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RESEARCH ARTICLE

Spatial association network of $PM_{2.5}$ and its influencing factors in the Beijing–Tianjin–Hebei urban agglomeration

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Abstract

In this paper, we empirically study the spatial association network of $PM_{2.5}$ and the factors influencing those correlations using the gravity model, social network analysis (SNA), and the quadratic assignment procedure (QAP) based on data from the Beijing–Tianjin–Hebei urban agglomeration (BTHUA) in China from 2005 to 2018. We draw the following conclusions. First, the spatial association network of $PM_{2.5}$ exhibits relatively typical network structure characteristics: the network density and network correlations are highly sensitive to efforts to control air pollution, and there are obvious spatial correlations within the network. Second, cities in the center of the BTHUA have large network centrality values, while cities in the peripheral region have small centrality values. Tianjin is a core city in the network, and the spillover effect of $PM_{2.5}$ pollution in Shijiazhuang and Hengshui is the most noticeable. Third, the 14 cities can be divided into four plates, with each plate having obvious geographical location characteristics and linkage effects. The cities in the association network are divided into three tiers. Beijing, Tianjin, and Shijiazhuang are located in the first tier, and a considerable number of $PM_{2.5}$ connections are completed through these cities. Fourth, differences in geographical distance and urbanization are the main drivers of the spatial correlations of $PM_{2.5}$. The greater the urbanization differences, the more likely the generation of $PM_{2.5}$ links is, while the opposite is true for differences in geographical distance.

Keywords Urban agglomeration · $PM_{2.5}$ · Spatial association · Social network analysis · QAP

Introduction

Compared with other pollutants (NOx and SOx), $PM_{2.5}$ is a long-lasting air pollutant and it negatively affects atmospheric visibility (Xiao et al., 2013; Khanna et al., 2018). Given its small particle size and ability to be easily enriched with toxic and harmful substances, $PM_{2.5}$ can enter the human bloodstream through the respiratory system and can cause harm to important organs, such as the heart and brain (Apte et al., 2018; Thiankhaw et al., 2022). China's crude style of economic growth in the recent past has led to severe $PM_{2.5}$ pollution, which is threatening the survival of residents and the stability of the ecosystem, hindering the sustainable development of society, and is becoming an environmental and social issue of key concern for the whole population (Wu et al., 2017; Zeng et al., 2019). For instance, chronic exposure to $PM_{2.5}$ pollution is the fourth leading cause of mortality in China (Wang et al., 2015), and in early 2013, $PM_{2.5}$ concentrations in some Chinese cities even exceeded 1000 μg/m^3, approximately 40 times higher than the health standard established by the World Health Organization (WHO). A national action plan was issued by the Chinese government to combat air pollution and protect the public's health. Data from the ambient air quality monitoring network show that haze pollution has recently decreased in some cities (Wang et al., 2017b; Lang et al., 2017; Wang et al., 2021).

The Beijing–Tianjin–Hebei urban agglomeration (BTHUA) is one of the most prosperous regions in China, but it is one of the most polluted regions in terms of $PM_{2.5}$. The Ministry of Environmental Protection released data showing that seven of the ten most polluted cities in 2020 were in the BTHUA. With the expansion of cities, the effects of $PM_{2.5}$ have become increasingly obvious due to both

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atmospheric circulation and atmospheric chemistry, and the dynamic associations between cities constitute an intricate and complex network in which cities are nodes, which creates great difficulties for pollution management (Mao et al., 2022). Therefore, in the BTHUA, each city should not only consider its own $PM_{2.5}$ emissions but also control the $PM_{2.5}$ emissions of its neighboring cities to accomplish its pollution control task. In this context, it is necessary to understand the spatial distribution of $PM_{2.5}$, clarify the spatial correlations and the spatial structure of $PM_{2.5}$ across individual cities, and formulate practical measures for pollution control.

$PM_{2.5}$ pollution control has been a topic of widespread concern among scholars. First, according to most scholars, $PM_{2.5}$ emissions mostly originate from industrial exhaust, automobile exhaust, cooking fumes, and other sources (Oishi et al., 2019; Saraga et al., 2019; Zhang et al., 2021; Rahmana and Thurston, 2022). Second, some scholars have explored the socioeconomic factors that drive $PM_{2.5}$ emissions, including economic development, population size, energy consumption, and industrial structure (Huang et al., 2016; Wang et al., 2018; Wang and Wang, 2021; Wang and Li, 2021). Other scholars have examined the impact of $PM_{2.5}$ on economic and social development (Hao et al., 2018; Nguyena et al., 2022) and evaluated its health effects (Huang et al., 2018; Requia et al., 2018; Liang et al., 2022). Due to accelerated regional integration and increasingly frequent economic activity at the regional level, $PM_{2.5}$ emissions in different regions interact with each other and exhibit certain spatial characteristics. Therefore, scholars have studied the following two main spatial characteristics of $PM_{2.5}$. First, the variation in $PM_{2.5}$ across different regions and seasons has been studied at multiple scales; for example, the $PM_{2.5}$ concentrations in winter and autumn are higher than those in spring and summer (Wang et al., 2016). $PM_{2.5}$ concentrations are higher in the northern reaches of the Yangtze River in China, and in the most polluted cities, including Beijing, Tianjin, Shandong, Henan, and Hebei, which are mainly located in the North China Plain (Wang et al., 2017c; Wu et al., 2018). Second, spatial statistical methods and spatial econometric models have been applied to investigate the spatial clustering characteristics of $PM_{2.5}$. It was found that $PM_{2.5}$ exhibits both global spatial correlations and local clustering characteristics among spatial units of different levels, such as countries, provinces, and cities; i.e., $PM_{2.5}$ in one area exacerbates $PM_{2.5}$ in surrounding areas (Chen et al., 2019; Ding et al., 2019; Yang et al., 2021; Zheng et al., 2022). In the BTHUA, $PM_{2.5}$ pollution often shows obvious spatial autocorrelation, with a strong spatial spillover effect between different cities (Wu et al., 2020). Overall, cities far from Bohai Bay, such as Shijiazhuang and Hengshui, demonstrated a high–high concentration of $PM_{2.5}$ pollution, while coastal cities, such as Chengde and Qinhuangdao, showed a low–low concentration (Yan et al., 2018). Discovering the interconnection and evolution pattern of $PM_{2.5}$ pollution in the region can provide a policy basis for joint regional pollution management and industrial and energy structure adjustment (Xu et al., 2022). The local contribution of Beijing played an important role in controlling the $PM_{2.5}$ concentrations from the surface to 0.1 km, while the regional transport was considerable from 0.1 to 2.0 km, particularly from the severely polluted upwind region. It is critical to enhance regional joint emission control, especially during pollution episodes (Sun et al., 2022).

In the 1960s, sociologists created the theory underlying social network analysis (SNA) with a set of mathematical analytical methods derived from graph theory, which can be used to effectively measure network structures. SNA is an interdisciplinary analytical method that uses relationships between a single actor and group of actors as a basis for quantification and describes the patterns in the network relationships with algebraic methods and tools from graph theory to analyze the overall, individual characteristics and structure of the spatial association network (Khan et al., 2016; Wang et al., 2017a). There are many applications for SNA, such as economics, management, and computer science (Yu and Ma, 2020; Zhang et al., 2020; Leng et al., 2021; Meng et al., 2021), which have provided very rich results and have become a new research paradigm. Recently, SNA has also been applied to the study of carbon emissions, pollution management, energy consumption, and other environmental and energy issues (Su and Yu, 2019; Bai et al., 2020; Shen et al., 2021). In $PM_{2.5}$ pollution research, complex networks can divide urban $PM_{2.5}$ by year and season to reveal the physical process of regional dispersion (Li et al., 2019). SNA can also be combined with spatial metrology to identify the spatial correlation network form of $PM_{2.5}$ pollution, reveal its overall characteristics, and then build a spatial network weight to explore the relationship between $PM_{2.5}$ pollution and economic development (Qi et al., 2023).

