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Article

Spatial Correlation Network and Driving Effect of Carbon Emission Intensity in China's Construction Industry

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Abstract: To explore the spatial network structure characteristics and driving effects of carbon emission intensity in China's construction industry, the investigation combined the modified gravity model and social network analysis method to deeply analyze the spatially associated network structure characteristics and driving effects of carbon emission intensity in China's construction industry, based on the measurement of carbon emission data of China's construction industry from 2006 to 2017. The results show that the regional differences of carbon emission of construction industry are significant, and the carbon emission intensity of construction industry show a fluctuation trend. The overall network of carbon emission intensity shows an obvious "core-edge" state, the hierarchical network structure is gradually broken. Economically developed provinces generally play a leading role in the network, and play an intermediary role to guide other provinces to develop together with them. Among the network blocks, most of the blocks play the role of "brokers". The block with the leading economic development has a strong influence on the other blocks. The increase of network density, the decrease of network hierarchy and network efficiency will reduce the construction carbon emission intensity.

Keywords: carbon emission intensity; gravity model; social network; driving effect; sustainable development; Construction industry

1. Introduction

Global warming has brought serious challenges to human survival and development, causing serious harm to the environment, and is a serious challenge to the future development of mankind [1,2]. In recent years, carbon dioxide emissions have been increased annually. In 2017, the total carbon emissions of China accounted for 27.2% of the world, and China has become the largest carbon emitter in the world [3]. China's carbon emission reduction pressure is huge [4], and it is the first developing country to formulate and implement the national plan to deal with climate change, which plays an important role in the world carbon emission reduction issue [5]. A large number of carbon emissions will bring great pressure to the ecological environment, leading to the change of a country's climate conditions, and then affect the production capacity, and is not conducive to sustainable economic development [6,7].

The construction industry is a typical energy-intensive industry with significant characteristics such as high energy consumption, high emissions and low efficiency [8]. The energy consumption of the construction industry accounts for about 36% of the total global terminal energy consumption, which generates about 40% of the global carbon emissions [9]. To address global climate change issue, the Chinese government has proposed to achieve peak CO_2 emissions around 2030 and carbon neutralization by 2060 [10]. Carbon emission reduction management in the construction industry is crucial [11,12].

Energy conservation and emission reduction in the construction industry is facing a more severe situation [13]. In this context, it is particularly important to analyze the current situation and influencing factors of regional construction carbon emission in China, which can provide a basis for the government to formulate relevant policies. Therefore, this problem has attracted extensive attention in the academic community [14-17].

With the rapid progress of urbanization in China and the rapid economic development of various regions [18], constrained by regional economic development, energy supply, economic, technological and other factors, the carbon emission of construction industry in each province is not independent. The continuous mutual flow and exchange of resources and information between regions inevitably leads to the existence of geospatial effects between neighboring regions, which strengthens the spillover effect of provincial construction carbon emissions and gradually strengthens the spatial correlation of construction carbon emissions in each region. The deepening connection between regional trade and services [19,20], and the proposal of regional development strategies such as the western development, the strategy of revitalizing northeast China and the pioneer development in the East, carbon emissions show the characteristics of spatial heterogeneity, and there are obvious regional differences [21,22]. There is a complex and multi-threaded correlation between construction carbon emissions in various regions. A clear understanding of the spatial correlation characteristics and influencing factors of construction carbon emission will help decision-making departments to take corresponding measures to implement construction carbon emission reduction management.

Research on carbon emission reduction management in the construction industry by scholars at home and abroad has mainly focused on the project and regional levels [23-26]. At the project level, the research on construction carbon emission reduction management mainly focuses on the measurement calculation method of construction carbon emission and collaborative emission reduction management. Carbon emission measurement and collaborative management of carbon emission reduction are carried out for different life cycle stages of buildings [27], building materials [28], building components and parts [29,30], building structure forms [31], etc., to provide reference for low-carbon building design and whole life cycle management.

At the regional level, the research on construction carbon emission has mainly focused on the calculation of construction carbon emission and the study of influencing factors. Du et al. investigated the relationship between construction carbon emission and economic growth with the Kuznets curve and elastic decoupling model, based on the calculation of construction carbon emission, and found the main factors affecting its elastic decoupling [32]. Huo et al. established China's building energy consumption and emission model, reasonably calculated the carbon emissions generated during building operation, and put forward suggestions on energy conservation and low-carbon development of the construction industry [33]. Based on previous studies, Chen et al. studied the carbon footprint of the whole life cycle of buildings which divided the whole life cycle of buildings into mining and production stages, construction stages, operation and maintenance stages and demolition and disposal stages of building materials, and analyzed the carbon emission sources of each stage, and put forward corresponding carbon emission reduction strategies [34]. Zhang et al. proposed a Chinese building construction model based on process life cycle assessment to find out the main driving factors and influencing direction affecting building carbon emission [35]. Tan et al. established the carbon emission prediction model system of China's construction industry and the model for assessing the potential of carbon emission reduction [36].

Due to local monetary development, electricity supply, economy, era and other elements, the carbon emission of construction industry in each province isn't always impartial. The continuous flow and exchange of resources and information between regions will inevitably lead to geospatial effects between adjacent regions, strengthen the spillover effect of provincial carbon emission of construction industry, and gradually strengthen the spatial correlation of carbon emission of construction industry in each region [37,38]. The carbon emission of construction industry shows significant spatial dependence [39,40]. At present, the research on the spatial correlation of construction carbon emissions is limited to "adjacent" or "similar" regions, while ignoring the correlation between construction carbon emissions at the regional level. Social Network Analysis (SNA) is used to study the association between individuals in social networks. Because it takes into account the overall association of the network and the influence status of individuals in the network, it has been widely used in many disciplines [41-45]. Zhu et al. used the social network analysis method to study the temporal and spatial variant characteristics of China's coal transportation network, and discussed the status and role of each network node in the coal transportation network, based on the coal output and input matrix data of China's provinces from 1990 to 2014 [46]. Yang et al. established China's industrial carbon emission efficiency network to study the convergence and influencing factors of regional ICEE of China's industrial carbon emission [47]. In addition, the carbon emission intensity of construction industry can more accurately reflect the development of construction industry than the total carbon emission. This is a deficiency in the research of carbon emission of construction industry in China [14]. Previous studies have focused on the management of construction carbon emission reduction at the project and regional levels. However, it does not consider the carbon emission intensity index, and it ignores the spatial characteristics of construction carbon emission. Therefore, this research uses the gravity model to calculate the influence degree of building carbon emissions among provinces, to construct the spatial network model about construction carbon emission intensity among provinces in China, analyzing the influence status of provinces in the network and the correlation between provinces. It provides a basis for formulating global and regional linkage construction carbon emission reduction policies.

