



Spatial correlation network structure of green innovation efficiency and its driving factors in the Bohai Rim region

Kaixuan Di¹ · Zuankuo Liu¹ · Shanglei Chai¹ · Kanyong Li² · Yu Li¹

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Abstract

As the integration point of green development and innovation-driven, green innovation has become the key to promote high-quality and sustainable development in the Bohai Rim region. This study calculates the green innovation efficiency (GIE) of 43 cities in the Bohai Rim region based on the super slacks-based measure (super-SBM) model, further using the social network analysis and quadratic assignment procedure analysis methods to explore the GIE spatial correlation network structure and its driving factors. The findings show that (1) the GIE between cities in the Bohai Rim region exhibits complex and stable network characteristics; (2) Beijing and Tianjin exert an important influence on the green innovation development of other cities; (3) each city is divided into four functional blocks, with strong spatial spillover effects between the blocks; and (4) the closer the geographical distance is, the more similar the environmental regulations are, and the easier it is for spatial associations to occur. The differences in the level of urban economic development, openness, human capital, and infrastructure are conducive to promoting the establishment of spatial associations. Finally, based on the conclusions, the study provides a theoretical basis and policy recommendations for improving the quality and efficiency of green innovation and collaborative development in the Bohai Rim region.

Keywords Bohai Rim region · Green innovation efficiency · Social network analysis · Super-SBM model · QAP analysis

✉ Zuankuo Liu
liuzuankuo@sdu.edu.cn

Kaixuan Di
dikaixuan2021@163.com

Shanglei Chai
shanglei@yahoo.com.cn

Kanyong Li
likanyong2018@163.com

Yu Li
sdnuly2021@163.com

¹ Business School, Shandong Normal University, Jinan 250358, Shandong, China

² School of Economics and Management, Shandong Jiaotong University, Jinan 250358, Shandong, China

1 Introduction

As a new driving force of economic growth, green innovation is not only an internal driving force that promotes high-quality economic development but also an important means of reducing carbon emissions (Edziah et al., 2022; Luo et al., 2020; Sun et al., 2019). With the rapid development of urbanization, urban agglomeration has become the spatial carrier of Chinese economic growth, and urban green innovation system is an important force for national economic development and global competition (Hu et al., 2022). The report of the 19th National Congress of the Communist Party of China clearly pointed out that the country should unswervingly implement the new development concepts of innovation, coordination, green, openness, and sharing. At the same time, it also stressed establishing a more effective new mechanism for coordinated regional development, thereby improving the efficiency of resource allocation and enhancing the synergy, linkages, and integrity of regional development. Therefore, green innovation and coordinated development have become one of the important themes of the sustainable development of urban agglomeration.

As one of the areas covered by the Beijing–Tianjin–Hebei coordinated strategy, “Belt and Road” construction, the transformation of old and new drivers, and the revitalization of northeast industries, the Bohai Rim region is one of three growth poles with the most comprehensive strength and development potential in China. From 2005 to 2021, the gross domestic product (GDP) of the Bohai Rim region increased from 4.32 trillion to 20.7 trillion. The Bohai Rim region plays an important role in driving the economic development of northern China and changing the unbalanced and inadequate development situation of China, which is strong in the south and weak in the north. However, with the rapid progress of industrialization and urbanization, environmental pollution, overcapacity, resource shortages, and regional development disharmony have become prominent. For example, in 2021, the industrial smoke emissions in the Bohai Rim region accounted for 25.07% of the national total, and the per capita GDP in Beijing was 3.4 times that of Hebei. These problems have seriously restricted the sustainable and coordinated development of the Bohai Rim region. *The Outline of Cooperation and Development in the Bohai Rim Region (2015)* proposed implementing policies such as scientific and technological innovation, ecological protection, and coordinated development. It is an inevitable trend that high-quality, sustainable, and coordinated development of the Bohai Rim economy will be driven by green innovation. Many existing studies have explored regional green innovation efficiency (GIE). From the perspectives of measurement methods, it mainly includes parametric stochastic frontier analysis (SFA) (Piao et al., 2022) and nonparametric data envelopment analysis (DEA). DEA is widely used in the research of green innovation efficiency, and many optimization models have been derived from it, such as the directional SBM-DEA model (Long et al., 2015) and SBM-DDF model (Zhang et al., 2020). From the perspectives of study object, the studies are conducted of national (Liao et al. 2023; Zhang et al., 2022a, 2022b), the great Changsha-Zhuzhou-Xiangtan city group (Wang et al., 2021), and the Yangtze River Delta areas (Zeng et al., 2021a, 2021b). From the perspective of influencing factors, econometric methods were used to quantitatively analyze the influencing factors of green innovation efficiency from industrial agglomeration (Liu et al., 2023; Zeng et al., 2021a, 2021b), financial investment in science and technology (Li et al., 2022a, 2022b), economic development level (Zhang et al., 2020, 2022a, 2022b), and other indicators.

In recent years, with the development of science, technology, and transportation infrastructure, geographical constraints have gradually weakened, and the flow of green innovation

elements such as people, finance, goods, and knowledge between cities has accelerated, which shows a strong spatial correlation feature. Most scholars use attribute data to explore the spatial effect of green technology innovation from the perspective of geographic "adjacency." Liao and Li (2023) used Moran index and spatial econometric models to analyzing the spatial effect of urban green innovation efficiency of China and found that the spillover effect of urban green innovation efficiency can have a significant demonstration effect on the surrounding areas. Zhao et al. (2021) and Zeng et al., (2021a, 2021b) introduced a spatial econometric model into the convergence analyses, chose China and the Yangtze River Delta cities, respectively, as a research sample and found spatial factors accelerate the convergence of China's green innovation efficiency. Recently, as human and economic geographers apply social network analysis (SNA) to innovation research, some scholars start to explore the spatial correlation characteristics of GIE using relational data and its driving factors. Fan et al. (2021) analyzed the spatial correlation network of China's green innovation by using SBM-DDF model and the SNA model verified the existence of spatial effects in China's green innovation correlation network. Liu et al. (2021) and Liang et al. (2022) explored the impacts of influencing factors on the green innovation efficiency of Chinese provinces and 144 countries, respectively. So, Given the background of economic agglomeration and unbalanced development in Bohai Rim region, the study issues come in mind: what is the status and function of the cities in the Bohai Rim region in the green innovation network structure? What are the characteristics of spatial correlation network? How about correlated conduction and spillover paths? What are the driving factors affecting the evolution of network structure?

