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Original Research

Spatial Carbon Emission Network in Beijing-Tianjin-Hebei County level: Structure and Influencing Factors

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Abstract

This study delves into the intricacies of the county-level carbon emission spatial correlation network within the BTH (BTH) region, employing Social Network Analysis (SNA) and the Quadratic Assignment Procedure (QAP) to reveal key structural traits and influential factors. Our findings can be summarized as follows: The spatial correlation network of carbon emissions in the BTH region displays a multifaceted, multi-threaded structure. Notably, it exhibits limited overall correlations, tending towards loose connectivity – a state characterized by "moderate central density with western sparseness." Furthermore, the carbon emissions' spatial correlation network assumes a distinctive "segmented" configuration, featuring well-defined boundaries and a proclivity for "each region to operate autonomously with localized centers." This network adheres to a "core-periphery" distribution model, with pivotal regions such as the Beijing Ring, Tianjin Ring, Shijiazhuang city center, Beijing-Tianjin axis, and Beijing-Guangzhou axis occupying central roles. These areas wield substantial influence over collaborative carbon reduction efforts in urban clusters. In contrast, regions at the periphery of the BTH, such as Chengde, Zhangjiakou, Qinhuangdao, Handan, and Cangzhou, exert limited impact within the spatial correlation network of carbon emissions. Lastly, geographical distance and population size differences positively correlate with the spatial correlation network of carbon emissions in the BTH region. Conversely, disparities in the development levels of secondary and tertiary industries, along with variations in technological levels, manifest negative correlations within this network. Our study employs SNA and QAP to unravel these complexities, offering insights vital for coordinated carbon reduction efforts in this crucial region.

Keywords: carbon emissions, spatial correlation, SNA, QAP, BTH county scale

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Introduction

In 2020, China set clear targets to peak carbon emissions before 2030 and achieve carbon neutrality by 2060. Achieving these dual carbon goals relies significantly on coordinated low-carbon development at the regional level [1]. China's various regional development strategies have strengthened spatial interconnections within regions, transforming carbon emissions' spatial relationships from simple „neighborly" connections into complex, multi-threaded network structures [2]. Thus, comprehending the morphology of regional carbon emission spatial correlation networks is essential for shaping effective regional coordinated carbon reduction strategies [3].

The BTH region, distinguished by its high population density, economic development, and substantial carbon emission reduction imperatives, necessitates tailored, finely-tuned emission reduction policies to fulfill its regionally coordinated carbon reduction objectives. This study centers on county-level administrative units, pivotal spatial entities for economic development and industrial relocation. It constructs a carbon emissions spatial correlation network for BTH from 2001 to 2019, assesses overall and individual network characteristics, elucidates trends in the spatial correlation network of carbon emissions in BTH over the past two decades, and identifies the roles of various counties and districts within the network. Additionally, this research delves into the factors shaping network structures. This study holds both theoretical and practical significance in establishing a coordinated carbon reduction mechanism in the BTH region.

Amid growing concern about climate change, scholars have increasingly explored various facets of carbon emissions, encompassing accounting practices across different scales and industries [4, 5], spatial characteristics [6, 7], peak emission predictions [8, 9], and emission reduction potential [10, 11]. Focusing on the spatial aspects, researchers broadly acknowledge significant spatial clustering and spillover effects in carbon emissions. These phenomena arise from macro-level economic, technological, and policy linkages across regions, as well as micro-level factors like energy consumption patterns and corporate environmental behaviors [12, 13]. While prior studies have utilized spatial weight matrices to depict geographical relationships between sample areas, they primarily relied on attribute data (e.g., regional GDP and population) that don't directly capture interregional associations. For instance, using Global and Local Moran's I to explore carbon emissions patterns, researchers identified strong positive spatial associations and pronounced clustering [14, 15]. However, carbon emissions exhibit spillover effects, where emissions can extend to other regions through natural and economic mechanisms like atmospheric circulation, industrial shifts, and economic activities [16]. Consequently, the research on carbon emissions' spatial characteristics has evolved from examining adjacent regions [17] to investigating the intricate network structures that span different domains [18, 19, 20]. Varying in research scales, Wang et al. (2018) employed social network analysis to confirm the intuitive spatial association network structure of carbon emissions among China's provinces [21]. Wang et al. (2021) shifted their focus to the Chengdu-Chongqing urban agglomeration, exploring spatial patterns and correlation effects in CO_2 emissions [22]. In terms of different sectors, Cai et al. (2012) mapped a spatially linked network of transportation-related carbon emissions in China, revealing a complex web of connections dominated by Henan and Jiangsu, serving as key regional hubs for transportation carbon reduction [23]. Zhou et al. (2018) built a carbon emission association network within China's power industry, highlighting robust inter-provincial linkages with Shanghai, Jiangsu, Tianjin, Beijing, and Zhejiang positioned at the network's core [24]. Moreover, precisely understanding the determinants of carbon emissions is fundamental for effective emission reduction efforts [25]. Presently, prominent methodologies and models employed in studying carbon emission factors encompass the autoregressive distributed lag cointegration model [26], structural decomposition analysis [27], LMDI [28], and STIRPATA model [29, 30], among others. The principal factors influencing carbon emissions encompass economic growth [31-33], urbanization rate [34], urban development patterns [35], technological advancement [36], energy mix [37], industrial composition [38], and more.