Although existing studies have shown that $PM_{2.5}$ is nonexclusive and noncompetitive because it results in spatial spillovers and transboundary pollution, the limitations of spatial econometric models mean that such studies have been able to only show that there are correlations in interregional $PM_{2.5}$. However, analyses of the correlations of $PM_{2.5}$, and even those that reveal the spatial structure of those correlations, are insufficient because of two main limitations. First, in all these analyses, attribute data are used instead of relational data, which makes it difficult to visualize the spatial association network of $PM_{2.5}$. Moreover, the network structure often determines the attributes, making relational data more valuable as an object of analysis. Second, previous studies have not further revealed the form of the spatial network structure of $PM_{2.5}$. In addition, traditional methods of measurement can only be used to examine the effect of the quantity of $PM_{2.5}$ conditional on spatial factors but cannot reveal the relational effects of the spatial associations in $PM_{2.5}$. The effects of the relationships in $PM_{2.5}$ cannot be identified. In addition, existing studies on the spatial associations in $PM_{2.5}$ are mostly based on national or provincial level data, and most studies only consider geographical proximity and fail to start at the smaller-scale city level, while the cities within urban agglomerations, as the most spatially dense form of urban development in China, have closer economic, trade, population, and energy ties than provincial agglomerations, and the corresponding spatial associations in $PM_{2.5}$ are more prominent. On this basis, it is of practical importance to reveal the structural patterns and clustering mode of the spatial associations in $PM_{2.5}$. Therefore, we use SNA to investigate the spatial association network of $PM_{2.5}$ in the BTHUA and its influencing factors. Our main contributions are as follows.

(1) This paper takes 14 cities of the BTHUA in China as research objects, discusses the association network structure of $PM_{2.5}$ among cities from a more microscopic perspective, and provides a new idea for the study of the collaborative governance of $PM_{2.5}$.
(2) An improved gravity model is used to identify the spatial association network of $PM_{2.5}$ among the 14 cities, and the structural patterns of the network are identified. The characteristics of the network are analyzed in detail at three levels, the overall, individual, and subgroup levels, revealing the role played by each city in the network.
(3) To avoid the problem of multicollinearity, the factors that affect the spatial association network of $PM_{2.5}$ are analyzed by applying the quadratic assignment procedure (QAP). Additionally, by decomposing the drivers of $PM_{2.5}$ in each city, differences between cities can be shown in more detail.

The following are the remaining sections of this paper. The study area, methods, and data sources are presented in the "Materials and methods" section. The results and discussion are presented in the "Results and discussion" section. Conclusions are presented in the "Conclusion and policy implications" section.

Materials and methods

Study area

In this paper, the BTHUA is selected as the study area. It had a total size of 218,000 km^2, a population of 110 million in 2021, and a GDP of 9.6 trillion yuan. As shown in Fig. 1, the BTHUA is located on the Bohai Sea in the heart of Northeast China and is the largest and most economically dynamic region in northern China, attracting increasing attention domestically and globally. However, heavy industry is also highly developed in this area, and it exhibits the most representative and severe cases of extreme air pollution. As China's economic and political center, the BTHUA has been shackled by its severe air pollution. As shown in Fig. 1, the BTHUA includes a total of 14 cities, including Beijing, Tianjin, and Anyang in Henan Province and Baoding, Tangshan, Langfang, Shijiazhuang, Qinhuangdao, Zhangjiakou, Chengde, Cangzhou, Hengshui, Xingtai, and Handan in Hebei Province.

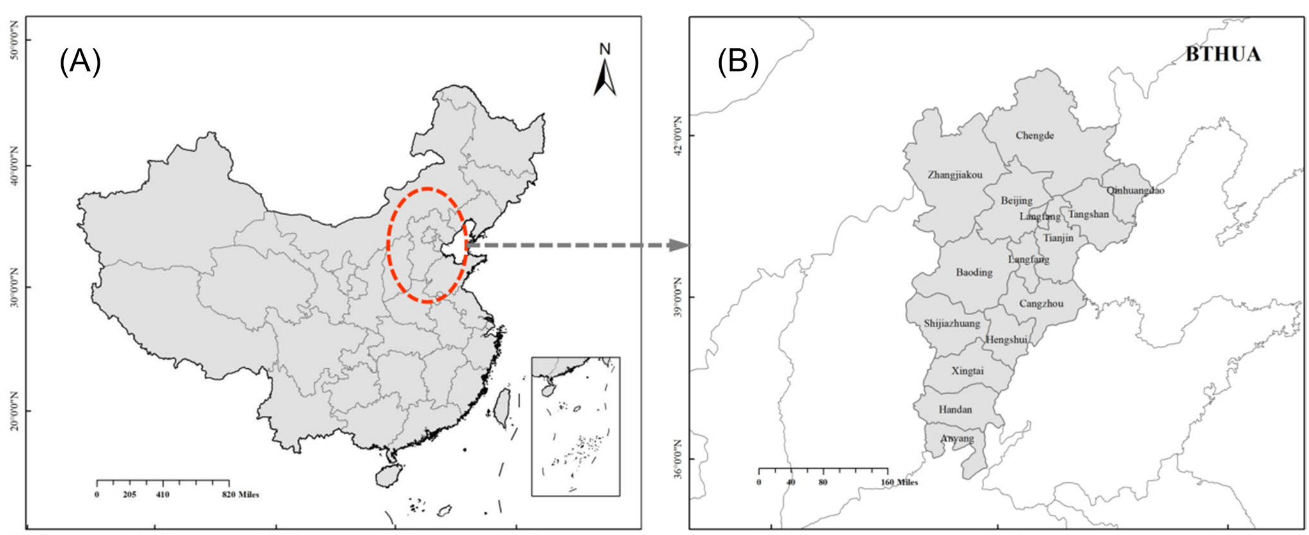

Fig. 1 Study area

Modified gravity model

The spatial association network of $PM_{2.5}$ in the BTHUA is a collection of interrelationships among 14 cities in terms of their $PM_{2.5}$. The network consists of two components, i.e., points and lines, and is expressed as G(V, E), with the points (V) representing each city and the lines (E) representing the correlations of $PM_{2.5}$ between cities. The establishment of a network is a prerequisite for network analysis, and the purpose behind constructing such networks is to identify spatial associations and relationships. According to the literature, there are two main methods for identifying such relationships: the vector autoregressive model (Li et al., 2014) and the gravity model (Yang et al., 2016). Because the vector autoregressive model is highly dependent on the choice of lag, it is difficult to comprehensively account for the economy, distances, and $PM_{2.5}$ pollution levels in establishing linkages. Due to the above factors, a gravity model is introduced to construct the network of intercity associations. In addition, the gravity model is modified to enhance its applicability. To prevent distance from having an excessive influence on intercity $PM_{2.5}$ associations, the friction factor is set at $b=1$. Equation (1) represents the modified gravity model:

$$y_{ij} = k_{ij}\frac{\sqrt[3]{G_iP_iC_i}\sqrt[3]{G_jP_jC_j}}{D_{ij}}, k_{ij} = \frac{C_i}{C_i + C_j} \tag{1}$$

where i and j denote different cities; y_{ij}characterizes the gravitational force between cities i and j in terms of $PM_{2.5}$; P_i and P_j denote the total year-end population of cities i and j; C_i and C_j denote the average annual $PM_{2.5}$ emissions of cities i and j; and G_i and G_j denote the gross regional product of cities i and j. D_{ij} denotes the geographical distance between cities i and j; k_{ij} characterizes the contribution of city i to the total $PM_{2.5}$ of cities i and j. Equation (1) is used to calculate the gravity matrix between $PM_{2.5}$. A row's mean value in the gravity matrix is used as a critical value, and any city with a gravitational force higher than the critical value for the row receives a 1, indicating that the $PM_{2.5}$ of the cities in that row are correlated with the $PM_{2.5}$ of the cities in the column; in contrast, if the gravitational force for a given city is lower than the critical value for the row, it is listed as a 0, showing that the $PM_{2.5}$ of the cities in the row are not correlated with those of the cities in the column.

Indicators of the spatial association network

In this paper, the $PM_{2.5}$ associations among the cities in the BTHUA are viewed as a spatial network. The cities are viewed as nodes in the network, and the intercity relationships are the linkages between nodes. Given this network construction, the characteristics of the $PM_{2.5}$ associations among cities can be quantified with the relevant indicators.