Exploring above problems is conducive to promoting the coordinated and sustainable development of the Bohai Rim region. By answering these questions, the study constructs spatial association network by using modified gravity model based on the GIE of 43 cities in the Bohai Rim region from 2005 to 2020, explores the GIE spatial association network structure and its driving factors by using SNA and QAP analysis methods. The marginal innovation and contribution of the study have the following three points: First, the study adopts super-SBM model to measure GIE, compared to other measure methos, super-SBM not only solves the angular and radial problems but also effectively deals with the efficiency sequencing problem of decision-making units. Second, the study modifies the gravity model by merging in geographic economic distance, compared to the traditional gravity model, it can better reflect spatial correlation. Third, from the perspective of relational data, the paper selects three different years to explore the influencing factors of the spatial structure of GIE in the Bohai Rim region by using QAP analysis method and analyze the changing characteristics of the influencing factors. This study can provide scientific basis for the theory of regional sustainable development and regional collaborative development and can also provide reference for other similar regions.

The rest of this study is organized as follows. Section 2 describes model and data. Section 3 presents analysis of GIE and its spatial correlation network structure in the Bohai Rim region. Section 4 analyzes the driving factors of the GIE spatial correlation network in the Bohai Rim Region. Section 5 presents conclusion and discussion. The roadmap of the study is shown in Fig. 1.

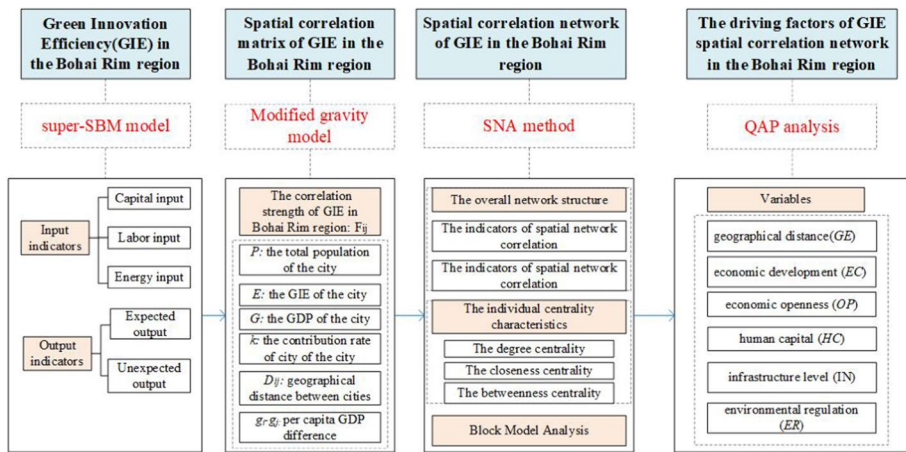


Fig. 1 The roadmap of the study

2 Method model and data

2.1 GIE measurement—super-SBM model

Drawn on the measurement method of carbon emission efficiency (Sun et al., 2023), this paper uses super-SBM model to calculate the GIE of 43 prefecture-level cities in the Bohai Rim region from 2005 to 2020 by using MaxDEA 8 Ultra. The super-SBM model is an optimization model of DEA and it is oriented around technical optimization (Liu et al., 2023) compared with SFA. Compared to other DEA methods, it not only solves the angular and radial problems but also effectively deals with the efficiency sequencing problem of decision-making units, thus achieving effective comparability of production frontiers (Jiang et al., 2021; Liu et al. 2019; Wang et al., 2022a, 2022b).

For the measurement indicators of GIE in Bohai Rim region, index introduction and selection basis and data source are as shown in Table 1. The economic data, such as science and technology expenditure, education expenditure, regional GDP, and price index deflation, was carried out based on price index in 2005 to eliminate the impact of price fluctuations. For the missing data, on the one hand, we searched from *China Environmental Statistical Yearbook*, the statistical bulletins of national economic and social development, and government work reports, and the remaining missing data were supplemented by the interpolation method.

2.2 Network construction—Modified gravity model

The establishment of relationships is the basis of network construction (Liu et al., 2017). The existing literature mainly uses the modified gravity model and the vector auto regression (VAR) model to judge the correlation relationship between individuals and then constructs the spatial correlation matrix. Because the VAR model is sensitive to the selection of lag order, it cannot accurately describe the dynamic evolution of the spatial correlation

Table 1 GIE indicators system in Bohai Rim region

First-level indicators	Secondary indicators	Unit	Selection basis	Date source
Capital input	Science and technology expenditure, education expenditure	10,000 yuan	(Zeng et al., 2021a, 2021b)	<i>China Urban Statistical Yearbook</i>
Labor input	Scientific and technical service personnel, water conservancy personnel	Persons	(Zeng et al., 2021a, 2021b)	<i>China Urban Statistical Yearbook</i>
Energy input	Total power consumption	10,000 kWh	(Shen et al., 2022)	<i>China Urban Statistical Yearbook</i>
Expected output	Weighted average value of invention patents, utility model patents and appearance patents (synthesized at the ratio of 0.5, 0.3 and 0.2)	–	(Bai et al. 2016)	<i>Enterprise Survey for Innovation and Entrepreneurship in China</i>
	GDP	RMB 100 mn	(Liu et al., 2023)	<i>China Urban Statistical Yearbook</i>
	Green coverage rate	%	(Dong et al., 2021)	<i>China Urban Statistical Yearbook</i>
Unexpected output	The output of industrial “three wastes” (waste water discharge, industrial smoke, industrial sulfur dioxide discharge, calculated by entropy weight method)	–	(Zhang et al., 2022a, 2022b)	<i>China Urban Statistical Yearbook</i>

network structure (Fan et al. 2021). Most gravity model only focus on geographical distance, drawn on the research of Wang et al., (2022a, 2022b), the study modified the gravity model by incorporating GIE and economic geographical distance to calculate the spatial correlation strength of GIE among 43 prefecture-level cities in the Bohai Rim region, thus better revealing the characteristics of spatial correlation network. The formula is as follows:

$$F_{ij} = k_{ij} \frac{\sqrt[3]{P_i \times E_i \times G_i} \sqrt[3]{P_j \times E_j \times G_j}}{\left(\frac{D_{ij}}{g_i - g_j}\right)^2}, k_{ij} = \frac{E_i}{E_i + E_j} \quad (1)$$