Overall, the above carbon emissions relevant research offers a wealth of insights, yet a particular niche deserving deeper exploration lies in the realm of spatial correlation networks. First, prevailing studies on carbon emission spatial correlations predominantly emphasize geographical proximity, overlooking the intricate multi-threaded spatial relationships within regions. This limitation hampers a comprehensive understanding of regional emissions dynamics. Second, earlier research tends to rely heavily on „attribute data" reflecting individual characteristics such as GDP and population, often neglecting the richer insights offered by „relationship data" that signify correlations between multiple entities. Nevertheless, analyzing regional carbon emission relationships gains significance within the context of coordinated emissions reduction. Lastly, current research predominantly centers on carbon emission spatial characteristics at broader scales, such as national, urban clusters, and provincial levels, leaving a dearth of fine-grained, small-scale investigations.

Hence, this study harnesses the power of Social Network Analysis (SNA) and the Quadratic Assignment Procedure (QAP) to explore county-level data from the BTH region spanning 2001 to 2019. It not only assesses the spatial correlation network's characteristics but also elucidates correlation patterns among diverse counties. Furthermore, it pinpoints the network positions of these entities and identifies the factors shaping and evolving the carbon emission spatial correlation network within the BTH region.

Material and Methods

Study Area

By 2019, the BTH region encompasses a total of 200 county-level administrative units. To streamline our study, we amalgamated administrative units with similar functional orientations, exemplified by Tianjin's Hedong, Heping, Hexi, Nankai, Hebei, Beichen, Xiqing, Jinnan, and Dongli Districts. Similar consolidation measures are applied to central urban areas within Beijing and various prefecture-level cities in Hebei Province. As a result, we curated 162 county-level units, which served as network nodes for our empirical investigation into the spatial correlation dynamics of carbon emissions within the BTH region from 2001 to 2019.

Methodology

Social Network Analysis

Social network analysis (SNA) is a vital research methodology within the fields of sociology and economics [39]. In essence, this approach centers on examining relationships and network structures established through internal connections among various actors. In this study, we conceptualize the entire BTH region as the overarching network, with each constituent county serving as an actor or node. Simultaneously, the connections between these counties are defined as edges, signifying the carbon emission correlation among the counties in BTH. These edges reflect the relationships between nodes within the network, offering insights into the carbon emission interplay across all counties in BTH. Consequently, we aim to quantify the nodes, edges, and network attributes characterizing the BTH carbon emissions spatial correlation network.

Modified Gravity Model

The construction of an association network is the first step of social network analysis. The Gravity model proves valuable in delineating spatial interactions. Unlike the Moran index and the Granger causality test, the Gravity model not only gauges the overall spatial correlation within a region but also assesses the spatial pathways through which interactions occur among individuals in the area. This model facilitates a more precise measurement of carbon emission spatial correlation. In this work, nodes represent counties, and edges represent carbon emission connections between counties. Considering that the gravity model can comprehensively take economy, distance, and emissions into consideration, this work uses an improved gravity model to construct BTH carbon emissions spatial correlation. The modified gravity model is as follows:

$$R_{ij} = k_{ij}\frac{\sqrt{G_iC_i}\cdot\sqrt{G_jC_j}}{[d_{ij}/(g_i-g_j)]^2} \quad , \quad k = \frac{\mathrm{E}_i}{\mathrm{E}_i+\mathrm{E}_j} \tag{3}$$

Where i and j represent county i and county j; R_{ij} is the carbon emission correlation strength between county i and county j, C is the carbon emission, G is the GDP of each county, d is the distance between two counties, and g is the per capita GDP. We assume the number of counties is k, then i = 1, 2, ..., k and j = 1, 2, ..., k.

To streamline network characterization, we binarize the BTH carbon emissions gravity matrix in this study. Recognizing that only a select few counties can exert substantial influence on others, we establish the threshold by computing the average value for each row within the matrix. When the gravity value surpasses the row's average, it is assigned a value of 1, signifying a significant correlation. In this context, the counties in the corresponding column influence the carbon emissions of those in the respective row.

Network Characteristics

Following the construction of the association network, we utilized overall and centrality network characteristics to quantify the attributes of the BTH carbon emission correlation network. These characteristics encompass various sub-items, as detailed in Table 1. To be specific, our study employs overall network characteristics to investigate the collaborative potential for carbon emission reduction in the BTH region, while centrality network characteristics serve as indicators of counties' roles in achieving synergistic carbon reduction. The Handbook of Social Network Analysis: A Handbook by Scott (2012) could supply more in-depth information [40].

Quadratic Assignment Procedure Method

The BTH carbon emission correlation network is influenced by various socioeconomic factors, and identifying these factors aids in policy decision-making. Factors such as geographical location, population size, industrial migration, and energy-saving technology levels, among others, have notable impacts on spatial carbon emission spillovers. Consequently, we have chosen five factors – spatial adjacency, population size, development levels of the secondary and tertiary industries, and technological progress – to elucidate the creation of the carbon emission spatial correlation network in the BTH, as outlined in Table 2.

Based on the above analysis, we can set up the model as follows:

$$N = f\,(D, P, IS, IT, T)$$

where N represents the spatial correlation matrix of BTH carbon emission and D represents the spatial adjacency matrix. The value is 1 if the counties are adjacent and 0 if the counties are not. P represents the matrix for

Table 1. Calculation methods of social network characteristics.