Overall network characteristics

The network correlation, network rank, and network density are applied to characterize the overall network. The network correlation is the sum of the number of directed line segments in the network, which reflects the robustness and vulnerability of the network. If many of the lines in the network are connected to the same city, then the dependence of the network on that city is high; in other words, the network may collapse if that city is removed. In the association network of $PM_{2.5}$ in the BTHUA, the network rank measures the extent to which city's access to other cities is asymmetrical. A higher network rank indicates a more rigid hierarchical structure among cities, with more cities being marginal and subordinate to other cities. The equation for network rank is given by Eq. (2).

$$H = 1 - \frac{V}{\max(V)} \tag{2}$$

where V denotes the number of symmetrically accessible pairs of points.

Network density indicates how closely cities are connected. The greater the network density is, the stronger the intercity $PM_{2.5}$ linkages. The formula for calculating network density is shown in Eq. (3).

$$D = \frac{M}{N(N-1)} \tag{3}$$

where N and M indicate the number of cities and $PM_{2.5}$ associations, respectively.

Individual network characteristics

In SNA, the most commonly used network structure characteristics at the node level are degree centrality (DC), betweenness centrality (BC), and closeness centrality (CC), which are applied to depict the centrality of the network.

In the spatial association network of $PM_{2.5}$ in the BTHUA, DC indicates the number of direct associations between one city and other cities. A city with a higher DC has more associations with nearby cities and is closer to the network center. In a directed network graph, nodes will send and receive association relations. Therefore, DC is also divided into out-degree centrality, which measures the number of associations in which the focal city sends $PM_{2.5}$ to other cities, and in-degree centrality, which denotes the number of associations in which $PM_{2.5}$ is passively received by the city from other cities.

BC represents the extent to which a city controls the relationships among other cities, i.e., the extent to which it is "in between" other cities. A higher BC means that the city controls more interactions between other cities and is closer to the network's center. The formula for BC is shown in Eq. (4).

$$BC = \frac{2\sum_{j}^{n}\sum_{k}^{n} g_{jk}(i)/g_{jk}}{n^2 - 3n + 2} \tag{4}$$

where n is the number of nodes, g_{jk} denotes the total number of shortest association paths between nodes j and k, $k \neq i \neq j$, and $j<k$.

CC is the indicator of a city's freedom from "control" by other cities in the pollution linkage process. A city's proximity to the center means more direct connections with other cities. The formula for calculating CC is shown in Eq. (5).

$$CC = \frac{\sum_{j=1}^{n} d_{ij}}{n-1} \tag{5}$$

where n is the number of nodes and d_{ij} denotes the shortest distance between two nodes.

Spatial clustering analysis

The blockmodel is one of the main cluster analysis methods in SNA, which enables an analysis of each block's role in the network. The CONCOR method used in the block model is an iterative correlation convergence method. It is based on the fact that if the correlation coefficients between the rows (or columns) of a matrix are calculated repeatedly, the result will be a matrix of correlation coefficients consisting of only 1 and −1. By rearranging the matrix with only 1 and −1 values, a partitioning of the corresponding actors is achieved. Based on this, the block in the spatial correlation network can play one of four roles. The first is the role of a net beneficiary. A member of this type of role receives connections both from members of other plates and from members within its own plate, and it receives a greater number of ties from outside than it sends. The second role is that of a net spillover position. This type of plate sends out significantly more connections to other plates than it receives from other plates. The third role is the two-way spillover role, in which the plate member sends out ties and receives ties from other plates, although relatively more ties come from members within the plate. The fourth role is the broker role. A plate member that is a broker sends out ties and receives ties from other plates, with more ties between that plate and the members of other plates.

A core–edge structure is a special type of network structure with a tightly connected center and sparsely dispersed periphery (Borgatti and Everett, 1999). If the blocks in the similarity matrix can be swapped so that the 1-blocks are concentrated in the upper left half of the image matrix and the 0-blocks in the lower right half, then a core–edge structure is evident in the block model. In simple terms, in a core–edge structure, the nodes along the edges maintain close ties with certain core nodes, although their connections to other peripheral nodes are sparse and scattered across the edges. This core–edge structure is often seen in the world economy system. Since the correlation matrix data used in this paper consist of binary 0–1 matrices, which are a type of fixed data, a discrete core–edge structure model is used. Hence, the final fitness of the rearranged matrix and the ideal matrix reaches the maximum.

QAP method

When conducting multiple linear regression, a prerequisite assumption is that the explanatory variables must be independent of each other and cannot be highly linearly correlated; otherwise, multicollinearity will result in severely inaccurate estimates. The variables in this paper are highly correlated with each other; therefore, traditional multiple linear regression is no longer appropriate. However, in the quadratic assignment procedure (QAP), the explanatory variables should all be highly correlated. In QAP, the underlying data are in matrix form, and the correlations between matrices are determined by comparing the differences between two matrices. First, the correlation coefficient between two known matrices is calculated. Second, a random permutation is performed on the rows and columns of one of the matrices at the same time (not just the rows or columns; otherwise, the original data would be broken). Then, the correlation coefficient between the permutation matrix and the other matrix is calculated, and this process is repeated hundreds or even thousands of times to obtain a distribution of correlation coefficients. Finally, the correlation coefficient observed in the first step is compared with the distribution of the correlation coefficient calculated according to the random rearrangement to determine whether the observed correlation coefficient falls into the rejection area or the acceptance area and then make a judgment.

The basic regression model for QAP is shown in Eq. (6).

$$Y = f\left(X_1, X_2, \ldots\ldots X_n\right) \tag{6}$$

Y denotes the explained variable, which represents the matrix of spatial correlations in $PM_{2.5}$. X_i denotes the explanatory variable, which represents the matrix of factors that influence the correlations.

Data sources

The sample period for this study is 2005 to 2018, and 14 cities in the BTHUA are used as network nodes. The following are the data sources and data processing steps. The data on the population, population density, and GDP are obtained from the China City Statistical Yearbook for the corresponding year. To remove the influence of price factors, GDP is deflated using 2005 as the base year. Technology innovation is measured by how many patents are granted per capita, which is obtained from the Patent Cloud database. Urbanization is calculated as the urban population divided by the total population. Environmental regulation is expressed as the comprehensive utilization rate for industrial solid waste. Industrial structure is expressed as the share of secondary industry value added in GDP. The data required for the above variables are derived from the China City Statistical Yearbooks. The geographical distance between cities is calculated with ArcGIS.

Results and discussion

Characteristics of the overall network structure

The spatial correlation characteristics of $PM_{2.5}$ in the BTHUA will be discussed from the three dimensions of overall, individual, and group. The overall analysis of the network focuses on its overall structure, the individual-level analysis investigates the position of each city within the network, and the group-level analysis is essential for investigating the relationships within and among subgroups. Figure 2 shows the distribution of $PM_{2.5}$ in the BTHUA in 2018, and the figure shows that the $PM_{2.5}$ in the coastal region is the most severe.

To depict the spatial correlation structure of $PM_{2.5}$, the gravity matrix for 2018 is calculated, as shown in Table 1, and the network diagram for 2018 is drawn using the UCINET visualization tool Netdraw, as shown in Fig. 3. The nodes in the diagram represent individual cities. The sizes of the points in the figure correspond to their DC; the larger points indicate greater DC, and smaller points indicate lower DC. The directed line segments between the nodes indicate the correlations between cities. The more correlations received by the nodes indicate that the greater the city can aggregate the key factors that form $PM_{2.5}$, and the higher the point entry degree of the city. The spatial associations in $PM_{2.5}$ follow a typical network structure pattern. The results verify the core concept of new regionalism, an important theoretical paradigm of regional development research proposed by Ethier (1998). The principle of new regionalism advocates for regional integration and coordinated development, and hence, a joint regional pollution governance approach provides a new path for environmental governance

