https://doi.org/10.1016/j.eneco.2009.10.003

Zhu, R., Zhao, R., Sun, J., Xiao, L., Jiao, S., Chuai, X., Zhang, L., & Yang, Q. (2021). Temporospatial pattern of carbon emission efficiency of China’s energy-intensive industries and its policy implications. *Journal of Cleaner Production*, *286*, 125507. https://doi.org/10.1016/j.jclepro.2020.125507