Network characteristics		Description
Overall network characteristic	Network density	$D = \frac{M}{N(N-1)}$, M is the sum of all actual network connections, and N is the number of nodes in the network. The higher the density, the closer the BTH carbon emission network is and the stronger the overall coordination state of the network is.
	Network reciprocity	Number of bidirectional connections as a percentage of all connections. The higher the network reciprocity, the more stable the BTH carbon emission correlation network is.
Centrality	Degree centrality	$De = \frac{L}{N(N-1)-1}$, L is the number of nodes directly associated with the node. A county with a higher degree of centrality has more connections with other counties and is more likely to become the center of the network.
	Betweenness centrality	$C_b = \sum_j^n \sum_k^n b_{jk}(i)$, j≠k≠i, j<k, $b_{jk}(i)$ is the ability of node i to control the connection between nodes j and k. The greater a county's betweenness centrality, the more influential it is in the inter-county carbon emission interactions within BTH and the more pronounced its synergistic impact on inter-county carbon reduction.
	Closeness centrality	$C_c = \frac{\sum_{j=1}^n d_{ij}}{N-1}$, d_{ij} is the distance between nodes i and j. Closeness centrality reflects the degree to which each county in the network is not controlled by the others.

Table 2. Variables and indicators.

Variable	Indicators	Variable description
Dependent variable	BTH carbon emission correlation network (N)	Spatial correlation matrix of BTH carbon emission
Independent variables	Spatial adjacency (D)	Spatial adjacency matrix
	Population size (p)	Population size difference matrix
	Secondary industry development level (is)	Secondary industry per unit of gdp difference matrix
	Tertiary industry development level (it)	Tertiary industry per unit of gdp difference matrix
	Technological progress (t)	Research and r&d funding per unit of gdp difference matrix

differences in population size. Additionally, IS, IT, and T represent the matrices for differences in the development of the secondary industry, tertiary industry, and R&D funding per unit of GDP, respectively.

Data Sources

We sourced county-level carbon emission data for Beijing, Tianjin, and Hebei Province from China Emission Accounts and Datasets (CEADS). Additionally, original data for counties in BTH are extracted from various annual statistical yearbooks, such as the "China County Statistical Yearbook," the "Beijing Statistical Yearbook," the "Tianjin Statistical Yearbook," the "Hebei Economic Yearbook," and statistical yearbooks of different prefecture-level cities in the Hebei Province. Geographical distances between counties are measured using spherical distances.

Results and Discussion

Overall Social Network Analysis of BTH Carbon Emission

To visually depict the spatial correlation network structure of carbon emissions in the BTH region for 2019, we created a visualization using a threshold of 2 (Fig. 1). The figure illustrates that the spatial correlation network of carbon emissions in the BTH region displays a distinctive "dense center, sparse periphery" pattern. This network extends beyond traditional geographical proximity, indicating a complex, multi-threaded structure. Understanding these characteristics is crucial for achieving carbon emission reduction in the BTH urban agglomeration. Moreover, it's essential to identify the roles and positions of counties within this network to enable effective regional cooperation.

Notably, carbon emission correlation relationships in areas surrounding Beijing, Tianjin, Tangshan, Shijiazhuang, and along the Beijing-Guangzhou corridor are notably stronger than in other regions. The economic development, infrastructure, and resource attraction capacity of these areas contribute to their higher correlation strength. However, it's essential to recognize that during the study period, the number of carbon emission correlation relationships in the BTH region accounted for only 18.5% of the total possible correlations, indicating a relatively low spatial correlation density. Therefore, fostering deeper cooperation for low-carbon development among BTH counties and cities while enhancing overall network connectivity is crucial for collaborative carbon reduction.

Analyzing network metrics, such as network connectivity, network degree, network efficiency, and network density (Fig. 2), provides insights: (1) Network Connectivity is consistently held at 1, signifying robust connectivity within the spatial correlation network of carbon emissions in the BTH region. (2) Network Degree remains at 0.0245, indicating symmetric and reachable correlation relationships between counties and cities, albeit limited in number, suggesting a Matthew effect. (3) Average Network Density at 0.185 suggests a relatively loose network structure with room for increased spatial cooperation and interaction. (4) Network Efficiency

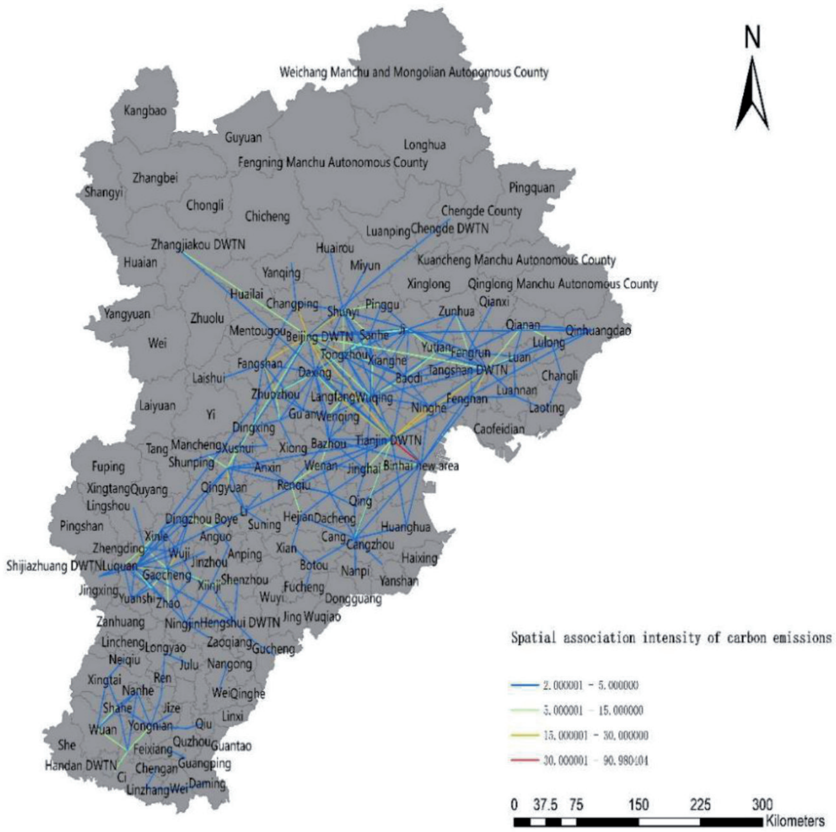

Fig. 1. Spatial Association Network of Carbon Emissions in BTH (Threshold = 2).