This paper contains five parts. A review of the state of research on the problem in question is provided in the introduction, followed by analysis methods data sources in Section 2. The third part is an empirical analysis. Section 4 present the discussion of results. The research conclusions are given in Section 5, the final section of this article.

2. Materials and Methods

2.1. Carbon emission estimation

At present, the main methods to calculate the carbon emission of the construction industry include emission coefficient method, input-output model, building lifecycle management, measurement and material balance equation [48]. The carbon emissions of construction industry are divided into direct and indirect types. Direct carbon emissions mainly include the increase of carbon emissions caused by the consumption of nine kinds of fossil energy, electric power and thermal energy. Indirect carbon emissions include the carbon emissions of five building materials industries: steel, wood, cement, glass, and aluminum [49]. It can be calculated as follows [50]:

$$CE_{i,j} = DCE_{i,j} + ICE_{i,j} \tag{1}$$

$$DCE_{i,j} = (\sum_{k=1}^{9} (\mathrm{EF}_{i,j,k} \times \mathrm{fe}_k) + \mathrm{TE}_{i,j} \times \mathrm{te}_j) \times \frac{12}{44} \times 10^{-6} + \mathrm{EE}_{i,j} \times \mathrm{ee}_i \tag{2}$$

$$ICE_{i,j} = \sum_{h=1}^{5} DE_{i,j,h} \times de_h^{*} (1 - \mathrm{a}_h) \tag{3}$$

Where, *CE*, *DCE*, and *ICE* are the construction carbon emissions (tons), direct carbon emissions (tons), and indirect carbon emissions (tons), respectively. *FE*, *EE*, *TE*, and *DE* are the energy consumption of fossil (tons), electric power (KW·h), heat (KJ), and building materials (kg), respectively. *fe*, *ee*, *te*, *de**, and a_h denote the carbon emission factors of fossil, electric power, heat, building, and recovery coefficient of building materials, respectively.

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i is the region, j is the year, k is the type of fossil energy, h is the type of building materials. 44/12 is the ratio of the molecular weights of CO_2 and C.

2.2. Social network analysis

SNA method is developed on the basis of graph theory [51]. It is a quantitative analysis method used to analyze "relational data" and to solve spatial network problems in economic system, mainly including overall network characteristics, individual network characteristics, structural hole analysis and spatial clustering analysis [52-54]. The spatial correlation network of interprovincial carbon emission intensity is a collection to explore spatial carbon emission relationships [54]. Constructing spatial association network is the foundation of social network analysis [6,55]. Previous studies have concluded that economic development level, population size and energy consumption are the main factors affecting carbon emissions [6,56-58]. Therefore, the gravity model was selected to determine the association relationship [53,54]. The calculation formula of the modified gravity model is as follows:

$$y_{ij}^{*} = k_{ij} \cdot \frac{\sqrt[3]{P_i C_i G_i}\sqrt[3]{P_j C_j G_j}}{\left[D_{ij}/(g_i - g_j)\right]^2}, \qquad \text{where } k_{ij} = \frac{C_i}{C_i + C_j} \tag{4}$$

Where, C_i and C_j respectively denote the construction carbon emission intensity of provinces i and j; g_i and g_j respectively denote Per capita GDP of provinces i and j in the current year, and the difference (g_i-g_j) is the variable of economic gap between the provinces i and j; P_i and G_i denote the proportion of urban population and the GDP, respectively; D_{ij} defined as the geographic distance between provinces i and j, and it is expressed by the straight-line distance between the two provincial capitals in the research. k_{ij} is the empirical carbon emission intensity constant. y_{ij}^{*} indicates the degree to which the construction carbon emission intensity of province i is affected by province j.

2.3. Data sources

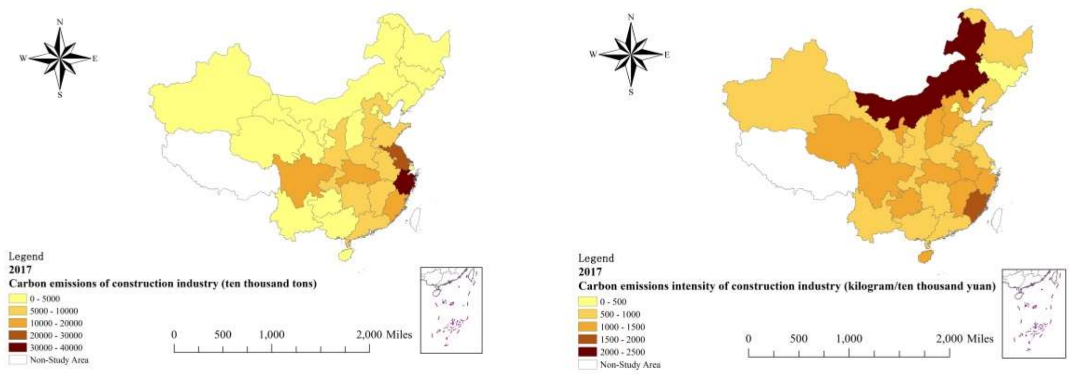
In this investigation, the samples are 30 provinces in China (excluding Tibet, Hong Kong, Macao and Taiwan), during 2006–2017. The geographical distance between provinces is represented by the spherical distance between provincial capitals, which is calculated by ArcGIS. The source consumption of the energy consumption and building material consumption of the construction industry are from China Statistical Yearbooks and China Energy Statistical Yearbooks, respectively. The GDP, population at the end of the year, and per capita GDP of each province required in the gravity model are all from China Statistical Yearbook. The coefficients of building carbon emission and recovery coefficients of building carbon emission are from the previous studies [50,59,60].