In formula (1), i and j represent prefecture-level cities in the Bohai Rim region. E represents the GIE of the city. F_{ij} is the correlation strength of GIE between cities i and j . P is the total population of the city at the end of the year. G represents the actual GDP of the city. g is the per capita GDP of the city, and K_{ij} represents the contribution rate of city i to F_{ij} (Fan et al. 2021). The data of P and GDP are obtained from *China Urban Statistical Yearbook* mentioned above. The geographical distance data, which represents the shortest driving distance between local and municipal governments, is obtained from the Open Platform API of Baidu Maps.

According to formula (1), we calculate the gravitation matrix between cities in the Bohai Rim region and set the average value of the row as the threshold value. If the gravitation value is higher than the threshold value of the row, it is set as 1 and otherwise 0. The two values, respectively, indicate whether there is any spatial correlation between the GIE of the corresponding cities in the row (1 = yes; 0 = no), finally forming a directed binary spatial correlation matrix of 43*43.

2.3 Analysis of GIE spatial correlation network—SNA method

SNA, which is a research method of studying and mapping social structures through graph theory (Lv et al., 2023), is widely used in social science fields, such as personality and social psychologists (Clifton et al. 2017), supply chain management (Wichmann et al. 2016), tourism competitiveness (Tan et al., 2023), project management (Zaefarian et al., 2022). At the same time, some scholars introduce SNA to efficiency studies such as innovation efficiency (Fan et al. 2021) and energy efficiency (Liu et al., 2023). The spatial correlation matrixes of GIE are processed by Ucinet 6.2, and then, the study employs SNA method to explore the spatial correlation network of GIE in the Bohai Rim region, including the overall network structure characteristics, individual centrality characteristics, and block model of the spatial correlation network.

The overall network structure characteristics mainly measure the network density, the number of correlation relationships, the network correlation degree, the network efficiency, and the network hierarchy; we then clarify the spatial correlation strength and spatial correlation network of GIE. The individual centrality characteristics are measured by the degree centrality, intermediate centrality, and closeness centrality to explore the power and role of node cities in the GIE spatial correlation network in the Bohai Rim region. The block model can be used not only to describe the clustering characteristics of the GIE spatial correlation network in the Bohai Rim region but also to explore the role and position of each city in the network, thus revealing the internal characteristics and spillover path of the spatial correlation network and further exploring the synergy of GIE between different

sectors (see the references for the relevant indicators and formulas involved in the network analysis) (Liu et al., 2021; Zhang et al., 2022a, 2022b).

2.4 The driving factors of the GIE spatial network—QAP analysis method

The QAP analysis method takes “relational data” as the analysis object without requiring strict independence between variables, and its parameter estimation results are more robust than traditional measurement methods. Because the formation of the spatial correlation network is driven by a variety of factors and there is a certain correlation between these factors, it cannot satisfy the statistical “variable independence hypothesis (Doreian et al. 2012). Therefore, this paper uses QAP analysis method to study the driving factors of the GIE spatial correlation network in the Bohai Rim region. The QAP analysis model is constructed as follows:

$$Q = f(GL, EC, OP, HC, IN, ER) \quad (2)$$

where Q represents the GIE spatial correlation matrix in the Bohai Rim region, which is calculated using the modified gravity model. Geographical distance has an important influence on the costs of transmission of innovation elements between cities (Feng et al., 2022), GL represents the geographical distance matrix measured using the shortest driving distance between the two cities’ municipal governments. The level of economic development is closely related to the network structure of innovation efficiency (Sun et al. 2017). EC represents the difference in economic development level, measured in terms of the per capita GDP of each city. Economic openness can facilitate the flow of innovative resources, improving the degree of innovation linkages between cities (Sun et al. 2022). OP represents the difference in economic openness, measured as the ratio of the actual utilization of foreign capital to the GDP of each city. Human capital is one of the most important elements of innovation, which plays an important role in innovation correlation (Lu et al., 2022). HC represents the difference in human capital, with the average years of education for each city used as the proxy variable. The improvement in infrastructure can promote the exchange of urban innovation elements (Wang et al. 2020). IN represents the difference in infrastructure level, measured using the actual road area of each city at the end of the year. As the driving force for enterprises to engage in green innovation, environmental regulation has an important impact on the correlation of urban green innovation (Li et al., 2022a, 2022b). ER refers to the difference in environmental regulation, which is measured in terms of the environmental regulation intensity of each city. The environmental regulation intensity is calculated using the averages of the comprehensive utilization rate of industrial solid waste and the centralized treatment rate of sewage. The data of GL are obtained from the Open Platform API of Baidu Maps, and the initial data of other variables are obtained from *China Urban Statistical Yearbook* and *China Environmental Statistical Yearbook*.

3 Analysis of GIE spatial correlation network

The GIE results of Bohai Rim region from 2005 to 2020 were analyzed from the perspective of three provinces and two cities, which includes Beijing, Tianjin, Hebei, Shandong, and Liaoning as shown in Fig. 2.