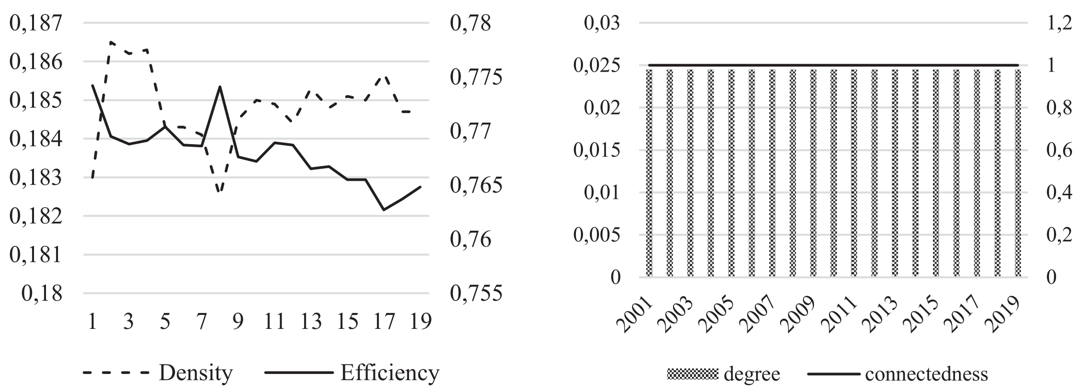

Fig. 2. Spatial association network density, efficiency, degree, and connectedness of carbon emissions in BTH.

exhibits fluctuations but showed a general trend toward stabilization. Periodic trends suggest variations in inter-county connections, influenced by factors like industrial transfer, economic cooperation, and transportation infrastructure improvements.

The increase in network density and decrease in network efficiency during the study period can be attributed to factors like industrial transfer, economic cooperation, and transportation infrastructure enhancements. The BTH region's shift from a "single-center radiating" transportation network to a "dual-center network" played a role, with the total length of highways increasing significantly. However, in 2008, influenced by low-carbon policies and global financial crises, there were inflection points in network density and efficiency. China's energy-saving and emission reduction policies restrained high-emission industrial transfers and cross-regional cooperation initially, but the subsequent investment plan in 2008 accelerated economic recovery, leading to fluctuations in spatial correlation network characteristics.

Local Network Analysis of BTH Carbon Emission

Using the CONCOR iterative method, we categorize subgroups based on their incoming or outgoing relationships, as well as their internal or external relationships. Our convergence criterion is set at 0.2, and we establish a maximum splitting level of 3. This process results in dividing the sample region into 8 blocks (Fig. 3 and Table 3), from which we obtain density matrices and image matrices (Table 4). In total, there are 4,817 relationships within these 8 blocks, comprising 2,491 relationships between blocks and 2,326 relationships within blocks. This clearly demonstrates the spillover effect of carbon emissions within the BTH region, alongside significant carbon emission correlations within the blocks themselves.

Overall, the internal density of each block exceeds the external density, indicating a degree of closure within the spatial correlation network of carbon emissions in the BTH region. This leads to a distinct "strip-block division" concerning spatial boundaries, somewhat limiting future collaborative low-carbon governance within the BTH region.

When examining individual block internal densities, we observe that Block 6 and Block 8, centered around Handan and Hengshui in the southern BTH region, display high internal densities of 0.8 and 0.88, respectively. These findings indicate strong carbon emission correlations within these blocks, signaling potential for future internal cooperation in low-carbon development. Conversely, Block 2, comprising Xiongan New Area, Bazhou City, and Cangzhou City in southwestern Tianjin, exhibits the lowest internal