3. Results

3.1. Construction carbon emission and construction carbon emission intensity

From 2006 to 2017, the carbon emission of China's construction industry increased from 74.31 million tons to 201.40452 million tons, with an average annual growth rate of about 14%. The GDP of the construction industry increased from 4150.78 billion yuan to 2137.564 billion yuan, with an average annual growth rate of about 34%. The provinces with large carbon emissions from China's construction industry are mostly in the southeast, extending from the eastern coastal areas to the West. The emission of Zhejiang Province is more prominent, and its surrounding Fujian Province, Jiangsu Province and Hubei Province also have high emissions, while the carbon emissions in the more remote areas in the north and south of China are mostly low. In 2017, the carbon emissions of China's provincial construction industry showed a prominent trend in the southeast, while the surrounding areas were low, and the regional differences of carbon emissions of construction industry were significant. From 2006 to 2017, the carbon emission intensity of China's construction industry first decreased, then increased and then decreased. From 2006 to

2009, the carbon emission intensity of China's construction industry showed a downward trend as a whole. This is because in 2003, the State Council issued a document to take China's real estate industry as the pillar industry of the national economy, and the output value of the construction industry increased rapidly. With the outbreak of the global economic crisis in 2008 [61], the development of the real estate industry was hit, the growth of the construction industry was slow, and the carbon emission intensity of the construction industry increased slightly. From 2010 to 2012, the carbon emission intensity of China's construction industry showed an obvious upward trend. During this period, China's real estate entered a relatively stable period of coordinated development period. From 2013 to 2017, the carbon emission intensity of China's construction industry showed a downward trend. The tendency of carbon emissions exhibit differences and the distributions of the regional economy and carbon emissions present spatial heterogeneity [62].



(**a**) (**b**)

Figure 1. Distribution map of provincial construction carbon emission and emission intensity in 2017: (**a**) Construction carbon emission; (**b**) Construction carbon emission intensity.

3.2. Spatial network analysis of Construction carbon emission intensity

3.2.1. Overall network Characteristics

According to the modified gravity model, a spatial correlation network of interprovincial construction carbon emission intensity was established. The Fig. 2 shows the typical spatial correlation network structure. The overall network characteristic index including network density, network efficiency, and network hierarchy were calculated according to the previous researches [43,54].

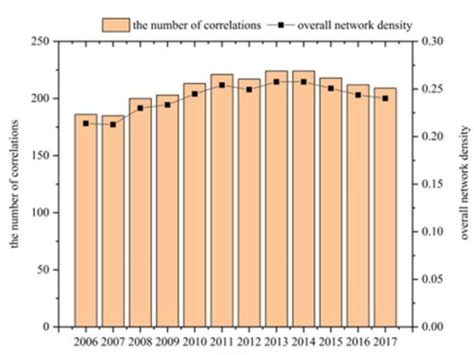


Figure 2. Overall network density and correlation of construction carbon emission network.

The overall network density of carbon emission intensity of China's construction industry from 2006 to 2017 was shown in Fig. 3. It can be seen that the number of correlation relations and the overall network density generally show a gradual upward trend. It can be concluded that in the process of economic and construction development, the correlation of interprovincial carbon emissions tends to be close. The network density increased significantly from 2007 to 2011, and fluctuated downward in 2012. Since 2013, the network density has shown a slow downward trend. In 2012, due to the sudden increase of emissions in Jilin, Shandong and Hubei, they occupied a key position in the network and weakened the relationship between other provinces.

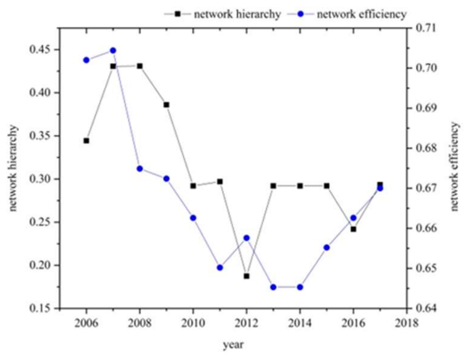


Figure 3. Network hierarchy and network efficiency of construction carbon emission network.

After 2013, the construction carbon emissions of provinces and cities have been slowed down, due to China's the "Twelfth Five-Year Plan" [32], while the economic and productivity levels are still improving steadily, narrowing the gap of construction carbon emission intensity between provinces, and slightly reducing the degree of correlation impact of provinces. Previous researches have proposed that the level of economic activity is strongly correlated to carbon emissions [32,63,64].

From 2006 to 2017, the overall network level of carbon emission intensity of China's construction industry showed a decreasing trend, as shown in Fig. 3. With the development of China's overall production capacity, the strict hierarchical structure in the association network has been gradually broken. Some of the provinces that originally had a lower level of development made great economic progress and began to have influence and began to have influence, and the status of provinces and cities has gradually become equal. Network hierarchy showed a significant decline in 2010, 2012, and 2016. The subprime mortgage crisis in 2008 had an impact on the original network status of provinces and weakened the dominant position of more developed provinces [61]. In addition, environmental protection policies in China have also been implemented, the policies focused on limiting the construction carbon emissions of economically developed provinces and maintaining the overall fairness of the network. Since 2013, the network hierarchy of each province has gradually stabilized, with only a small fluctuation in 2016, making the status of each province in the network more equal. The reduction shows that the provinces that were originally in a dominant position begin to have influence, and the provinces with better economic development are easier to drive the common development of other provinces, which helps to slow down the overall construction carbon emission.