During the sample period, GIE showed an overall upward trend of fluctuations, and its average value basically remained in the 0.75–0.93 range. Compared with the average GIE

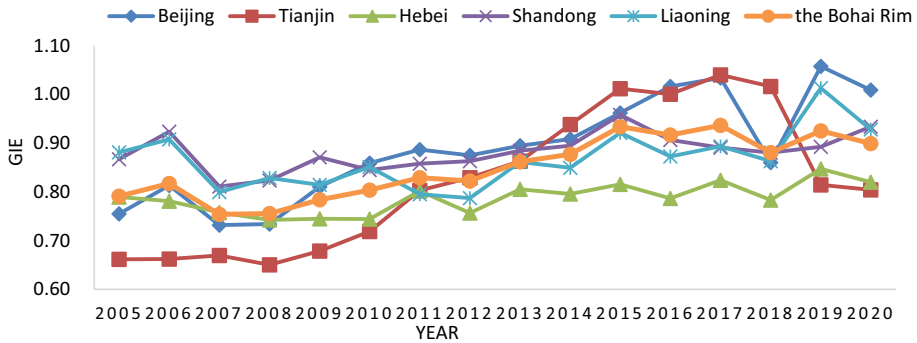


Fig. 2 Average trend of the change in GIE in the Bohai Rim region from 2005 to 2020

of the Bohai Rim region, the efficiency of green innovation in each region shows obvious spatial disequilibrium: (1) Beijing and Shandong have excellent economic conditions, profound scientific research backgrounds, numerous universities, and a high level of GIE development. (2) The economic development level of cities in Hebei is relatively backward, and the weak competitiveness of talent leads to insufficient innovation. GIE is lower than the average in this study. (3) The GIE of Tianjin and Liaoning showed fluctuating changes compared with the average value in the sample period. The GIE of Tianjin showed an increasing trend in the early stage of the sample but a downward trend at the end of the study, and the GIE of Liaoning showed a downward trend at first and then a rebound trend.

3.1 Analysis of overall network characteristics

Due to space limitations, this paper selects three sections in 2005, 2012, and 2020 and uses ArcGIS10.8 to draw the spatial correlation network diagram. From Fig. 3, we can see that the efficiency of GIE among the regions in the Bohai Rim region is tightly networked, showing complex and stable network characteristics, along with a significant imbalance and a clear center-periphery structure. We also note that the spatial correlation of GIE is no longer limited by traditional geographical space; it exhibits spatial correlation not only with the GIE of adjacent cities but also with non-adjacent cities.

Beijing and Tianjin were firmly at the core of the GIE connection network in this region. As time went by, the number of spatial connections between their GIE and other cities increased. The influence of the Beijing-Tianjin region on the GIE of the Bohai Rim region increasingly strengthened, reflecting the effectiveness of the implementation of the policies outlined in the *Outline of Cooperation and Development in the Bohai Rim Region* and *Opinions on Establishing a More Effective New Mechanism for Regional Coordinated Development*. Beijing and Tianjin acted as the center and led the development of the Beijing-Tianjin-Hebei urban agglomeration, promoting the coordinated development of the Bohai Rim region.

The overall characteristics of the GIE network in the Bohai Rim region can be described in terms of two aspects: spatial correlation intensity (network density, number of correlation relations) and spatial network correlation (network correlation degree, network efficiency, network level).

Spatial correlation strength. As shown in Fig. 4, the maximum values for network density and the number of correlations appeared in 2014, which were 0.194 and 351,

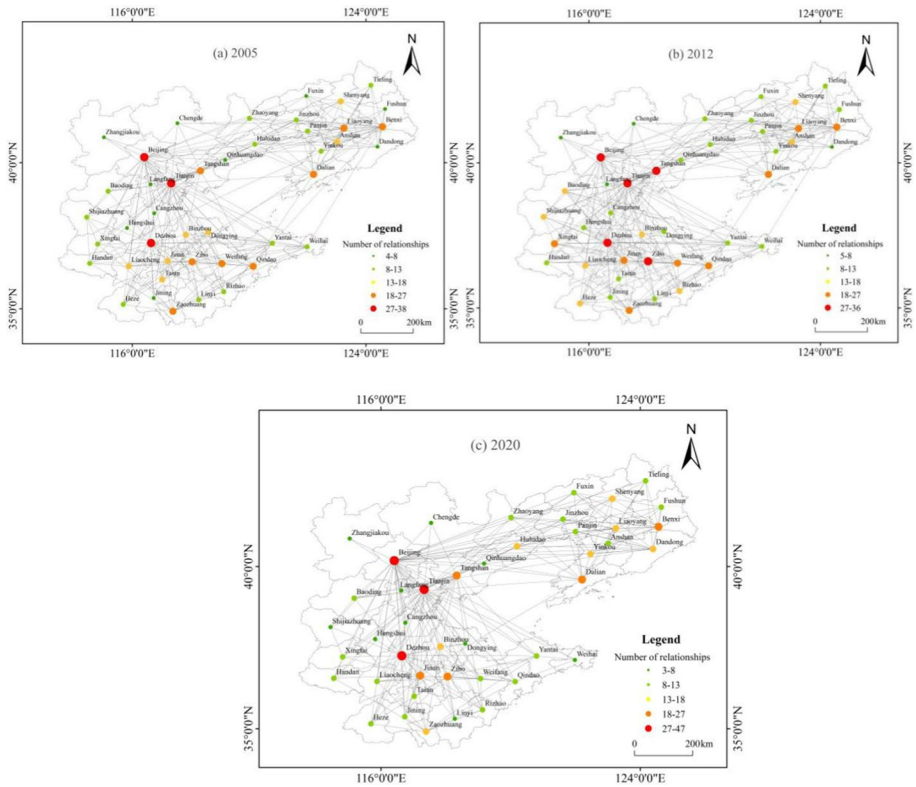


Fig. 3 GIE spatial correlation network in the Bohai Rim region in 2005, 2012, and 2020

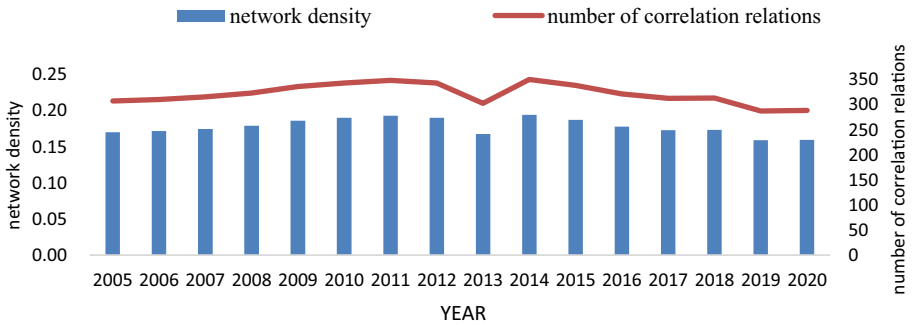


Fig. 4 Temporal evolution of space correlation strength

respectively. However, there was still a big gap between them, as well as between the theoretical maximum network density of 1 and the maximum correlation number of 1806, indicating that the spatial network of urban GIE in the Bohai Rim region still had abundant room for optimization and that the collaborative development of regional green innovation needs to be strengthened.