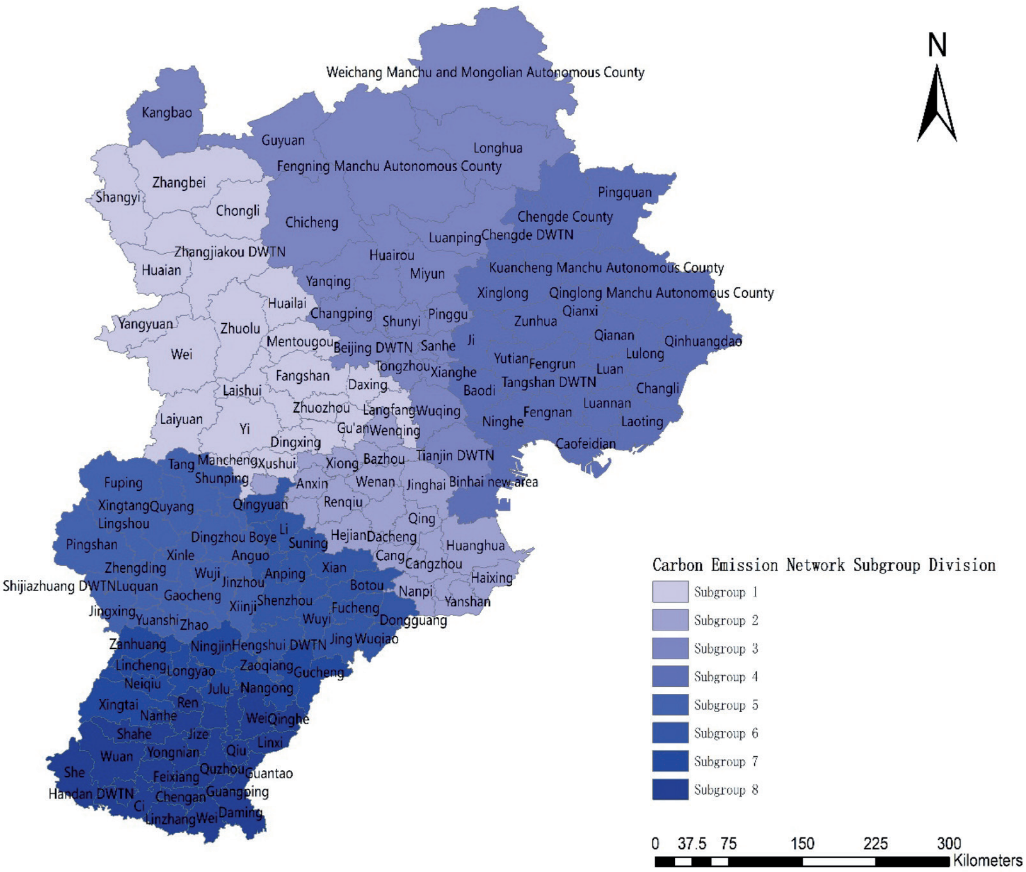

Fig. 3. Division of spatially related subgroups of carbon emissions in BTH.

density of 0.584, possibly influenced by its economic development. This block displays fewer internal carbon emission correlation relationships and requires further development.

Regarding inter-block relationships, we find that carbon emissions spillover between blocks exhibits geographical proximity characteristics. Notably, there is a trend of mutual carbon emission correlations north of the boundary line formed by Block 1 and the southern part of Block 2 (Laiyuan County-Mancheng District-Baoding-Gaoyang County-Hejian-Cang County-Nanpi County). North of this boundary line, carbon emissions are interconnected, mirroring a similar pattern south of the boundary line. Interaction between the north and south is limited, as evidenced by the density matrix. The core carbon emission absorption area north of the boundary line includes Block 3, encompassing Beijing and Tianjin city centers, while the core carbon emission absorption area south of the boundary line features Block 5, comprising Shijiazhuang city center, Anguo City, and Dingzhou City. This trend suggests a "north-south isolation with distinct local centers" concerning economic transactions, industrial transfers, and population mobility within the BTH urban agglomeration. Consequently, inter-block relationships enhance local collaborative low-carbon development while diminishing cooperation with counties and cities outside the blocks, affecting overall collaborative low-carbon development in the BTH region.

Individual Network Analysis of BTH Carbon Emission

To evaluate the roles of various counties and districts within the BTH carbon emission spatial correlation network, we are calculating their centrality in terms of carbon emissions for the 162 counties and districts, and the results are displayed in Fig. 4.

Regarding degree centrality, the top ten counties and districts include Beijing, Tianjin, Shijiazhuang, Binhai New Area, Baoding, Tongzhou, Shunyi, Langfang, Xinji, and Renqiu. These regions exhibit a higher degree of correlation with other BTH regions in the carbon emission spatial correlation network, placing them at central positions. This prominence is attributed to their location in economically developed areas like the Beijing metropolitan area, the Tianjin metropolitan area, the Beijing-Tianjin corridor, and the central area of Shijiazhuang. These regions possess substantial industrial influence, population concentration, and well-established transportation networks, which are the primary factors driving their pivotal roles in the network. Conversely, counties and districts with lower degree centrality, such as Mengcun Hui Autonomous County, Ci County, Yanshan County, Dachang Hui Autonomous County, Lulong County, Linzhang County, Cang County, Changli County, Guangping County, and Wei County, display fewer correlations with other regions, locating them at the periphery of the correlation network. Their marginal geographical positions and smaller economic scales make it challenging for them to

Table 4. Subgroup Density Matrix and Image Matrix.

		1	2	3	4	5	6	7	8
Density Matrix	1	0.636	0.23	0.402	0.032	0.142	0.043	0	0
	2	0.23	0.584	0.177	0.063	0.063	0.294	0	0
	3	0.305	0.068	0.692	0.342	0.007	0	0	0
	4	0.044	0.04	0.438	0.772	0	0	0	0
	5	0.079	0.078	0.043	0	0.757	0.247	0.207	0.011
	6	0.051	0.412	0.094	0.018	0.353	0.8	0.178	0.034
	7	0	0.012	0.023	0	0.415	0.212	0.737	0.5
	8	0	0	0.008	0	0.089	0.039	0.404	0.88
mage Matrix	1	1	1	1	0	0	0	0	0
	2	1	1	0	0	0	1	0	0
	3	1	0	1	1	0	0	0	0
	4	0	0	1	1	0	0	0	0
	5	0	0	0	0	1	1	1	0
	6	0	1	0	0	1	1	0	0
	7	0	0	0	0	1	1	1	1
	8	0	0	0	0	0	0	1	1

Table 3. Spatial association subgroup model analysis of carbon emissions in BTH.