Fig. 2 Distribution of $PM_{2.5}$ in the BTHUA in 2018

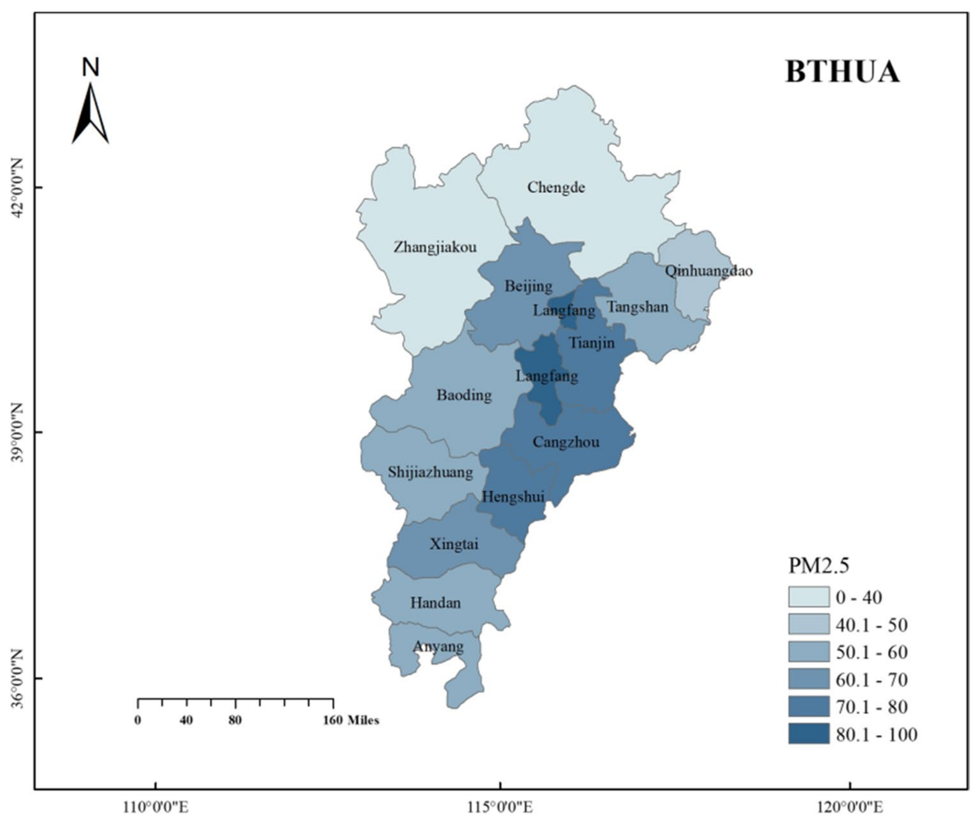

Table 1 Gravity matrix in the BTHUA in 2018

	Beijing	Tianjin	Tangshan	Shijiazhuang	Cangzhou	Baoding	Handan	Langfang	Anyang	Xingtai	Zhangjiakou	Chengde	Hengshui	Qinhuangdao
Beijing	0	6447	2698	1775	2357	2782	953	7547	602	856	472	565	1027	518
Tianjin	3910	0	2861	1348	3954	1917	803	3680	506	718	178	297	1008	441
Tangshan	2089	3652	0	641	1163	782	412	1411	267	356	115	319	427	547
Shijiazhuang	1327	1662	619	0	1149	1689	1297	782	685	1522	124	115	1310	152
Cangzhou	1369	3787	873	893	0	1129	540	1061	330	488	80	113	861	176
Baoding	2211	2511	803	1795	1544	0	693	1351	408	673	158	145	972	177
Handan	728	1011	406	1325	710	666	0	436	2058	2767	69	75	730	108
Langfang	3959	3183	956	549	958	892	300	0	188	272	92	135	358	156
Anyang	450	624	258	685	425	384	2016	269	0	897	43	48	385	70
Xingtai	611	845	329	1453	599	605	2588	370	856	0	57	60	691	85
Zhangjiakou	1164	724	367	409	341	490	222	435	141	196	0	123	192	99
Chengde	991	859	723	270	341	319	172	453	112	147	88	0	155	210
Hengshui	624	1010	335	1065	900	743	581	414	313	588	47	54	0	79
Qinhuangdao	551	773	752	217	323	237	150	316	100	126	43	128	138	0

at this stage. This also further expands Su and Yu's (2019) conclusion that $PM_{2.5}$ pollution not only has a spatial correlation network structure at the provincial level but also has an obvious spatial correlation network structure at a more microscopic urban level.

Figure 4 depicts the evolution of network correlation and network density from 2005 to 2018. The number of relationships fluctuates sharply between 65 and 74 in the period 2005–2012, while it varies slightly between 67 and 69 in the period 2013–2018. Network density and network correlations started to decrease significantly in 2010 and 2012. This is consistent with the research conclusion of Wu et al. (2020); that is, the air quality in the BTHUA improved significantly during these two time periods, as evidenced by the significant decrease in network density and network correlation. The possible reason is that in 2010, the State Council placed great emphasis on the control of air pollution and inspected the work to save energy and reduce emissions in 18 key regions in 6 batches. Specifically, in May 2010, the State Council launched a strategic environmental assessment of the Beijing–Tianjin–Hebei, Yangtze River Delta, and Pearl River Delta regions and established a new mechanism for pollution prevention. In 2012, the BTHUA and other regions took the lead in $PM_{2.5}$ detection and increased their overall management of air pollution.

Numerically, the maximum number of possible relationships among all cities is 182 (13 × 14), and the lowest number of actual relationships is 65. The CC for the spatial association network of $PM_{2.5}$ is very high, and the network exhibits very clear spatial associations and spillover effects. This is consistent with the research conclusion of Li et al. (2019). With the rapid development of high-tech industries, backward industries and technologies in developed cities are often eliminated and may be transferred to surrounding underdeveloped cities (Zhang et al., 2019). This process manifests itself as a spatial spillover effect of $PM_{2.5}$ pollution (Zheng et al., 2022). As the BTHUA continues to expand, industrial transfers and industrial agglomerations within the urban agglomeration gradually occur, trade between cities becomes increasingly concentrated, and the degree to which cities within this urban agglomeration are associated should deepen. However, as the importance of managing $PM_{2.5}$ in China gradually increases, the number of redundant links in the network may gradually be reduced, thus gradually decreasing and stabilizing the density of the network and effectively alleviating the difficulty of managing $PM_{2.5}$ caused by high intercity correlations in $PM_{2.5}$. In addition, the rank of the network has been maintained at 0.375, which indicates that the status of each city in the network is very stable, and the core–edge relationships have remained relatively clear.

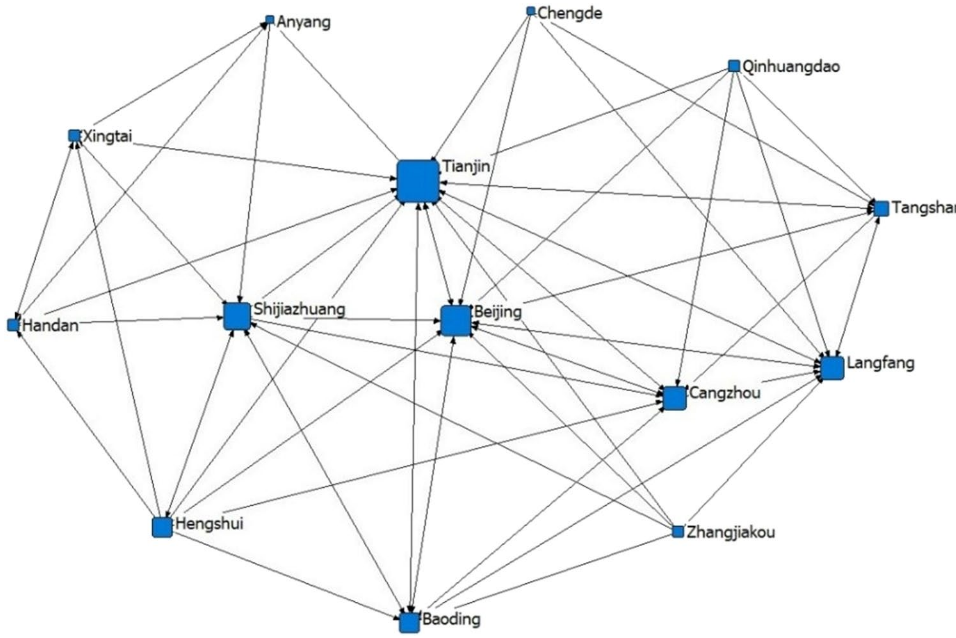

Fig. 3 Spatial association network of $PM_{2.5}$ in the BTHUA in 2018

Centrality analysis

To further analyze the centrality of each city in the network, this paper calculated DC, BC, and CC measures for 2018, and the results are presented in Table 2.