Spatial network relevance. As shown in Fig. 5, during the sample period, the degree of GIE network correlation in the Bohai Rim region always remained at 1, indicating that the overall GIE network structure in the region was relatively stable with good connectivity and accessibility. The network level was low and the change range not large, indicating that GIE spatial networks among cities in the region had relatively stable correlation relationships and that there were no obvious network-level characteristics. The network efficiency shows a slight upward trend from 2005 to 2020, indicating that the network stability decreased, and GIE collaborative development among cities in the Bohai Rim Region becomes an urgent problem to be solved.

3.2 Analysis of individual centrality

The SNA method adopted in this paper facilitates not only analyzing the characteristic evolution of the overall GIE correlation network in the Bohai Rim region, but also discussing the status and role of each node city across the entire spatial correlation network and then analyzing the influence of green innovation efficiency of each city on the GIE spatial correlation network. Accordingly, this section evaluates the degree centrality, closeness centrality, and betweenness centrality of each city. The specific results are shown in Table 2.

First, the degree centrality is used to represent the degree of the GIE spatial correlation network center in the Bohai Rim region. As shown in Table 2, The out-degree of each city in the region is greater than 0, indicating that the GIE of each city has a spatial spillover effect. From the perspective of the time evolution trend, we can see that for 2005, 2012, and 2020, the average values of the degree centrality show a slight downward trend overall. The top three cities in terms of degree centrality have changed slightly, although Beijing and Tianjin have always been in the top two. Meanwhile, since 2012, Tangshan has replaced Benxi as third in the rankings, gradually highlighting the core position of the Beijing-Tianjin-Tangshan Industrial Base, one of the four major industrial zones in China, in the Bohai Rim region. Overall, the GIE spatial correlation network in the region is obviously unbalanced and asymmetric, indicating that the matching degree of GIE supply among cities is not high, and there is an imbalance in the allocation of green innovation elements among cities in the region.

Second, closeness centrality is used to judge the difficulty of GIE spatial correlation between cities. From the perspective of time trends, during the sample period, Beijing and Tianjin's inner closeness centrality was always among the top three and had the greatest

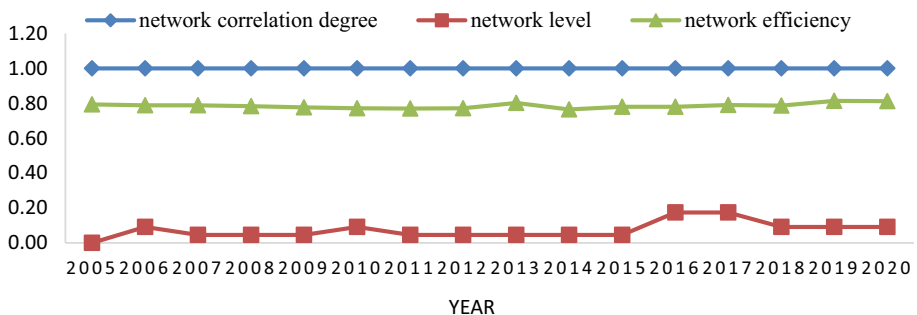


Fig. 5 Temporal evolution of GIE spatial correlation

Table 2 Centrality analysis of GIE spatial correlation structure in Bohai Rim region

Region	2005				2012				2020			
	Out-degree	In-degree	Degree centrality		Out-degree	In-degree	Degree centrality		Out-degree	In-degree	Degree centrality	
Beijing	7	31	73.81		7	28	66.67		7	40	95.24	
Tianjin	7	28	69.05		6	30	71.43		5	28	66.67	
Shijiazhuang	6	5	16.67		9	5	21.43		5	3	11.91	
Tangshan	10	12	38.10		13	15	47.62		7	17	45.24	
Qinhuangdao	6	1	14.29		8	2	19.05		5	3	14.29	
Handan	9	2	21.43		9	4	21.43		7	2	16.67	
Xingtai	8	3	19.05		10	9	28.57		7	4	16.67	
Baoding	5	6	14.29		5	12	28.57		2	7	16.67	
Zhangjiakou	3	1	7.14		4	2	9.52		2	1	4.76	
Chengde	4	3	11.91		5	3	14.29		3	1	7.14	
Cangzhou	3	4	9.52		4	6	14.29		4	4	9.52	
Langfang	2	3	7.14		2	3	7.14		2	3	7.14	
Hengshui	3	2	7.14		4	9	21.43		3	1	7.14	
Jinan	10	8	28.57		13	8	33.33		9	11	30.95	
Qingdao	10	10	30.95		11	11	33.33		8	4	21.43	
Zibo	8	14	33.33		14	16	42.86		9	11	28.57	
Zaozhuang	9	13	33.33		10	15	35.71		9	9	26.19	
Dongying	6	10	26.19		7	3	19.05		6	2	14.29	
Yantai	11	1	26.19		10	2	23.81		8	1	19.05	
Weifang	11	9	30.95		12	9	30.95		8	5	21.43	

Due to space constraints, only the top 20 data results of centrality analysis are presented, and the remaining results can be obtained by contacting the author

impact on the green innovation efficiency of other cities, which was mainly caused by their strong economic foundation and superior location conditions for innovation. From 2005 to 2020, the respective order of Weihai, Dalian, and Dandong changed to Yantai, Weihai, and Dalian. The GIE of Weihai and Dalian is easily affected by other cities. The source of innovation channels in marginal cities is relatively single, and the GIE is greatly affected by related cities.