3.2.2. Individual network Characteristics

The data of 2017 is calculated from the statistical yearbook data of the latest year, and the network density, network level and network efficiency of that year have fluctuated compared with previous years. Therefore, this study selects the data of 2017 to study the individual network characteristics of carbon emission intensity of construction industry. The overall network shows an obvious "core-edge" state, and the provinces with more

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relationships in the middle are Beijing, Tianjin, Shanghai, Jiangsu and Zhejiang, as shown in Fig. 4. The economic development of these provinces is relatively rapid, and the level of production technology is very high. These provinces are closely related to the economic development of other provinces, and the carbon emission intensity of the construction industry is strongly related to other provinces [32,65]. The calculation of individual network indicators of carbon emission intensity of construction industry is shown in Table 1.

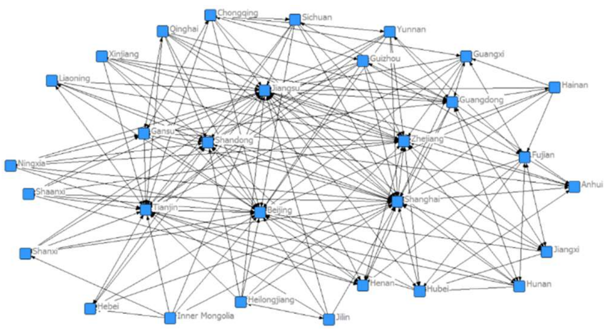

Figure 4. Spatial network of China's inter provincial construction carbon emission in 2017.

The average degree centrality of the network is 37.45 in the province spatial correlation network of China's construction carbon emission intensity. In Shanghai, Jiangsu, Beijing, Tianjin, Zhejiang, Shandong, Guangdong, Gansu, and Fujian, the degree centrality of these provinces is higher than the national average, and there are many local correlation relationships in the spatial correlation network of construction carbon emissions. Among them, the degree centrality of Shanghai and Jiangsu are the highest, reaching 93.1. The degree centrality indicated that there was a close spatial correlation between the economic development of Shanghai and Jiangsu and other provinces [66]. Most of these provinces are located in the Bohai Rim, Yangtze River Delta, and Pearl River Delta except Gansu and Fujian. In terms of in-degree, the top five provinces are Jiangsu, Shanghai, Beijing, Tianjin, and Zhejiang, respectively. These provinces are located in the eastern coastal area, with developed economy and convenient transportation.

From the calculation results of out-degree, the average value of out-degree of all provinces in China was 6.97, and the gap between provinces was not obvious. Among them, the higher ranking provinces are Guangdong, Gansu, Chongqing, Guizhou, and Yunnan. These provinces are relatively affected by the construction carbon emissions of other provinces in the associated network. Most provinces are located in the middle and north of China, which is limited by logistics and hinders the development of economy and productivity. Due to its superior geographical location and rapid economic development, the eastern coastal area has a strong influence on the spatial correlation and spillover effect of building carbon emissions.

Table 1. Analysis on the network centrality of inter provincial construction carbon emission in 2017.

Province	Degree centrality				Closeness centrality		Betweenness centrality	
	Out-degree	In-degree	Centrality	No.	Centrality	No.	Centrality	No.
Beijing	5	23	79.30	3	82.90	3	10.50	3
Tianjin	6	20	72.40	4	78.40	4	7.90	4
Hebei	4	5	20.70	26	55.80	26	0.10	24
Shanxi	5	4	20.70	26	55.80	26	0.10	24
Inner Mongolia	6	0	20.70	26	55.80	26	0.10	24
Liaoning	6	2	20.70	26	55.80	26	0.10	24
Jilin	5	1	17.20	30	54.70	30	0.00	30
Heilongjiang	7	1	24.10	19	56.90	19	0.20	18
Shanghai	9	25	93.10	1	93.50	1	14.60	1
Jiangsu	4	27	93.10	1	93.50	1	14.60	1
Zhejiang	7	18	65.50	5	74.40	5	5.60	5
Anhui	3	7	24.10	19	56.90	19	0.20	18
Fujian	8	6	37.90	8	61.70	8	1.20	8
Jiangxi	7	5	24.10	19	56.90	19	0.20	18
Shandong	8	15	58.60	6	70.70	6	3.60	6
Henan	6	9	31.00	10	59.20	10	0.50	12
Hubei	6	6	31.00	10	59.20	10	0.70	9
Hainan	8	4	27.60	16	58.00	16	0.30	16
Guangdong	11	10	48.30	7	65.90	7	2.50	7
Guangxi	7	4	31.00	10	59.20	10	0.60	11
Hainan	7	1	24.10	19	56.90	19	0.20	18
Chongqing	9	4	31.00	10	59.20	10	0.40	15
Sichuan	8	2	27.60	16	58.00	16	0.30	16
Guizhou	9	2	31.00	10	59.20	10	0.50	12
Yunnan	9	2	31.00	10	59.20	10	0.50	12
Shaanxi	7	1	24.10	19	56.90	19	0.10	24
Gansu	10	4	37.90	8	61.70	8	0.70	9
Qinghai	8	1	27.60	16	58.00	16	0.20	18
Ningxia	7	0	24.10	19	56.90	19	0.10	24
Xinjiang	7	0	24.10	19	56.90	19	0.20	18
Mean value	6.97	6.97	37.45	-	62.94	-	2.23	-

It can be seen from Table 1 that the mean value of closeness centrality is 62.94. The closeness centrality of Shanghai, Jiangsu, Beijing, Tianjin, Zhejiang, Shandong, and Guangdong is higher than the national average. These provinces are the centers of economy, commerce, and culture in the county. They are in the central position in the spatial correlation structure network of building carbon emission intensity and play the role of central actors in the network. Provinces with central leadership make use of their own advantages in resources, policies, technology, and funds to send the correlation of construction carbon emission intensity to the surrounding provinces, and this affected the economic and productivity development of other provinces. Provinces with closeness centrality less than the average, such as Shanxi, Jilin, and Inner Mongolia, play the role of marginal actors in the network, and their construction carbon emission intensity will be affected by the surrounding provinces.