Plate	Receive relation number		Emission Relation Number		County area
	Inside the plate	Outside the plate	Inside the plate	Outside the plate	
1	294	316	294	382	Mentougou District, Fangshan District, Huaian County, Laiyuan County, Zhuolu County, Daxing District, Yi County, Xushui District, Laishui County, Gu'an County, Wei County, Yangyuan County, Zhuozhou City, Huailai County, Shangyi County, Gaobeidian City, Zhangbei County, Langfang City, Dingxing County, Chongli County, Zhangjiakou Downtown, Mancheng District
2	221	319	221	326	Hejian City, Huanghua City, Rongcheng County, Jinghai District, Baoding City, Dacheng County, Haixing County, Mengcun Hui Autonomous County, Yongqing County, Xiong County, Gaoyang County, Wen'an County, Yanshan County, Bazhou City, Nanpi County, Renqiu City, Cangzhou Downtown, Anxin County, Cang County, Qing County
3	266	515	266	325	Beijing Downtown, Dachang Hui Autonomous County, Kangbao County, Tongzhou District, Changping District, Luanping County, Tianjin Downtown, Pinggu District, Wuqing District, Yanqing District, Fengning Manchu Autonomous County, Miyun District, Weichang Manchu and Mongolian Autonomous County, Chicheng County, Longhua County, Huairou District, Guyuan County, Shunyi District, Sanhe City, Xianghe County
4	426	218	426	252	Qian'an City, Caofeidian District, Changli County, Luan County, Pingquan County, Qianxi County, Lulong County, Yutian County, Tangshan Downtown, Ninghe District, Baodi District, Fengrun District, Ji County, Zunhua City, Qinhuangdao City, Laoting County, Xinglong County, Kuancheng Manchu Autonomous County, Qinglong Manchu Autonomous County, Fengnan District, Chengde Downtown, Binhai New Area, Chengde County, Luannan County
5	354	436	354	284	Wangdu County, Shijiazhuang Downtown, Quyang County, Anguo City, Shunping County, Zhao County, Xinle City, Luancheng District, Shenze County, Zhengding County, Xingtang County, Luquan District, Yuanshi County, Jingxing County, Xinji City, Jinzhou City, Lingshou County, Pingshan County, Dingzhou City, Fuping County, Tang County, Wuji County, Gaocheng District
6	177	274	177	382	Jing County, Wuqiao County, Shenzhou City, Botou City, Wuyi County, Qingyuan District, Raoyang County, Fucheng County, Li County, Dongguang County, Boye County, Hengshui City, Wuqiang County, Xian County, Suning County, Anping County
7	110	230	110	338	Longyao County, Baixiang County, Nangong City, Gaoyi County, Zanhuang County, Lincheng County, Julu County, Zaoqiang County, Gucheng County, Xingtai County, Neiqiu County, Ningjin County, Xinhe County
8	478	183	478	202	Linzhang County, Linxi County, Guantao County, Guangping County, Qiu County, Jize County, Ren County, Nanhe County, Cheng'an County, Daming County, She County, Ci County, Feixiang County, Yongnian County, Qinghe County, Handan City, Xingtai Downtown, Shahe City, Wei County, Quzhou County, Wu'an City, Guangzong County, Pingxiang County, Wei County

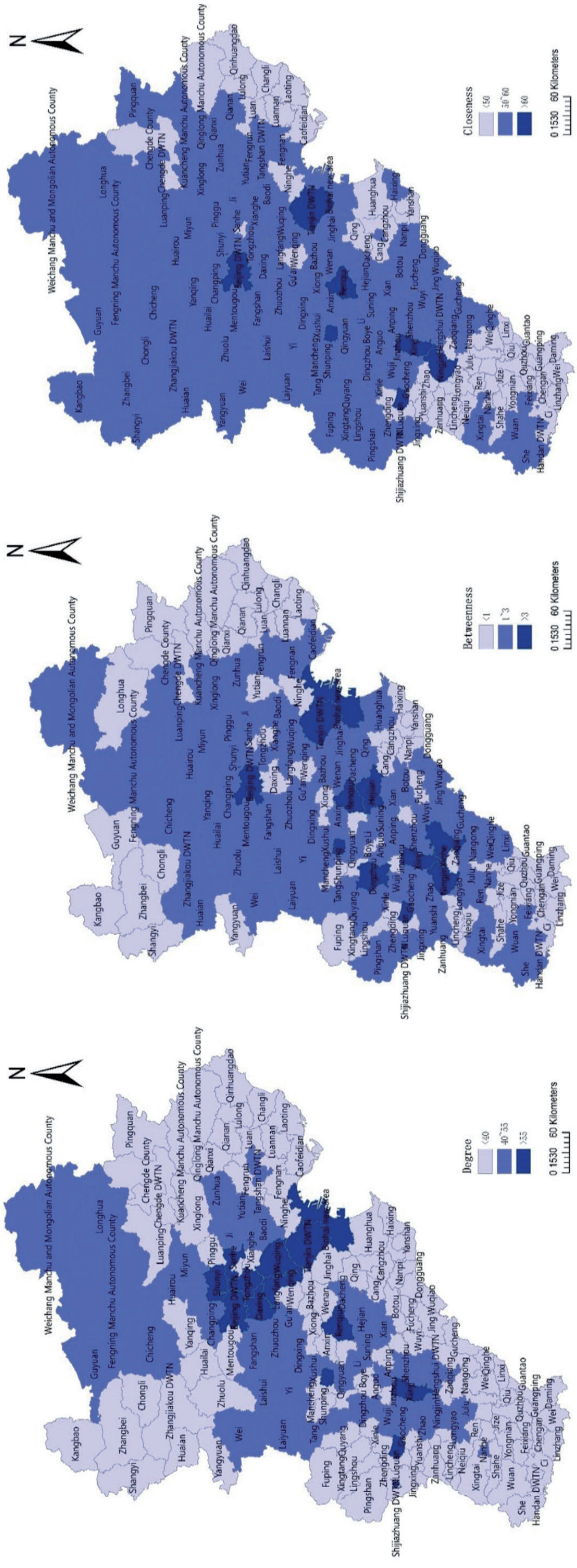

Fig. 4. The centrality of the spatial association network of carbon emissions in BTH.

establish significant carbon emission spatial correlation relationships with other counties and districts.