Betweenness centrality is used to measure the intermediary role of each city in the GIE spatial correlation network in the Bohai Rim region, reflecting its ability to control green innovation resources. The results during the sample period are shown in Table 2. The betweenness centrality of Beijing and Tianjin accounted for 64.2% of that of the Bohai Rim region in 2020, indicating that Beijing and Tianjin exert strong control over green innovation resources, play an important role in the GIE spatial correlation network in the Bohai Rim region, and also play an important role in the flow channel and efficiency of regional green innovation resources. The betweenness centrality between Zhangjiakou and Langfang is always less than 0.07 during the sample period, implying that the intercommunication between these two cities and other cities is weak, and their communication and collaboration with other cities with high GIE need to be strengthened.

3.3 Block Model Analysis

From the above analysis, the status and role of cities in the GIE spatial correlation network in the Bohai Rim region are different. In order to further explore the role of each city in the network and the interaction between cities, based on the GIE spatial correlation network of the Bohai Rim region in 2020, using the iterative correlation convergence method CONCOR, the 43 cities of the Bohai Rim region were divided into four plates. The plate relationship diagram is shown in Fig. 6, and the spillover effect of GIE spatial correlation plates in Bohai Rim region is shown in Table 3.

From Table 3, we can see that there are 305 associations in the GIE spatial correlation network in the Bohai Rim region: 38 are within-plate associations, and 267 are

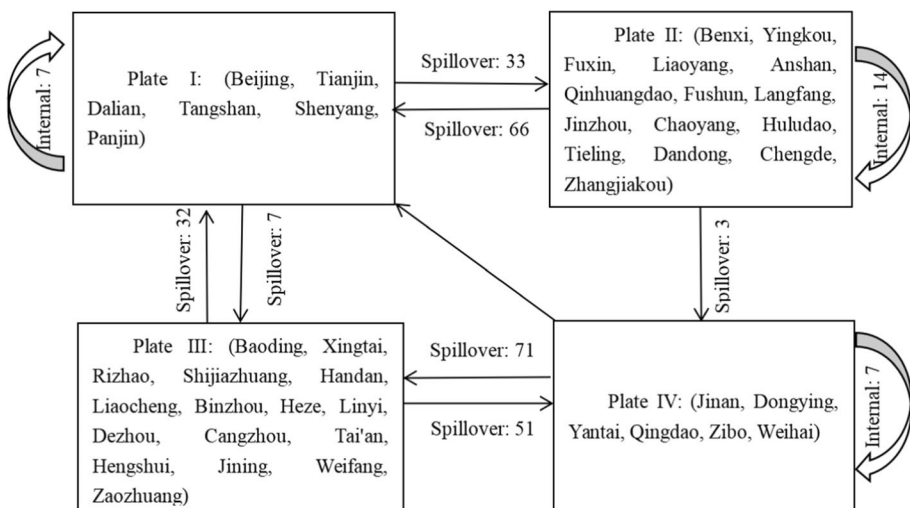


Fig. 6 GIE plates and relationship in the Bohai Rim region

Table 3 Spillover effect of GIE spatial correlation plates in Bohai Rim region

Plate	Total number of accepted relationships		Total spillover relationship		Expected internal relationship ratio	Actual internal relationship ratio	Plate characteristics
	Within the plate	Outside the plate	Within the plate	Outside the plate			
Plate I	7	102	7	40	12	17	Net benefit plate
Plate II	14	33	14	69	33	20	Net spillover plate
Plate III	10	78	10	83	36	12	Two-way spillover plate
Plate IV	7	54	7	75	12	9	“Broker” plate

between-plate associations, accounting for 12% and 88%, respectively. This shows that although there are obvious agglomeration characteristics between cities within a plate, the spatial correlation effect is not significant, and there are obvious spatial spillover effects between the plates. A detailed examination reveals the following: Plate I belong to the “net benefit” category. The beneficial effect of GIE in Beijing, Tianjin, and other cities is greater than the spillover effect. Plate II belongs to the “net spillover” category. The members of this group of plates not only develop green innovation in their region but also promote its development in other regions. Plate III has a large number of relationships, both inside and outside, and it belongs to “two-way spillover” category. Plate IV plays the role of a “bridge” and an “intermediary” in the GIE spatial association network around the Bohai Rim region, belonging to the “broker” category.

In addition to the spillover effect of GIE spatial correlation plates in the Bohai Rim region, this paper calculated the density of each plate and between plates for 2020, and the density matrix is converted into an image matrix (see Table 4).

The probability of the main diagonal from Plate I to Plate IV is 1, indicating that urban green innovation in Plate I and Plate IV has significant relevance. In Fig. 6, we can clearly see the spillover relationship between the various sectors. The spillover effect between plates is obvious, and Plate II and Plate III mainly produce spillover effects to Plate I and Plate IV. The green innovation resources of the cities in Plate II and Plate III are close to those of the cities in Plate I and Plate IV, thus promoting the green innovation development of the cities in Plate I and Plate IV. In addition, by virtue of its economic, talent, and energy advantages, Plate I not only have green innovation correlations in its own cities

Table 4 Density matrix and image matrix between GIE plates in the Bohai Rim region

Plate	Density matrix				Like matrix			
	Plate I	Plate II	Plate III	Plate IV	Plate I	Plate II	Plate III	Plate IV
Plate I	0.233	0.367	0.073	0	1	1	0	0
Plate II	0.733	0.067	0	0.033	1	0	0	0
Plate III	0.333	0	0.042	0.531	1	0	0	1
Plate IV	0.111	0	0.740	0.233	0	0	1	1

but also accepts the spillover of green innovation from the other three plates. The main reason is that Plate I, by virtue of its economic and geographical advantages, gathers the green innovation resources of other cities, resulting in a “Matthew effect” that continually promotes the improvement in its GIE. However, in the long run, this is not conducive to the coordinated and balanced development of GIE in the Bohai Rim region.

4 The driving factors of the GIE spatial correlation network in the Bohai Rim Region

4.1 Correlation analysis

Using Ucinet 6.2, we select 5,000 random permutations and carry out QAP correlation analysis on the GIE spatial correlation matrix and various driving factors in the Bohai Rim region for 2005, 2012, and 2020, respectively. The results are shown in Table 5. It is preliminarily determined that the smaller the geographical distance between cities is, the more conducive it is to the generation of GIE spatial correlation; the difference in economic development level and economic openness between cities is conducive to the establishment of spatial correlation; and human capital and infrastructure differences are positively correlated with the spatial correlation of GIE in the Bohai Rim region.