Table 2. Structural hole index system of carbon emission intensity of construction industry in 30 provinces of China.

Province	Effective scale	Efficiency	Limit degree	Grade degree	Effective scale ranking	Limit degree ranking
Beijing	19.768	0.859	0.193	0.253	3	3
Tianjin	17.673	0.842	0.219	0.270	4	4
Hebei	3.167	0.528	0.547	0.099	27	27
Shanxi	3.167	0.528	0.547	0.099	27	27
Inner Mongolia	3.167	0.528	0.560	0.023	27	29
Liaoning	3.938	0.656	0.517	0.073	24	26
Jilin	2.667	0.533	0.617	0.139	30	30
Heilongjiang	4.438	0.634	0.468	0.038	21	20
Shanghai	21.912	0.812	0.165	0.165	2	2
Jiangsu	22.194	0.822	0.163	0.157	1	1
Zhejiang	15.260	0.803	0.269	0.340	5	6
Anhui	3.700	0.529	0.514	0.135	26	25
Fujian	8.000	0.727	0.350	0.188	8	10
Jiangxi	4.667	0.667	0.437	0.076	19	18
Shandong	11.630	0.684	0.261	0.185	7	5
Henan	5.900	0.656	0.364	0.080	13	14
Hubei	5.000	0.556	0.398	0.063	16	17
Hainan	5.625	0.703	0.391	0.080	14	16
Guangdong	11.833	0.845	0.273	0.254	6	7
Guangxi	6.091	0.677	0.354	0.043	12	11
Hainan	4.313	0.616	0.480	0.089	22	22
Chongqing	5.000	0.556	0.341	0.014	16	9
Sichuan	5.550	0.694	0.388	0.036	15	15
Guizhou	6.455	0.717	0.355	0.062	10	12
Yunnan	6.455	0.717	0.355	0.062	10	12
Shaanxi	4.188	0.598	0.492	0.051	23	24
Gansu	7.107	0.646	0.306	0.029	9	8
Qinghai	4.722	0.590	0.440	0.071	18	19
Ningxia	3.714	0.531	0.491	0.029	25	23
Xinjiang	4.571	0.653	0.476	0.054	20	21

The province spatial correlation network of China's construction carbon emission intensity gradually presents a "center-edge" structure. According to the calculation, the average value of betweenness centrality of the spatial correlation structure network is 2.23. The values of Shanghai, Jiangsu, Beijing, Tianjin, Zhejiang, Shandong, and Guangdong exceeded the country average. Shanghai and Jiangsu have the highest value of 14.6, respectively. As economically developed provinces, Shanghai and Jiangsu are at the core of the spatial correlation network of building carbon emissions and play the role of "bridge". In 2017, the betweenness centrality of the spatial correlation network of construction carbon emission intensity was 66.8, while the sum of the betweenness centrality of the top seven provinces accounted for 88.77% of the national total. These provinces strongly guide

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the spatial correlation of construction carbon emissions among other provinces in the spatial correlation network. The betweenness centrality of Inner Mongolia, Jilin, Shaanxi, and Ningxia provinces is lower. The economic development speed of these provinces is slow and it is not easy to have a strong transmission effect. It can be seen that the construction carbon emission is restricted by the geographical location, population scale and economic development level of each province.

The structural hole of provincial spatial correlation network of carbon emission intensity of China's construction industry in 2017 is shown in Table 2. The larger the effective size of the individual in the network, the easier it is to have structural holes in the network, and the smaller the degree of repetition of the network [67]. The higher the efficiency of a specific province in the network, the greater the impact of the province on other provinces, and can act more efficiently. In the spatial network of carbon emission intensity of construction industry, the provinces with lower restrictions are in an open position in the network, which have a strong ability to control other provinces, and there will be more structural holes. The higher the level of carbon emission intensity of the construction industry, which indicates that the province is in the center of the network, it is more likely to become the leader and controller of the network. The provinces with an effective scale greater than the average value of 7.73 are Jiangsu, Shanghai, Beijing, Tianjin, Zhejiang, Guangdong, Shandong, and Fujian. Most provinces have not yet formed a relatively perfect effective relationship network, and few provinces have effective scale advantages in the associated network.

From the perspective of limitation, Jiangsu, Shanghai, Beijing, Tianjin, Shandong, Zhejiang, Guangdong, Gansu, Chongqing, Fujian, Guangxi, Guizhou, Yunnan, Henan, Sichuan, and Hunan are below the average value of 0.391 among the 30 provinces. From the perspective of effective scale and limitation, the top seven provinces are Jiangsu, Shanghai, Beijing, Tianjin, Zhejiang, Guangdong, and Shandong, which play an important role in the overall network, which are in the structural hole of the network.

3.3. Spatial cluster analysis

CONCOR method was used to analyze the spatial clustering characteristics of the network with the data of 2017, and 30 provinces are divided into 4 blocks. In the province spatial correlation network structure of China's construction carbon emission intensity, there are 209 correlation relationships among the four blocks. There is an obvious spatial correlation and spillover effect between the four blocks of carbon emission intensity of construction industry. In order to visually describe the relationship between blocks, the number of relationships within and between blocks is shown in Fig. 5.