Degree centrality

According to Table 2, the mean DC value for the BTHUA is 52.75. There are seven cities with DC values higher than this mean value, namely, from high to low, Tianjin, Beijing, Shijiazhuang, Cangzhou, Langfang, Baoding, and Hengshui. These seven cities have the most relationships with other cities in the network. Of these cities, Tianjin and Beijing, the two largest core cities in the BTHUA, have a greater influence on other cities in terms of economic pull and population agglomeration. In the city cluster, they are responsible for controlling $PM_{2.5}$, the results of which radiate throughout the BTHUA, and they are at the core of the network. Notably, Tianjin not only has significantly higher DC than other cities but also ranks first in BC and CC. The mean value for in- and out-degree centrality in the 14 cities is 5. There are two cities with out-degree values higher than this mean value, namely, Shijiazhuang and Hengshui, which indicates that the $PM_{2.5}$ from these two cities has strong spillover effects on other cities and should be the key control target of $PM_{2.5}$, which is consistent with the research conclusions of Yan et al. (2018). There are six cities with higher than average $PM_{2.5}$ in-degree values, namely, from high to low, Tianjin, Beijing, Cangzhou, Langfang, Shijiazhuang, and

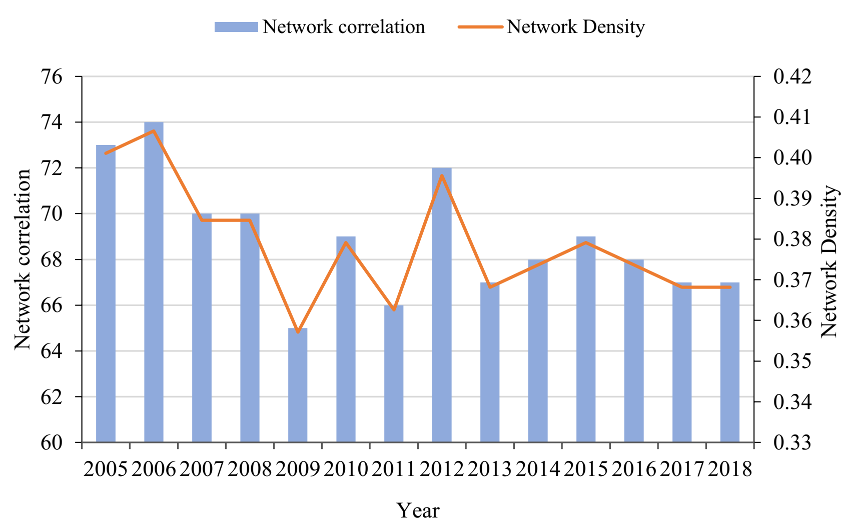

Fig. 4 Trends in network correlation and network density, 2005–2018

Table 2 Network centrality analysis

City	In-degree	Out-degree	Degree	Betweenness	Closeness
Beijing	10	5	76.92	7.14	81.25
Tianjin	13	5	100.00	29.25	100.00
Tangshan	5	4	46.15	0.64	65.00
Shijiazhuang	6	7	70.23	7.31	76.47
Cangzhou	8	4	61.54	2.93	72.22
Baoding	6	5	53.85	1.15	68.42
Handan	4	4	38.46	0.32	61.90
Langfang	8	4	61.54	3.25	72.22
Anyang	2	4	30.77	0.00	59.09
Xingtai	4	4	38.46	0.32	61.90
Zhangjiakou	0	5	38.46	0.26	61.90
Chengde	0	4	30.77	0.00	59.09
Hengshui	1	7	53.85	2.56	68.42
Qinhuangdao	0	5	38.46	0.00	61.90

Baoding. Of these cities, Beijing and Tianjin have much larger in-degree centrality values than out-degree centrality values due to the size and relatively limited self-sufficiency of these two cities in terms of resources; they are highly dependent on resources from other cities, which requires industrial enterprises to cluster in the surrounding cities to provide resource support. Moreover, the density and technological development level of industrial enterprises are important triggers for $PM_{2.5}$, which in turn causes Beijing and Tianjin to be dependent on the surrounding cities. Cangzhou, Baoding, and Langfang are located at the center of the triangle formed by Beijing, Tianjin, and Shijiazhuang and are vulnerable to spillovers of $PM_{2.5}$ from these large neighboring cities, so their DC is also higher.

Betweenness centrality

The mean BC value is 3.94. There are three cities with BC values higher than this mean value, namely, from high to low, Tianjin, Shijiazhuang, and Beijing. These cities have a stronger ability to control exchanges of $PM_{2.5}$ than other cities in the network and act as a communication bridge between other cities. $PM_{2.5}$ management should be implemented in cities with high BC, as by controlling $PM_{2.5}$ emissions in these cities, we can block the relationships among other cities in terms of $PM_{2.5}$ and control spillovers of $PM_{2.5}$. In addition, the BC values for Tangshan, Handan, Anyang, Xingtai, Zhangjiakou, Chengde, and Qinhuangdao are all below 1, accounting for only 2.8% of the BC value for the overall network. These cities have BC values that are much lower than those of other cities. These cities are located at the edge of the BTHUA and are characterized by small economies, low consumption expenditures, and small population sizes. Therefore, it is difficult for them to assume a dominant role in regulating the $PM_{2.5}$ of other cities in the network.

Closeness centrality

The mean CC value is 69.27. There are 5 cities with CC values higher than this mean value, namely, from high to low, Tianjin, Beijing, Shijiazhuang, Cangzhou, and Langfang. These cities are linked to other cities through the shortest paths; i.e., they can connect more quickly and deeply with other cities. The cities of Beijing, Tianjin, and Shijiazhuang have large economies, large population sizes, and high levels of technological development, and they act as central actors in the network. While Cangzhou is dominated by light industry, Langfang is geographically located between Beijing and Tianjin—the two cities with the highest DC. The $PM_{2.5}$ flows from Beijing and Tianjin to other cities are efficient, and it is easy for these two cities to establish connections with surrounding cities through industrial transfers and technology spillovers; thus, the CC value for Langfang is also high.

Spatial clustering analysis

This paper reveals the locations and roles of different subgroups in the network through block model analysis and core–edge analysis. Based on the above analytical approaches, the spatial hierarchy of the $PM_{2.5}$ distribution in the BTHUA in 2018 is mapped.

Blockmodel analysis

We analyze the spatial clustering of each city in the network with a blockmodel and adopt the CONCOR iterative method from UCINET. We choose a maximum segmentation depth of 2 and a concentration criterion of 0.2 to divide the 14 cities into four plates. The results are presented in Table 3. Plate I contains 6 members: Beijing, Tianjin, Tangshan, Cangzhou, Baoding, and Langfang. There are three members

Table 3 Analysis of spillover effects

Block number of provinces	Receive relationship		Overflow relationship		Expected internal relationship ratio	Actual internal relationship ratio
	Inside	Outside	Inside	Outside		
I	26	24	26	1	38	96
II	0	0	0	14	15	0
III	2	5	2	12	8	14
IV	6	4	6	6	15	50

in plate II: Zhangjiakou, Qinhuangdao, and Chengde. There are 2 members in plate III: Hengshui and Shijiazhuang. Finally, there are 3 members in plate IV: Anyang, Xingtai, and Handan.

This paper further reveals the positions of the four plates in the network through the blockmodel, as shown in Table 3. According to the previous measurement results, there are 67 relationships in the overall network, with 34 relationships between plates and 33 relationships within plates, indicating that the spatial correlations between plates are more obvious. The total number of receiving relations for plate I is 50, and the total number of sending relations is 27. The total number of receiving relations outside the plate is 24, which is many more than the corresponding number for other plates. According to this plate, the internal relationship ratio is 96%, higher than the theoretical value of 38%. A member of this plate receives connections from members of other plates and from members within its own plate, and it receives a greater number of ties from outside than it sends. Therefore, plate I is a net beneficiary plate. The total number of incoming relationships for plate II is 0, and the total number of outgoing relationships is 14, all of which are out-of-plate relationships. The actual internal relationship ratio for this segment is 0%, which is below the expected ratio of 15%. This plate sends out significantly more connections to other plates than it receives from other plates. Therefore, plate II is a net spillover plate. In plate III, there are 7 incoming relationships, 14 outgoing relationships, and 2 internal relationships. The expected internal ratio for this segment is 8%, and the actual internal ratio is 14%. This plate member both sends out ties and receives ties from other plates, with more ties between that plate and the members of other plates. According to the definitions given, plate III is a broker plate. The total number of incoming relationships in plate IV is 10, the total number of outgoing relationships is 12, and the number of relationships internal to the plate is 6. The expected internal ratio of this plate is 15%, and the actual internal ratio is 50%. Plate IV is a bilateral spillover plate, in which the plate member sends out ties and receives ties from other plates, although relatively more ties come from members within the plate. The fourth role is the broker role.