4.2 Regression analysis

Using Ucinet 6.2, based on the constructed QAP analysis model, QAP regression analysis was carried out on the GIE spatial correlation matrix and the driving factor matrix for the Bohai Rim region for 2005, 2012, and 2020. 5,000 random permutations were carried out. The regression results are shown in Table 6.

The adjusted R^2 values for 2005, 2012, and 2020 were 0.431, 0.392, and 0.446, respectively, all of which passed the 1% significance test, indicating that the above driving factors can contribute to explaining the evolution of GIE spatial correlation in the Bohai Rim region. As for the perspective of geographical spatial location, from the regression coefficients of GL for 2005, 2012, and 2020, it shows that the influence of the geographical distance matrix on the establishment of a spatial correlation gradually weakens over time, which may be due to the improvement in high-speed railways, expressways, and other transportation facilities, as well as electronic information systems, which allow the

Table 5 QAP correlation analysis

Variable	2005	<i>p</i> -value	2012	<i>p</i> -value	2020	<i>p</i> -value
<i>GL</i>	−0.517***	0.000	−0.500***	0.000	−0.418***	0.000
<i>EC</i>	0.418***	0.000	0.383***	0.000	0.474***	0.000
<i>OP</i>	0.155***	0.004	0.063***	0.003	0.256***	0.000
<i>HC</i>	0.159	0.160	0.013	0.333	0.143***	0.001
<i>IN</i>	0.043	0.132	0.039*	0.084	0.214***	0.000
<i>ER</i>	0.002	0.464	−0.079**	0.011	−0.117***	0.001

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 6 QAP regression analysis

Variable	2005			2012			2020		
	Coefficient	Probability I ^a	Probability I ^b	Coefficient	Probability I ^a	Probability I ^b	Coefficient	Probability I ^a	Probability I ^b
<i>GL</i>	-0.541***	1.000	0.000	-0.447***	1.000	0.000	-0.399***	1.000	0.000
<i>EC</i>	0.373***	0.000	1.000	0.387***	0.000	1.000	0.354***	0.000	1.000
<i>OP</i>	0.035	0.159	0.841	0.083***	0.005	0.995	0.121***	0.004	0.996
<i>HC</i>	-0.034*	0.067	0.933	0.007	0.376	0.624	0.062**	0.012	0.988
<i>IN</i>	0.059	0.018	0.982	0.064**	0.011	0.989	0.089***	0.003	0.997
<i>ER</i>	-0.008	0.625	0.375	-0.037**	0.957	0.043	-0.056**	0.015	0.985
<i>R</i> ²	0.432***			0.394***			0.447***		
Adj <i>R</i> ²	0.431***			0.392***			0.446***		
Sample size	1806***			1806***			1806***		

***, *p* < 0.01, **, *p* < 0.05, *, *p* < 0.1

establishment of the correlation of green innovative development between cities to transcend the limits of geographical distance.

As for the perspective of urban economic development modeling, from the regression coefficients of *EC*, it shows that the existence of regional differences in economic development level is conducive to the establishment of a spatial correlation. Driven by economic resources and geographical advantages, green innovation resource elements, such as labor and capital, will converge to cities with a high level of economic development level and eventually form core areas with leading development advantages. Moreover, it will help cities with low levels of economic development to improve and progress in talent, capital, knowledge, and other factors through their own efficiency level and further promote spatial linkages of GIE in the Bohai Rim region. *OP* did not exhibit significance for 2005 but was positively correlated for 2012 and 2020, with coefficients of 0.083 and 0.121, respectively. They both passed the significance test of 1%, indicating that the difference in economic openness between cities can promote the establishment of GIE spatial correlation in the Bohai Rim region. At the same time, the absolute value of the correlation coefficient shows an increasing trend. It indicates that the influence of the difference in the degree of economic openness between cities on the establishment of spatial correlation gradually increases over time.

As for the perspective of the green innovation environment, from the correlation coefficient of *HC*, it can thus be seen that the difference in human capital has been changed from having a negative to a positive impact on the establishment of relationships. Talent tends to gather in cities with a good innovation environment, forming intercity talent flows and promoting the connection of green innovation efficiency between cities. From the correlation coefficients of *IN*, differences in urban infrastructure are conducive to the establishment of spatial correlation. Due to interregional cooperation and exchanges, cities with a high infrastructure level will drive surrounding cities to improve their own infrastructure level and further promote the spatial correlation of green innovation. From the correlation coefficients of *ER*, it shows that cities with similar environmental regulations are more conducive to collaborative environmental governance, promote the establishment of GIE spatial linkages between cities, and gradually increase the impact of environmental regulations on the establishment of spatial linkages.

4.3 Robustness test

In order to further test the robustness of regression results, threshold values were set according to different proportions of the average gravity value of GIE in 2005, 2012 and 2020, that is, 80% and 120% of the average value were taken as breakpoints (Sun et al., 2023), and different binary spatial correlation matrices were constructed as new explained variables. QAP regression analysis was carried out with the original influencing factor matrix as explanatory variables. Table 7 shows the QAP analysis results after 80% and 120% of the gravitational mean value are taken as breakpoints to the new matrix.

Whether the mean value is 80% or 120% as the base value, the adjusted- R^2 of each year passes the significance test at the level of 1%, indicating that the influencing factor matrix has a better explanatory power to the GIE spatial correlation matrix. The symbols of each variable did not change, indicating that the direction of the influence of each variable on the GIE correlation network in the Bohai Rim region is stable. At the same time, except that the significance of *OP*, *HC* and *IN* is slightly different from the regression analysis results in individual years, the significance level of most other

Table 7 Robustness test results

Variable	80% of the average			120% of the average		
	2005	2012	2020	2005	2012	2020
<i>GL</i>	-0.451***	-0.431***	-0.403***	-0.420***	-0.419***	-0.364***
<i>EC</i>	0.430***	0.421*	0.437***	0.356***	0.389*	0.397***
<i>OP</i>	0.065**	0.064	0.042*	0.082***	0.037	0.042*
<i>HC</i>	-0.009*	0.056	0.025*	-0.015*	-0.042	0.009
<i>IN</i>	0.071	0.038**	0.048**	0.077*	0.055**	0.049*
<i>ER</i>	-0.015	-0.024**	-0.049**	-0.016	-0.031**	-0.042**
R^2	0.531***	0.384***	0.434***	0.473***	0.462***	0.447***
Adj- R^2	0.528***	0.383***	0.432***	0.471***	0.461***	0.446***
Sample size	1806	1806	1806	1806	1806	1806

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

influencing factors has not changed, indicating that the regression analysis results of this study are relatively robust and the conclusion is credible.