The internal connection of block 1 is the most close, and it has accepted many spillover relationships from block 3, and block 4, which proves that the construction carbon emission generated by its own development has a great impact on blocks 3 and 4, and there is also an impact relationship on carbon emission among provinces within the block, with less impact on block 2. Most of the cities included in block I are located in the Yangtze River Delta, with strong geographical advantages, rapid economic development and large carbon emissions, which are easy to spread to other provinces, especially the nearby areas with low development status. Block 2 contains few provinces and has no internal relationship, but there are a considerable number of sending and receiving relationships between the network and other plates, which is in the position of a typical "broker". These provinces included in the plate are in the forefront of China's development status and play an "intermediary" role in the network. Connecting the provinces with better development status with other provinces is conducive to balancing the status of each province in the network and reducing the gap of carbon emission intensity. The number of internal relations of block 3 is relatively large. Because the provinces included are not dominant in geographical location and low economic level, the overall development speed is slow, and they are more affected by other blocks in the network, but they are easy to be related internally. From the above analysis, it can be seen that the "broker" effect is significant in

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the spatial network of construction carbon emission intensity, where block 2 and block 4 play an intermediary role in the network. The construction carbon emission of provinces with lower development level will be significantly affected by developed areas. "Broker" plays a certain role of "bridge" in the network, can convey the impact relationship of construction carbon emission, and can also alleviate the large grade gap between provinces. The "beneficiary" role of block 1 is also very important. It has received a lot of spillover relations from other plates in the overall network. Therefore, it should maintain and make use of its advantages of high economic development level to drive other provinces to jointly develop productivity and make the network structure more equal.

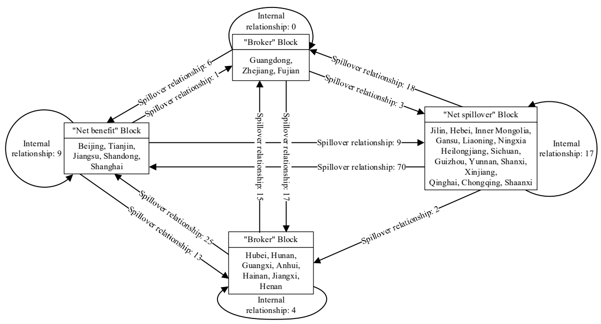

Figure 5. Correlation between the four parts of associated network.

3.4. Carbon emission intensity effect of the construction industry

After analyzing the characteristics and transmission mechanism of inter provincial carbon emission spatial correlation network in China, and the driving effect of network structure should be investigated. The driving effect of construction carbon emission intensity is studied by econometric regression analysis. Several pre-analysis checks were performed on the panel data to analysis [68-70].

3.4.1. Overall spatial network structure effect analysis

The construction carbon emission intensity in each year and the standard deviation of inter province carbon emission intensity are selected as dependent variables, and the network density, network hierarchy and network efficiency of construction carbon emission intensity are used as dependent variables for regression analysis with OLS method. In order to eliminate the dimensional influence, all variables in the study take the natural logarithm, and the calculation results are shown in Table 3.

It can be seen from Table 3 that in models (1) to (3), the national construction carbon emission intensity is negatively correlated with network density and network hierarchy, and positively correlated with network efficiency. The network density and network hierarchy are increased by 1%, respectively, the building carbon emission intensity will be reduced by 0.463% and 0.275%, respectively, while the network efficiency are increased by 1%, the construction carbon emission intensity will be increased by 0.935%. The reduction of the network efficiency of construction carbon emission intensity means the increase of the number of effective connections in the network [43], which is conducive to reducing the difference of development level between provinces, making the network structure more stable and reducing the construction carbon emission intensity.

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Table 3. Effect analysis results of the overall network structure.

Dependent variable	National building carbon emission intensity			Standard deviation of building carbon emission intensity in Province		
Model	（1）	（2）	（3）	（4）	（5）	（6）
Constant	-9.476***	-9.140***	-8.436***	-1.955	-12.742***	-14.235***
Network density	-0.463			5.346		
Network hierarchy		-0.275			-2.679**	
Network efficiency			0.935			-11.475
R-squared	0.009	0.040	0.007	0.145	0.463	0.129
RESET test	0.94	5.63	0.43	1.00	3.32	0.78
	（0.4704）	（0.0279）	（0.7361）	（0.4486）	（0.0866）	（0.5433）
BP test	0.79	6.76	0.48	0.78	5.69	0.56
	（0.3743）	（0.0093）	（0.4876）	（0.3776）	（0.0170）	（0.4560）
BG test	2.774	4.21	2.809	0.791	3.065	0.813
	（0.0958）	（0.0402）	（0.0937）	（0.3739）	（0.0800）	（0.3672）

Note：1. ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively; 2. Values in parentheses are the parameter P estimating value.

However, the regression coefficients of models (1) to (3) are not significant, R2 is relatively small, and the regression results and corresponding analysis of model (2) are inconsistent with expectations, which is caused by the excessive growth of national carbon emissions in 2011 and 2012. 2011 is the first year of the 13th five year plan. In response to national policies, major construction enterprises have increased their efforts to develop real estate projects, resulting in the rapid development of the construction industry. In 2011, the GDP of construction enterprises exceeded one billion yuan for the first time, making the growth rate of national construction carbon emission reach an extreme value, resulting in great fluctuations in the intensity of national construction carbon emission over the years, and the fitting degree of the model is reduced. The model results can still reflect the impact direction of the overall network indicators on the national construction carbon emission intensity.

3.4.2. Individual spatial network structure effect analysis

The construction carbon emission intensity of each province is selected as the dependent variable, and the degree centrality, closeness centrality, and betweenness centrality of construction carbon emission intensity are used as dependent variables for regression analysis with OLS method. In order to eliminate the influence of dimension, all variables are calculated by taking the natural logarithm, and the results are shown in Table 4.

Table 4. Effect analysis results of individual network structure.

Model	（7）	（8）	（9）
Constant	-9.355***	-9.619***	-9.109***
Degree centrality	-0.367***		
Closeness centrality		-1.401***	
Betweenness centrality			-0.030
F			0.58
Wald	17.01***	21.23***	
Hausman	0.12	0.15	3.4*
FE/RE	RE	RE	FE

Note：1. ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively; 2. FE: Fixed effect; RE: Random effect.

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Degree centrality and closeness centrality have a significant impact on construction carbon emission intensity. The regression coefficient of model (9) is less significant, due to the construction carbon emission intensity of Hebei, Jilin and, Jiangsu provinces changed unstable in 2011 and 2012. But it still correctly indicates the impact direction of betweenness centrality on construction carbon emission intensity. According to the regression coefficients of each model, when the centrality of individual space network increases, it will reduce its own construction carbon emission intensity.