In terms of betweenness centrality, the top ten counties and districts are Beijing, Tianjin, Shijiazhuang, Hejian, Hengshui, Renqiu, Ningjin County, Baoding, Binhai New Area, and Xinji. These regions assume intermediary roles in the BTH carbon emission spatial correlation network, wielding substantial influence over carbon emission correlations between other counties and districts. They hold pivotal positions and are critical areas for consideration in regional collaborative carbon reduction governance. Conversely, the bottom ten counties and districts include Lulong County, Guangping County, Changli County, Shangyi County, Linzhang County, Leting County, Dachang Hui Autonomous County, Ci County, Cangzhou, and Cang County. These regions experience more constraints in the carbon emission spatial correlation network, resulting in weaker control and influence over other regions.

In terms of closeness centrality, the top ten counties and districts encompass Beijing, Tianjin, Shijiazhuang, Baoding, Xinji, Renqiu, Ningjin County, Dingzhou, Gaocheng District, and Hengshui. These regions occupy central roles in the network, with their carbon emissions being less susceptible to control by other regions. The bottom ten counties and districts, including Lincheng County, Baixiang County, Qiu County, Gaoyi County, Feixiang County, Cheng'an County, Wei County, Linzhang County, Ci County, and Guangping County, are primarily situated in the southern part of the BTH region. This indicates a weaker spatial correlation of carbon emissions with other regions, placing them in the position of "peripheral actors" in the county-level carbon emission spatial correlation network. This can be attributed to their relatively marginal geographical locations and smaller economic scales, which hinder their significant impact on carbon emissions in other regions.

In summary, economically developed areas within the BTH urban agglomeration, such as the surrounding counties and districts of Beijing, the surrounding counties and districts of Tianjin, the Shijiazhuang city center, the Beijing-Tianjin corridor, and the Beijing-Guangzhou corridor, demonstrate prominent indicators across various aspects and occupy central positions in the network. They exert a controlling role over the carbon emissions of other regions, making them a primary focus for future urban collaborative carbon reduction efforts. Specifically, the "Beijing-Tianjin corridor," "Tongwu corridor," and "Tianjin-Binhai twin cities" all assume central positions within the BTH county-level carbon emission spatial correlation network and possess significant controlling influence over the overall network. Conversely, counties and districts located at the periphery of the BTH urban agglomeration, such as Chengde, Zhangjiakou, Qinhuangdao, Handan, and Cangzhou, generally exhibit lower indicators and are situated at the periphery of the correlation network. This is primarily due to their geographical marginalization and smaller economic scales, resulting in weaker influence in the collaborative carbon reduction governance of the urban agglomeration.

Factors Affecting the BTH Carbon Emission Spatial Correlations Network

QAP Correlation Analysis

We have calculated the correlations between various influencing factors and the spatial correlation network structure of carbon emissions in the BTH region using the QAP method (Table 5). The results demonstrate that five categories of factors, including geographical distance, population size, variations in secondary industry development levels among counties, disparities in tertiary industry development levels among counties, and discrepancies in technological input, all withstand the significance test, indicating a substantial correlation with the formation of the carbon emission correlation network in the BTH region. Specifically, the correlation coefficients between the geographical adjacency matrix and the population size difference matrix are positive. In contrast, the correlation coefficients for the other factors are negative. This implies that geographic distance and population size differences exhibit a positive correlation with the carbon emission correlation network, while differences in secondary and tertiary industry development levels among counties, along with disparities in technological input, manifest a negative correlation with the carbon emission correlation network.

Table 5. Results of the QAP correlation analysis of the matrix N and influencing factors.

	Coefficient	Significance	Average	Std Dev	Minimum	Maximum	P≥0	P≤0
D	0.369^{***}	0.000	-0.000	0.008	-0.025	0.030	0.000	1.000
P	0.114^{***}	0.000	-0.000	0.016	-0.042	0.083	0.000	1.000
IS	-0.021^{***}	0.008	0.000	0.008	-0.040	0.024	0.993	0.008
IT	-0.052^{***}	0.000	0.000	0.008	-0.035	0.028	1.000	0.000
T	-0.03^{**}	0.001	0.000	0.009	-0.038	0.036	0.999	0.001

***, **, and * indicate significance at 1%, 5%, and 10% confidence levels, respectively.

Table 6. Results of the QAP correlation analysis for each influencing factor.