To investigate the associations in $PM_{2.5}$ among the plates, a network density matrix for each plate is calculated based on the associations, as presented in Table 4. In addition, according to the previous measurements, the density of the spatial association network in 2018 was 0.368. Plates with a network density above the overall network density are assigned a value of 1, and plates with a network density below the overall network density are assigned a value of 0. A multivalued density matrix can thus be changed into a binary matrix, as presented in Table 5. The correlations among the four plates are depicted in Figure 5, and the cities within each plate are clearly similar in terms of their geographical location. Plate I is located in the middle of the BTHUA, and the cities on the plate are geographically adjacent, have high economic development, and a relatively limited supply of resources, so they have a higher need for resources from other cities. This results in a large number of receiving relationships outside the plate and a low number of sending relationships outside the plate. Among these six cities, Tianjin, Tangshan, and Baoding all have industry and manufacturing as their economic support, while Tianjin, Cangzhou, and Tangshan have rich marine resources and strong advantages in terms of new energy development. Therefore, in addition to receiving surplus resources from the remaining three plates, plate I has more internal correlations and communication. The members of this plate

Table 4 Subgroup density matrix

Block number of provinces	I	II	III	IV
I	0.867	0.000	0.083	0.000
II	0.722	0.000	0.167	0.000
III	0.667	0.000	1.000	0.667
IV	0.167	0.000	0.500	1.000

Table 5 Similarity matrix

Block number of provinces	I	II	III	IV
I	1	0	0	0
II	1	0	0	0
III	1	0	1	1
IV	0	0	1	1

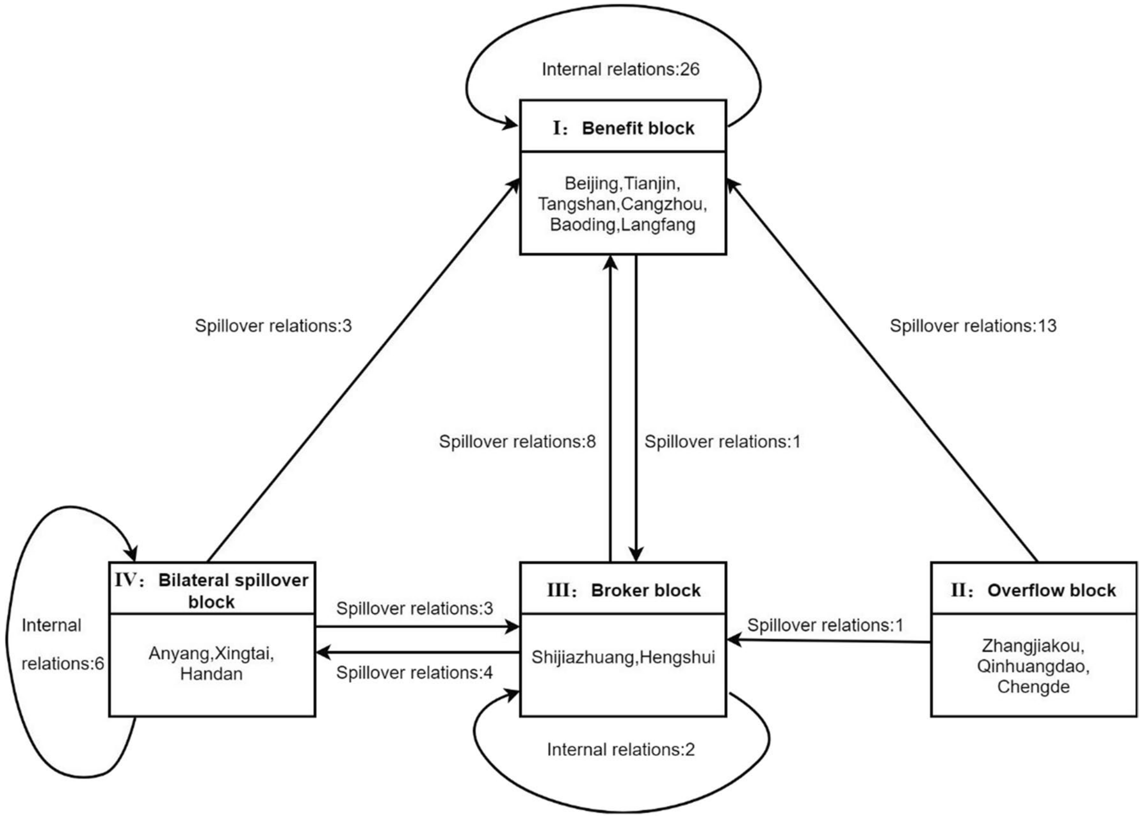

Fig. 5 Correlations among the four plates in 2018

serve as the "core" and "top and bottom" of the network, with the greatest difficulty and the highest marginal benefits of treatment. Plate II is located in the northern part of the BTHUA, with cities that have large areas, small populations, abundant energy resources, little external support, and clear spillover effects. These cities are the engine of the spatial association network. Plate III and plate IV are located in the southern part of the BTHUA, and both receive and send out relations. For example, Shijiazhuang, located in plate III, is an outward-oriented industrial city with manufacturing, chemical, pharmaceutical, and textile industries, so plate III sends out more relations to cities outside of itself than does plate IV. In summary, in the spatial correlation network of $PM_{2.5}$ in the BTHUA, each plate is closely connected, and it is necessary to focus on subpartitions and consider the linkages between the plates.

Core–edge analysis

In this paper, we choose the core–edge relationship elimination model to perform a core–edge analysis of the spatial association network of $PM_{2.5}$ in the BTHUA in 2018. The core cities in Fig. 1 are moved to the middle and marked in red, thus making it easy to see the relationship between the core and edge cities, and the processing results are shown in Fig. 6. The final fitness between the rearranged matrix and the ideal matrix is 0.420, and a larger final fitness value indicates that the actual data are more similar to the ideal model after rearrangement. The results show that the core–edge structure of the network is highly significant and that the number of core nodes and edge nodes in the network is 7 each. The core cities are Beijing, Tianjin, Shijiazhuang, Tangshan, Cangzhou, Langfang, and Baoding. The density matrix in Table 6 shows that the density of the core cities is 0.738, which is higher than the overall network density of 0.368, indicating that the core cities are closely connected. The density of the edge cities is only 0.190, indicating that cities near the edge of the network are less connected. The density of the connections from edge cities to core cities is much higher than that from core cities to edge cities, further confirming that large cities located in the core are more highly dependent on their neighboring cities for resources. This result is similar to the above result that the in-degree centrality of core cities is generally greater than the out-degree centrality. In the above core–edge analysis, because the number of core nodes is small and there is no clear core–edge distribution within the core nodes themselves, a secondary core–edge analysis of the core nodes is not conducted.