In order to study the impact of structural hole characteristics of each province on its own construction carbon emission intensity, carbon emission intensity is taken as the dependent variable, and effective scale, efficiency, restriction degree, and grade degree are taken as the independent variables for regression. All variables are standardized to eliminate the dimensional influence. According to the regression results in Table 5, the regression coefficients of the effective scale, efficiency, restriction degree and grade degree of the spatial correlation of the carbon emission intensity of the construction industry are -0.251, -0.218, 0.263, and -0.146, respectively, and it indicates that the network structure of the spatial correlation of the carbon emission intensity of the construction industry has a significant impact on the carbon emission level of the construction industry. After the efficiency is improved, some leading provinces have more influence in the network, retain "comparative advantages" in energy conservation, and can drive themselves and surrounding provinces to jointly reduce the regional construction carbon emission intensity. At the same time, the central position of economically developed provinces in the network and the ability to control structural holes are strengthened, which is conducive to reducing carbon emissions from the construction industry.

Table 5. Effect analysis results of structural hole index.

Explained variable	**Carbon emission intensity of construction industry**			
Model	（10）	（11）	（12）	（13）
Constant	0.346***	0.370***	0.148*	0.323***
Effective scale	-0.251**			
Efficiency		-0.218*		
Restriction degree			0.263*	
Grade degree				-0.146
R-squared	0.136	0.120	0.124	0.034

Note：1. ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.

4. Discussion

As can be seen from Fig. 1, the emission intensity of Inner Mongolia and Fujian Province was high in 2017. The emission intensity of most provinces is between 500-1500 kg/10000 yuan. It indicated that China's overall emission intensity is in a relatively balanced state. 2011 and 2012 are the first two years of the 12th Five Year Plan. China launched a series of policies to accelerate the transformation of economic development mode, adjust economic structure and promote steady and rapid economic development, to improve the quality of China's overall economic development [32]. In addition, major construction enterprises also began to vigorously develop the real estate industry, thus accelerating the development speed of the construction industry and increasing the carbon emission of the construction industry to a great extent [71]. In 2011, the consumption of cement materials in Hebei and Jiangsu increased suddenly, which greatly increased the total emission in 2011; while the consumption of cement in Jilin increased from 1950 million tons in 2011 to 114964 million tons in 2012, resulted in a sharp increase in the total emission in 2012. After 2013, Chinese government strongly advocated the development of resource-saving cities guided by energy conservation and emission reduction [61].

From 2006 to 2017, the overall network efficiency of carbon emission intensity of China's construction industry showed a downward trend, but there was a certain fluctuation in the downward process. It can be seen that the change trend of network efficiency

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corresponds to the network density, and the overall network tends to be stable. The network efficiency fluctuated upward in 2012. Due to the inadequate carbon emission control, the total emission in that year was much higher than that in other years, even reaching the peak during the development of the construction industry. However, the change trend of carbon emission was inconsistent with its economic development level, resulting in greater emission correlation to the surrounding provinces. The trendency reduced provincial correlation degree of the entire network and improved the network efficiency. The annual carbon emission intensity of each province has decreased steadily since 2014, which has been effectively controlled, and the network efficiency also shows a slight upward trend. The entire network has a significant spatial association effect, and it has no isolated individuals [72].

The spatial fairness of carbon emission intensity of construction industry is an important factor affecting construction carbon emission reduction and regional difference policies of construction carbon emission reduction [32,73,74]. The network hierarchy and network efficiency are increased by 1%, respectively, the standard deviation of construction carbon emission intensity will be reduced by 2.679% and 11.475%, respectively, while the network density are is increased by 1%, the standard deviation of construction carbon emission intensity will be increased by 5.346%. Due to the sharp increase of building emissions in Hebei, Jiangsu, Jilin, and other provinces in 2011 and 2012, the standard deviation of construction carbon emission intensity fluctuated greatly, resulting in low significance of the model. Therefore, reasonable allocation and adjustment of China's province construction carbon emission spatial network structure will help to reduce China's construction carbon emission intensity and narrow the difference of province construction carbon emission intensity [32,60].

The top seven provinces in degree centrality are Shanghai, Jiangsu, Beijing, Tianjin, Zhejiang, Shandong, and Guangdong, which are several provinces with more local construction carbon emission spatial relationships in the spatial network. These provinces are located in the eastern coast and cover economically developed areas such as "Beijing Tianjin Hebei", "Yangtze River Delta", and "Guangdong Hong Kong Macao Bay Area", which have more spatial correlation of construction carbon emissions, more exchanges in economy, talents and technology among regions, and the rapid development of economic integration has reduced the spatial difference of construction carbon emissions, Lead to the reduction of construction carbon emission intensity [75]. The provinces with higher intermediary centrality play a stronger "intermediary" role in the spatial network structure of construction carbon emission, and it helps to adjust the direction and degree of carbon emission impact among provinces, strengthen the leading role of economically developed provinces in other provinces, finally reduce the overall construction carbon emission intensity. In order to reduce the intensity of construction carbon emission, it should be managed as follows:

- Establish a unified and standardized carbon emission statistical accounting system to improve building energy efficiency. Actively participate in the research on international carbon emission accounting methods, enhance the capacity-building of carbon emission statistical accounting, deepen the research on accounting methods, and promote the establishment of a more fair and reasonable carbon emission accounting method system. Promote green low-carbon building materials and green construction methods, accelerate the industrialization of new buildings, vigorously develop prefabricated buildings, promote the recycling of building materials, strengthen green design and green construction management, advocate the concept of green low-carbon planning and design, and enhance the climate resilience of urban and rural areas [76]. Accelerate the update of standards for building energy conservation and municipal infrastructure, and improve the requirements for energy saving and carbon reduction. Strengthen the R&D and promotion of energy-saving and low-carbon technologies applicable for different climate zones and different building types, and promote the large-scale development of ultra-low energy consumption buildings and low-carbon buildings. Accelerate the energy-saving transformation of residential and public buildings, and continue to promote the energy-saving and carbon reduction transformation of municipal infrastructure such as old heating pipe networks. Accelerate the optimization of building energy consumption structure, promote energy-saving technology and equipment, and carry out the construction of energy management system to achieve energy saving and efficiency.