	Standardized coefficient	Significance	P≥0	P≤0
D	0.366431	0.000	0.000	1.000
P	0.121169	0.000	0.000	1.000
IS	-0.012112	0.068	0.933	0.068
IT	-0.042457	0.000	1.000	0.000
T	-0.020768	0.013	0.988	0.013

***, **, and * indicate significance at 1%, 5%, and 10% confidence levels, respectively.

QAP Regression Analysis

We conducted a QAP regression analysis on the influencing factors of the spatial correlation network of carbon emissions in the BTH region (Table 6). The results reveal that the coefficients of the geographic adjacency matrix and population size difference matrix are positive, signifying that close geographic proximity and smaller population differences play a significant role in promoting the formation of the spatial correlation network. This phenomenon arises because closer geographic proximity between counties facilitates more frequent resource transport and population mobility, consequently enhancing spatial connections. Conversely, the coefficients for differences in the development levels of the secondary and tertiary industries among counties, as well as differences in technological input, are negative. This implies that smaller disparities in the development of the secondary and tertiary industries among counties are more conducive to the establishment of the spatial correlation network of carbon emissions. Moreover, regions with similar technological levels exhibit stronger carbon emission relationships, indicating that areas with fewer technological differences find it easier to engage in production exchanges, economic interactions, and industrial cooperation. This results in a denser carbon emission correlation network, laying the foundation for interregional cooperation in emission reduction.

Conclusions and Suggestions

Conclusions

(1) Overall Network Characteristics: The spatial correlation network of carbon emissions in the BTH region during the study period transcends geographical constraints, revealing a complex, multi-threaded pattern. However, it falls short in terms of the overall number of correlations, and the network's correlation density remains relatively low. Notably, carbon emission correlation relationships exhibit a Matthew effect, whereby the strong become stronger and the weak become weaker. In essence, the correlations follow a "central-dense-west-sparse" pattern. To progress towards low-carbon development in the BTH region, it's imperative to enhance network density and diminish network hierarchy.

(2) Local Network Characteristics: The spatial correlation network of carbon emissions in the BTH region displays a degree of closure at the local level. This limited low-carbon cooperation and interaction among regions result in a distinctive spatial pattern characterized by "strip-block segmentation." Furthermore, carbon emission overflow between regions reflects geographical proximity, with a spatial trend of "each to their own in the north and south, with clear local centers." In essence, the restricted carbon emission correlations among regions may impede further advancements in low-carbon collaborative development in the BTH region.

(3) Individual Network Characteristics: Certain counties and cities, primarily those within the Beijing Ring, Tianjin Ring, along the Beijing-Tianjin axis, and the central area of Shijiazhuang, assume pivotal roles in the spatial correlation network of carbon emissions in the BTH region. These regions wield substantial control and influence over the requisite resource elements for collaborative carbon reduction in urban clusters. Conversely, counties and cities within the areas of Chengde, Zhangjiakou, Qinhuangdao, Handan, and Cangzhou, situated on the outskirts of the BTH urban cluster, occupy peripheral positions in the spatial correlation network of carbon emissions. Consequently, they have a weaker impact on collaborative carbon reduction governance in the urban cluster.

(4) QAP Analysis Results: The outcomes of the QAP analysis reveal that geographical proximity and diminishing differences in population size significantly foster the formation of the spatial correlation network of carbon emissions in the BTH region. Smaller disparities in the development levels of secondary and tertiary industries, as well as technological levels, contribute to a denser spatial correlation network of carbon emissions among counties and cities.

Suggestions

(1) Integrated Carbon Emission Management: Regional governments in the BTH area should shift from isolated carbon emission management to a focus on the spatial correlation of carbon emissions among

counties and cities, fostering cross-regional collaborative governance. Firstly, establish a dedicated institution to oversee comprehensive carbon emission governance in the BTH region, harmonizing management efforts across regions. Develop specific laws and regulations delineating the roles and collaboration mechanisms of these institutions and departments. Secondly, institute an assessment and accountability system for collaborative carbon emission control. Periodically evaluate the effectiveness of regional collaborative governance, rewarding high-performing regions and penalizing those with inadequate cooperation or benefiting from the efforts of others. Lastly, promote the exchange and cooperation of low-carbon technologies and talent resources, particularly in peripheral areas, to expand carbon emission correlation channels. This will increase network density, enhance the stability of the carbon emission spatial network, and reduce hierarchical disparities.

(2) Strengthening Low-Carbon Resource Synergy: Enhance the interconnectedness of low-carbon development resources across various blocks in the spatial correlation network of carbon emissions in the BTH region. Place special emphasis on fostering low-carbon cooperation and exchanges between northern and southern regions, dismantling clear boundaries and segmented patterns among blocks. This lays the groundwork for comprehensive low-carbon collaborative development in the BTH region. Simultaneously, regions such as Block 3 and Block 5, primarily responsible for carbon absorption with Beijing, Tianjin, and Shijiazhuang city centers as their cores, should vigorously develop new energy and green manufacturing industries. Implement stringent entry criteria for highly polluting industries while extending technical and financial support to other regions, expediting their successful transformation.

(3) Prioritized Collaborative Carbon Emission Control: Tailor collaborative carbon emission control priorities to the specific circumstances of each county and region. In the collaborative governance process, concentrate efforts on key areas such as the Beijing Ring, Tianjin Ring, Shijiazhuang city center, Beijing-Tianjin axis, and Beijing-Guangzhou axis, all of which wield significant influence in the network. Concurrently, implement proactive measures to reduce carbon emissions in counties and districts situated at the network's periphery. Strengthen the interconnection of low-carbon resource elements between core and peripheral counties and districts, facilitating balanced and coordinated low-carbon development.

(4) Focused Approach Based on Contributing Factors: Pay heed to influential factors like geographical distance, population size, economic dynamics, and technological factors that contribute to the formation of the spatial correlation network of carbon emissions in the BTH region. Direct collaborative carbon reduction efforts toward counties and districts with shorter geographical distances, smaller population disparities, fewer economic development disparities, and relatively similar energy-saving technology levels. This will foster an overarching reduction in carbon emissions throughout the BTH region.

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