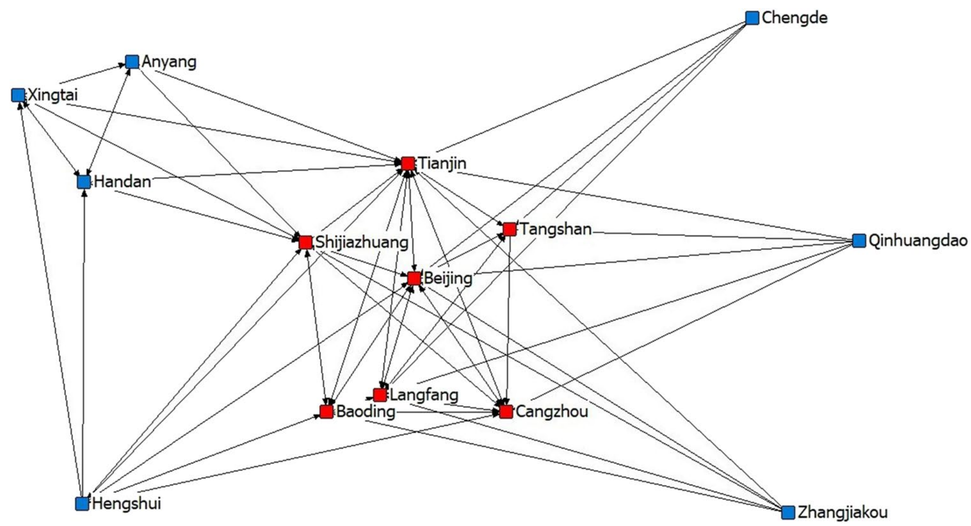

Fig. 6 Spatial association network of $PM_{2.5}$ in 2018

The top ranked cities are generally located in the core area, as presented in Table 2. Taking BC as an example, the top 8 cities in terms of their BC ranking are all core cities except for Hengshui, which means that the other 7 cities are very closely connected and belong to a tight-knit group. They are also on the shortest paths connecting other cities, thus controlling the exchanges among most cities. According to Borgatti and Everett (1999), the extent to which a node is a core node is also a measure of centrality. This paper therefore uses "centrality" as the criterion for classifying cities within a hierarchy. ArcGIS software is used to draw the spatial hierarchical distribution of $PM_{2.5}$ in the BTHUA, as shown in Fig. 7. The classification process is as follows: first, the 7 edge cities are identified via core–edge analysis, and these 7 cities are classified as third-tier cities. After that, the seven core cities are further divided into two tiers. Because Beijing, Tianjin, and Shijiazhuang have the highest DC, BC, and CC values, these three cities are classified as first-tier cities, and Tangshan, Cangzhou, Langfang, and Baoding are classified as second-tier cities. Thus, there is a three-tier hierarchy of cities in the BTHUA in terms of $PM_{2.5}$. Beijing, Tianjin, and Shijiazhuang may transfer their $PM_{2.5}$ through trade and industrial transfers, so they play the most important role in the network. Cangzhou, Langfang, Baoding, and Hengshui are either geographically adjacent to the first-tier cities or in the middle of the triangle formed by the first-tier cities, and they all have high DC, BC, and CC values. These cities transfer their $PM_{2.5}$ through diffusion. The remaining cities are the third-tier cities, which are in the edge clusters in the core–edge analysis. Their $PM_{2.5}$ pollution is not highly correlated with that of other cities, and their dependence on neighboring cities is strong. The possible reason is that their economies are small and located at the edge of the BTHUA. In conclusion, the distribution of centrality measures for each city in the network follows a non-equilibrium pattern, with cities that have large centrality values in the middle of the BTHUA and those with small values along the periphery, and a considerable number of $PM_{2.5}$ linkages travel through Beijing, Tianjin, and Shijiazhuang.

Table 6 Density matrix for the core and edge subgroups

Subgroup	Core	Edge
Core	0.738	0.061
Edge	0.510	0.190

Factors influencing the spatial correlations in $PM_{2.5}$

QAP correlation analysis

Before conducting the QAP regression analysis, a correlation analysis is applied to identify which factors influence the spatial correlations in $PM_{2.5}$. The factors that are found to have significant correlations are used as the explanatory variables. With the availability of relevant data, this study constructs a difference matrix in which the elements are the differences among the different cities in terms of six different characteristics—economic development level (GDP), technological innovation (TI), environmental regulation (ER), urbanization rate (UR), industrial structure (IS), and population density (PD)—and uses the geographic distance between cities to construct a geographic adjacency matrix (GD). In this paper, the number of random permutations is 5000; i.e., the rows and columns of the matrix are permuted simultaneously to obtain a sufficient amount of correlation

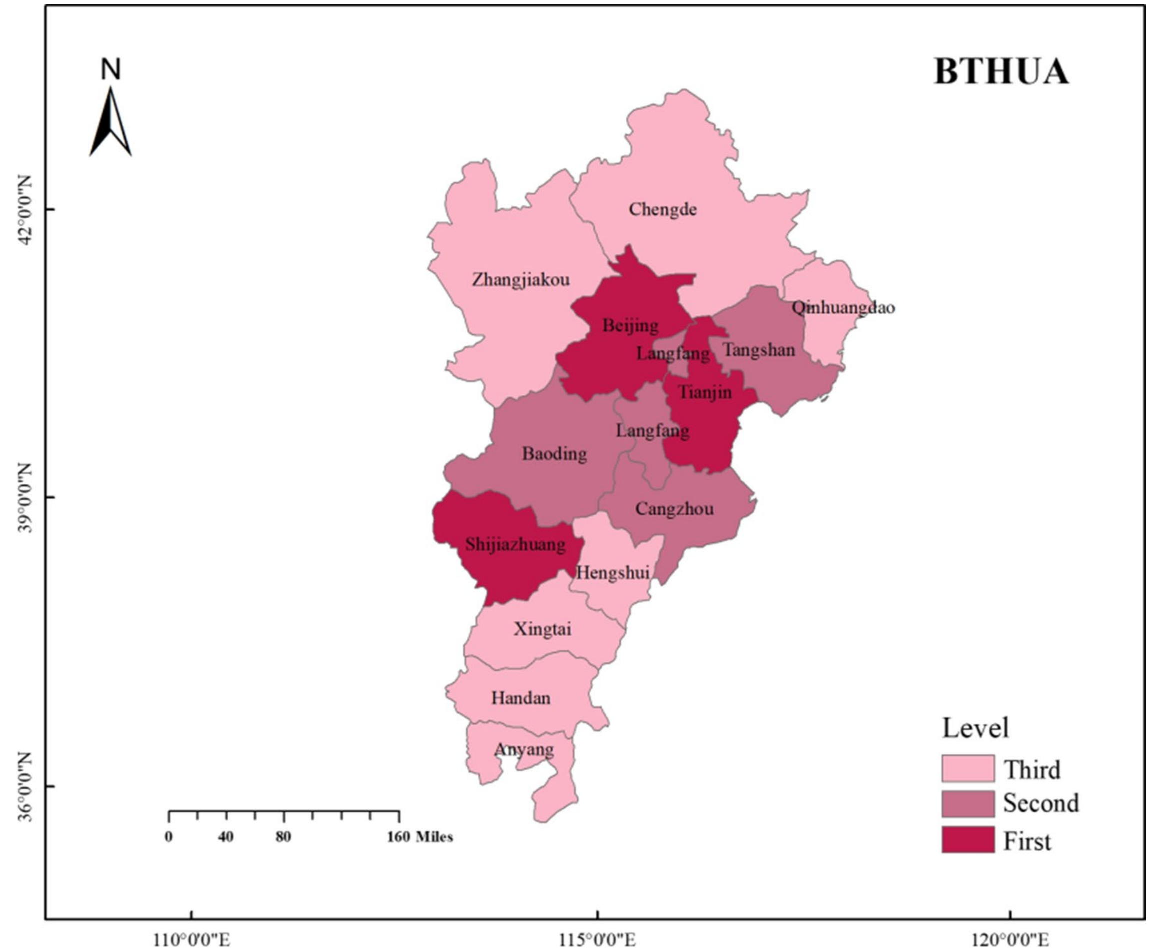

Fig. 7 Spatial stratification of $PM_{2.5}$ in the BTHUA in 2018

data, and then descriptive statistics are calculated. The detailed results are presented in Table 7.

As Table 7 shows, the geographical distance and urbanization rate are significant at the 1% level, and economic development, technological innovation, and environmental regulations are significant at the 5% level, showing that these five explanatory variables all affect the spatial correlations in $PM_{2.5}$. The effects of industrial structure and population density are not significant. To test whether the five explanatory variables above are correlated, a further QAP correlation analysis of the explanatory variables is needed, and Table 8 presents the results. It is clear that there is an obvious linear correlation between some explanatory variables; for example, the correlation coefficient between economic development and technological innovation is as high as 0.668. If a traditional linear regression method is used, it may lead to pseudoregression. Therefore, a QAP regression is applied to analyze the factors affecting the spatial correlations in $PM_{2.5}$.