5 Conclusion and discussion

5.1 Conclusion

Taken 43 prefecture-level cities in the Bohai Rim region as its research object, the study uses the super-efficiency SBM model to calculate their GIE from 2005 to 2020, constructs the GIE spatial correlation relationship based on the modified gravity model, and uses SNA and QAP analysis method to explore the GIE spatial correlation network and its driving factors in the Bohai Rim region. The main conclusions are as follows:

In terms of the overall network characteristics, the GIE between cities in the region presents complex and stable network characteristics without a strict spatial structure, and it has good connectivity and accessibility. At the same time, the spatial a correlation of GIE in this region still needs to be strengthened.

In terms of individual centrality, the centrality of cities in the Bohai Rim region presents a spatial imbalance as the degree centrality, betweenness centrality, and closeness centrality of Beijing and Tianjin rank at the top, indicating that these two cities are at the core of the GIE spatial correlation network in the Bohai Rim region. According to the block model analysis, the correlation within plates is sparse, and the relationship between plates is relatively close, resulting in a strong spillover effect.

In terms of driving factors, spatial correlations are more likely to occur between cities in close geographical proximity and with similar environmental regulations. Differences in urban economic development, openness, human capital, and infrastructure are conducive to the establishment of spatial correlations.

5.2 Policy suggestion

Based on the above conclusions, there is unbalanced development of GIE spatial correlation network structure in the Bohai Rim region, and there is still abundant room for improvement to achieve coordinated development. Therefore, it is necessary to continuously adjust and optimize the GIE spatial correlation network structure in terms of top-level design and grassroots practice so as to promote the improvement in GIE and coordinated development in the region. The following policy-making suggestions are thus put forward:

1. The government should strengthen the construction of major cross-regional infrastructure, breaking down regional barriers and improving the level of connectivity. First, urban transportation facilities should be connected organically between railways, highways, and airports, which eliminates geographical space constraints and achieve “zero distance transfer.” It can accelerate cross-regional flow and industrial cooperation, realizing cross-regional coordinated development of GIE in the Bohai Rim region. Second, the information system should be improved by building a digital, intelligent, integrated, and comprehensive information infrastructure and improving the level of regional public information services in the Bohai Rim region. It can reduce the cost of cross-domain interaction and accelerate the flow, intercommunication, and integration of innovation elements between cities, promoting regional linkages and synergistic improvement in GIE.
2. The government should formulate different development strategies according to the status and role of each node city in the GIE correlation network, counteracting the “Matthew effect” and promoting the coordinated development of green innovation. (1) “Net benefit” cities such as Beijing and Tianjin should make full use of their core position in innovation resources and the economy, view their respective green innovation development from the perspective of the overall picture of the development of the Bohai Rim region, promoting the radiation of their respective advantages. (2) “Intermediary” cities such as Jinan and Dongying should actively integrate the advantages of green innovation resources and implement new technologies, improving their respective green innovation resources and expanding the scope of spillover effects. (3) “Net spillover” cities such as Benxi and Yingkou, except acting as the “power source” of GIE in the Bohai Rim region, should actively improve the infrastructure, formulate preferential policies for talent, absorb and utilize the experience and resource advantages of other cities’ green innovation, forming late-development advantages. (4) “Two-way spillover” cities such as Baoding and Xingtai should actively strengthen the deep integration of industry, education, and research, improve their respective green innovation capabilities, and drive the development of green innovation in related cities.
3. The government should actively improve the level of openness, promote the cross-regional flow of green innovation elements, and promote the coordinated development of the Bohai Rim Economic Circle. As an area included in major national strategies such as the “Belt and Road” initiative and the China–Europe Railway Express, the Bohai Rim region should fully realize the policy dividends of free trade pilot zone node cities. Tangshan, Qingdao, and other cities should be actively integrated into the China–Europe Railway Express and transform their own advantages in production capacity, technology, experience, and capital into market and cooperation advantages so as to achieve all-round opening up, improve the green innovation capacity of the entire Bohai Rim

region, and further promote the construction of free trade pilot zones. The four free trade zones in Tianjin, Hebei, Shandong, and Liaoning should make use of their policy advantages and excellent business environment to attract foreign investors. Moreover, the region should strengthen the interaction and cooperation between cities in the free trade zones, promote the cross-regional flow of innovative elements such as talent, knowledge, and technology, improving GIE so as to achieve coordinated development.

5.3 Limitations and future research

Although the study deeply explores the correlation network of GIE and its driving factors in the Bohai Rim region and draws some meaningful conclusions and policy suggestions, there are still some limitations. First, as for the driving factors for the GIE spatial correlation network in the Bohai Rim region, this study only considers six indicators; however, the GIE spatial correlation network may be influenced by other factors. More driving factors should be considered in the future study, such as the digital level of the city and financial development. Second, QAP analysis has found whether relevant indicators have an impact on the GIE spatial correlation network and the degree of the impact. Future studies can combine with quantitative research methods to further explore the threshold of relevant factors, such as the indicator of geographical distance and environmental regulations. Third, the study analyzes the influence factors of the GIE spatial correlation network, but does not analyze the effect of the network, which is the impact of the GIE spatial correlation network on urban GIE. Future studies can further explore the network effect.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [KD] and [ZL]. The first draft of the manuscript was written by [KD], and [ZL, SC, KL, YL] commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability The data that support the findings of this study are available on request from the corresponding author.

Declarations

Conflict of interests The authors have no relevant financial or non-financial interests to disclose.

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