- Pay attention to the spatial correlation of provincial construction carbon emissions, optimize and adjust the spatial network structure of interprovincial construction carbon emissions, improve the spatial allocation efficiency of construction carbon emissions, and realize spatial collaborative carbon emission reduction to realize the new regionalism development [77]. The enhancement of the correlation between China's construction carbon emission intensity enables the country to coordinate the actions of all parties under the overall ideas of national chessboard, forming a 1+1>2 emission reduction effect. The strengthening of the correlation between construction carbon emission intensity requires further strengthening of regional spatial, economic and technological relationships.
- Implement construction carbon emission reduction according to local conditions and strengthen the overall carbon emission reduction. Different levels of economic development lead to great differences in construction carbon emission intensity and uneven spatial distribution. Location factors should be taken into account when formulating collaborative emission reduction regulations [78]. In line with the distribution traits of construction carbon emissions and the situation of the province, the administration should construct an advanced demonstration area focusing on the Yangtze River Delta, Pearl River Delta and Beijing-Tianjin-Hebei Urban Agglomeration, drive the surrounding provinces through radiation and interaction among cities, and link the carbon emission reduction management of adjacent regions. Fully consider the plate structure characteristics of the spatial correlation network of construction carbon emission, formulate regional differentiated construction carbon emission reduction policies, and implement the classified management of construction carbon space. Due to the different status and roles of China's regions in the construction carbon emission intensity correlation network, the dependence of regional carbon emissions should be fully considered when formulating and allocating emission reduction tasks. Make use of the block's own technical advantages and management experience, adjust the ideas of the block's economic and social development, promote the transformation of economic development mode, and implement the management of construction carbon emission reduction according to local conditions.
- Give full play to the positive role of the overall network structure and individual network structure of the spatial correlation of building carbon emissions in reducing the intensity of building carbon emissions and enhancing the spatial equity of building carbon emissions. Accelerate the establishment of the construction carbon emission reduction market system, further play the role of the market in resource allocation, and continuously narrow the gap in economy, resources and technology among provinces in the spatial correlation network of construction carbon emission, to promote the reduction of the overall construction carbon emission intensity. Improve the stability of construction carbon emission spatial network structure, give play to the spillover effect of construction carbon emission, and continuously improve the equity of construction carbon emission intensity and spatial emission under the condition of generally reducing the emission intensity of each province in the construction carbon emission spatial correlation structure network [79]. While maintaining the current emission reduction level, promote the development of the construction industry and effectively reduce construction carbon emissions by increasing industry output value and developing green building technology [80].

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5. Conclusions

Based on the measurement of China's construction carbon emission from 2006 to 2017, this paper constructs the spatial correlation network of construction carbon emission intensity by using the modified gravity model. This paper analyzes the structural characteristics of the spatial correlation network of construction carbon emission intensity at the provincial level, and then analyzes its driving effect. The main conclusions are as follows:

- China’s construction carbon emissions increased from 74.31 million tons in 2006 to 201.40452 million tons in 2017, with an average annual growth rate of about 14%. In the process of development, China’s construction carbon emissions are mainly concentrated in Zhejiang, Jiangsu, Hebei, and other provinces, accounting for nearly half of the country’s total emissions. However, Ningxia, Qinghai, Hainan, and other provinces ranked last in the construction carbon emissions, and the total emissions of the last ten provinces were less than 10% of that of the whole country, showing significant regional differences. The carbon emission intensity of construction industry show a fluctuation trend.
- The network density of interprovincial spatial correlation of China’s construction carbon emission intensity showed an increasing trend annually. The network hierarchy of spatial correlation of construction carbon emission intensity in China shows a downward trend, and the hierarchical network structure is gradually broken. The network efficiency generally shows a downward trend, there are small fluctuations up and down, and the spatial correlation network is more complex and stable. Shanghai, Jiangsu, Beijing, Tianjin, Zhejiang, Shandong, and Guangdong are in the forefront of the standardized degree centrality, closeness centrality, and betweenness centrality values are higher than the national average, respectively. They play a core role in the spatial association network of construction carbon emissions, and can also act as a “bridge”.
- The results of space block model analysis show that the first block is composed of Beijing, Tianjin, Jiangsu, Shandong, and Shanghai. The first block is in the “net benefit” in the spatial correlation structure model of construction carbon emission; Guangdong, Zhejiang, and Fujian belong to the second sector and are in the “broker” position in the spatial correlation structure model of construction carbon emission. Jilin, Hebei, Inner Mongolia, Gansu, Liaoning, Ningxia, Heilongjiang, Sichuan, Guizhou, Yunnan, Shanxi, Xinjiang, Qinghai, Chongqing, and Shaanxi belong to the third block, and it is in the “net overflow” in the spatial correlation structure model of construction carbon emission; Hubei, Hunan, Guangxi, Anhui, Hainan, Jiangxi, and Henan belong to the fourth block and are in the “broker” position in the spatial correlation structure model of construction carbon emission.
- The indicators such as network density, network hierarchy, and network efficiency have an impact on the national construction carbon emission intensity, and the indicators such as point degree and centrality will also significantly affect the construction carbon emission intensity of each province. The spatial correlation network structure of construction carbon emission intensity will also affect the difference of construction carbon emission intensity. The individual spatial network structure has a significant impact on the construction carbon emission intensity. The province correlation in the network will be closer with degree centrality, closeness centrality, and betweenness centrality increasing, which resulted in the reduction of construction carbon emission intensity. The spatial correlation network of construction carbon emissions has gradually developed a "center-edge" structure in the process of development.

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