Table 7 Correlation analysis between the explanatory variable and explained variables

Variables	Coefficients	Sig.	Average	Std Dev	Minimum	Maximum	$P \geq 0$	$P \leq 0$
GD	0.423	0.000	−0.002	0.083	−0.291	0.321	0.000	1.000
GDP	−0.241	0.036	−0.001	0.124	−0.370	0.302	0.977	0.036
TI	−0.264	0.020	0.000	0.125	−0.410	0.366	0.989	0.020
ER	0.221	0.034	0.002	0.111	−0.338	0.385	0.034	0.980
UR	−0.305	0.002	0.002	0.112	−0.328	0.462	1.000	0.002
IS	0.046	0.404	0.001	0.135	−0.406	0.379	0.404	0.654
PD	0.065	0.295	−0.001	0.106	−0.302	0.408	0.295	0.769

Table 8 Correlation analysis among explained variables

Variables	GD	GDP	TI	ER	UR
GD	1.000***				
GDP	0.005	1.000***			
TI	−0.092	0.668***	1.000***		
ER	0.095	−0.127	−0.089	1.000***	
UR	0.026	0.375**	0.404***	−0.020	1.000***

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

QAP regression analysis

The results of the QAP regression analysis and the corresponding influencing factors are obtained through 5000 random permutations, as presented in Table 9. The adjusted discriminant coefficient is 0.308 and is significant at the 1% level, indicating that geographical distance, economic development, technological innovation, urbanization, and environmental regulations can explain 30.8% of the spatial associations in $PM_{2.5}$. As shown in Table 9, the regression coefficient on the geographic proximity matrix is significantly positive at the 1% level and as high as 0.412, indicating that the proximity between two cities has a strong positive influence on the network and has promoted the formation of the existing spatial network. The regression coefficient on the matrix for the differences in urbanization rates is significantly negative at 1%, showing that the linkages between cities in terms of the level of haze pollution decrease with an increase in the difference in their urban population ratios. The coefficient for the environmental regulation matrix is significantly positive at 5%, indicating that although environmental regulation helps reduce $PM_{2.5}$, the variability and lack of uniformity in environmental regulation across cities do not help weaken the $PM_{2.5}$ associations among cities. The coefficients on the matrices for economic development and technological innovation are not significant, indicating that the differences in these characteristics between cities do not have a significant effect on the spatial association network of $PM_{2.5}$.

Table 9 Results of the QAP regression analysis

Variables	Un-stdized coefficient	Stdized coefficient	Significance	$P \geq 0$
GD	0.434	0.412	0.000	0.000
GDP	0.082	0.075	0.300	0.300
TI	0.004	0.003	0.490	0.490
ER	0.157	0.159	0.024	0.024
UR	−0.230	-0.233	0.001	0.999
R^2	0.324 (0.308)			

Conclusion and policy implications

Conclusion

In this paper, the relevant data on the BTHUA from 2005 to 2018 are used to reexamine the spatial association network of $PM_{2.5}$. A modified gravity model is constructed, and SNA is used to analyze the structure of the spatial association network and its influencing factors. The main conclusions are as follows.

(1) Regarding the overall network, the density of the network and the correlations within the network in the BTHUA are highly sensitive to efforts to control air pollution, and there are many close spatial correlations, with very obvious spatial spillover effects.

(2) Regarding the individual network structure characteristics, the distribution of city centrality measures is such that cities in the middle region have large centrality values and those in edge regions have small values. Tianjin has the highest DC, BC, and CC values. The in-degree centrality values for Beijing and Tianjin are higher than the average value and much larger than their out-degree centrality values, which indicates that these two cities are highly dependent on other cities for resources. Those cities with higher than average out-degree centrality values are Shijiazhuang and Hengshui, indicating that these two cities exert stronger spillover effects on other cities. Tianjin, Shijiazhuang, and Beijing are more capable of controlling $PM_{2.5}$ pollution exchange among other cities in the network.

(3) The blockmodel analysis shows that the six cities of Beijing, Tianjin, Tangshan, Cangzhou, Baoding, and Langfang, which are concentrated in the central part of the BTHUA, play the role of "net beneficiary" in the network. Zhangjiakou, Qinhuangdao, and Chengde, which are located in the northern part of the BTHUA, are located on the "net spillover" plate within the network. Anyang, Xingtai, and Handan, which are located in the southern part of the BTHUA, are located on the "two-way spillover" plate. The cities of Shijiazhuang and Hengshui play the role of "broker." In addition, when the results of the core–edge analysis and the centrality analysis are combined, the 14 cities can be divided into three tiers, with Tianjin, Beijing, and Shijiazhuang categorized as the core (first-tier) cities; Tangshan, Cangzhou, Langfang, and Baoding as the second-tier cities; and the other cities as the third-tier cities.

(4) The QAP regression analysis shows that differences in geographic proximity and environmental regulations have promoted the formation of the existing network,

while differences in urbanization rates undermine the existing network. Differences in economic development levels and technological innovation do not have a significant impact on the network.

Policy implications

The above findings suggest that there is a complex spatial correlation in $PM_{2.5}$ pollution in the BTHUA. The results of the study provide a scientific basis for the development of stable and long-term regional environmental management policies in the BTHUA. According to the conclusions of this paper, the following suggestions are proposed:

(1) The government in the BTHUA should abandon the model of individual cities controlling $PM_{2.5}$ emissions and instead focus on the spatial correlation of urban $PM_{2.5}$ emissions and implement cross-regional collaborative management. The existing decentralized environmental management has led to “free-rider” behavior, which is the focus and difficulty of transboundary pollution management. Local governments should establish a $PM_{2.5}$ emissions information sharing platform to disclose relevant pollution monitoring data and the process and effect of interregional collaborative management in real time to form the best state of joint collaboration and benefit sharing in air pollution management.

(2) The evolutionary characteristics of network density and efficiency indicate that constraining policies to reduce $PM_{2.5}$ emissions have achieved some success, but the importance of $PM_{2.5}$ pollution management in China still needs to be strengthened. The government should tailor specific policies to local conditions and should clearly perceive that the difficulty of governance lies in cities with high degree centrality. At the same time, we focus the treatment on cities with high betweenness centrality because by controlling $PM_{2.5}$ pollution emissions in these cities, the $PM_{2.5}$ pollution correlations among other cities can be blocked. For example, Tianjin is located at the core of the network, its haze pollution is very serious, and effective control of pollutant emissions in Tianjin is conducive to improving the surrounding environment. In addition, the central government department should strengthen the driving and leading role of the core cities in the BTHUA when coordinating the overall emission reduction planning, reduce unnecessary investment of resources to the peripheral cities, and make full use of the different categories of cities to achieve coordinated emission reduction.

(3) In view of the various factors affecting the spatial correlation of $PM_{2.5}$ pollution, the government's macro-control function should be considered. The construction of transportation infrastructure should be strengthened, the invisible distance between regions should be shortened as much as possible, and the flow and sharing of technology, talent and other resources should be promoted to reduce the various costs required for $PM_{2.5}$ pollution control. Environmental regulation should be strengthened to improve its adaptability to the pollution status of each city and prevent some enterprises from transferring backward production capacity to areas with weak environmental regulation to avoid supervision and thus improve the governance effect of environmental regulation. In view of the rapid population growth, accelerated air pollution and other issues brought about by urbanization, local governments should strengthen talent introduction and promote efficient urban development through talent gathering. In addition, we should limit the development scale of high-density large cities, actively develop small and medium-sized cities with low density, advocate green development strategies, and encourage industrial enterprises with high pollution and high emissions to carry out green transformation.

There are still some deficiencies in this paper. In terms of research methods, the determination of $PM_{2.5}$ correlation between cities mainly depends on the gravity model, but the construction method of the gravity model is not unique, so the research results may change accordingly. In addition, this paper mainly focuses on the relationship data of $PM_{2.5}$ pollution between cities. If quantitative analysis is conducted with attribute data at the same time, the research results may be more comprehensive. In terms of research objects, we only analyze the spatial correlation network of $PM_{2.5}$ within the BTHUA but do not consider the impact of $PM_{2.5}$ pollution in surrounding cities.

Author contribution All authors contributed to the study conception and design. Literature search, data collection, and analysis were performed by Huiping Wang and Qi Ge. The first draft of the manuscript was written by Huiping Wang and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability All data generated or analyzed during this study are included in this published article. More detailed data is available from the corresponding author upon reasonable request.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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