The structure of spatial correlation network of carbon emission and its drivers in industrial enterprises above designated size: evidence from Taizhou City, Zhejiang Province

Liangchu Song [a,b] , Binghua Gu [a,b], Xin Wang [a,b] , Jue Zhang [a,b] , Hao Wang [a,b] and Peili Zhang [*a,b]

[a] Taizhou Pollution Control Technology Center Co. LTD., China

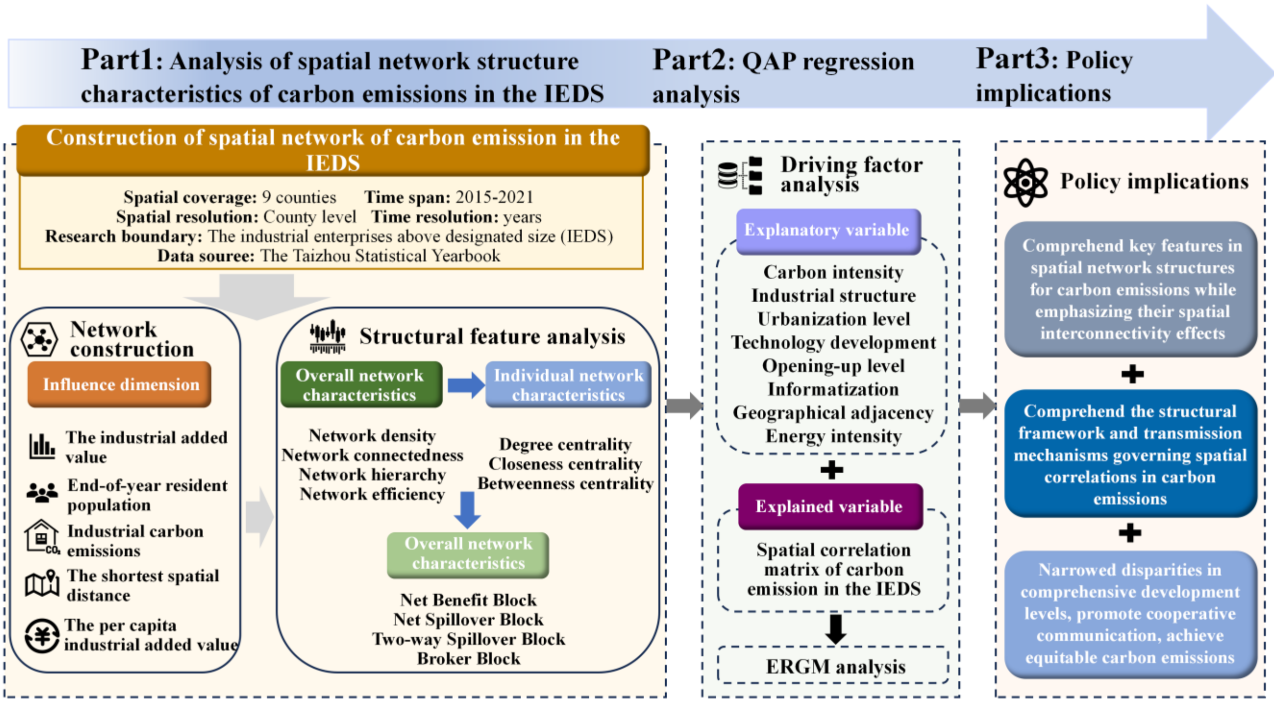
[b] Key Laboratory of the Eco-environmental Big Data of Taizhou, China

* Corresponding author: Peili Zhang, Senior Engineer.

Email: cugsongxiaoqing@163.com (Peili Zhang)

ORCID: https://orcid.org/0009-0003-0881-851X

Graphical Abstract



Abstract

To support China's strategic goals of achieving carbon peaking and carbon neutrality, this study explores the spatial network structure characteristics of industrial carbon emissions and their significance in promoting energy conservation and emission reduction in the industrial sector. Taking Taizhou City in Zhejiang Province as a case study, we construct a spatial correlation network of carbon emissions based on data from industrial enterprises above the designated size (IEDS) across nine counties from 2015 to 2021, and apply an improved gravity model, integrated with social network analysis, to equantify inter-county linkages and identify key driving factors. Our results indicate that: (1) the spatial network correlation degree of IEDS carbon emissions remained at 1 throughout the study period, whereas network density gradually increased and network hierarchy as well as efficiency steadily decreased; (2) Economically advanced eastern counties—Yuhuan, Wenling and Jiaojiang—form the network core and exert marked influence on spatial carbon-emission linkages, whereas the less-developed counties of Sanmen, Tiantai and Xianju lie at the periphery with limited impact; (3) Based on network positions, Jiaojiang, Xianju, Wenling, and Linhai are classified as 'Broker Block', Sanmen and Tiantai as 'Net Spillover Block', Huangyan as 'Two-way Spillover Block', and Luqiao and Yuhuan as 'Net Benefit Block'; (4) The ERGM analysis revealed a hierarchical influence structure with five factors showing extremely high significance ($p<0.001$). Carbon emission intensity emerged as the strongest negative inhibitor ($\beta = -18.245$), while energy intensity showed the strongest positive effect ($\beta = 14.567$) . This research reveals that while industrial carbon emissions exhibit significant spatial correlations across regions, there remains considerable potential for strengthening inter-regional coordination, suggesting the need to establish cross-regional collaborative emission reduction mechanisms to promote industrial energy conservation and emission reduction.

Keywords: Carbon emissions, The industrial enterprises above designated size (the IEDS), Spatial correlation, Social network analysis, Driving factors.

1. Introduction

Achieving carbon peak and carbon neutrality is a strategic imperative for addressing resource and environmental constraints and advancing sustainable development in China. It also reflects the nation's commitment to fostering a global community with a shared future. As a key pillar of the national economy, the industrial sector contributes nearly 80% of China's total carbon emissions (Wang *et al*. 2024), underscoring the critical role of its green transformation in meeting the dual carbon goals. However, with the increasing mobility of production factors and the ongoing transfer of industries, the spatial distribution of industrial carbon emissions has become more dynamic and heterogeneous. The efficiency of resource allocation and interregional coordination mechanisms plays a pivotal role in emission reductions, highlighting the systemic and cross-jurisdictional nature of carbon mitigation that cannot be addressed through isolated efforts (Fang *et al*. 2024). Moreover, deepening division of labor along supply chains and the associated flows of intermediate goods and services have led to hidden emissions and carbon leakage across regions. This has given rise to a complex spatial network of emissions, structured around regional nodes and interconnected through industrial linkages. Driven by both market dynamics and policy interventions, this network forms a multi-level and interdependent system. Therefore, accurately mapping the characteristics of the industrial carbon emission spatial network and identifying its underlying drivers are essential for formulating effective cross-regional carbon reduction strategies, facilitating low-carbon industrial transformation, and optimizing spatial planning.

Following the introduction of China's dual carbon targets, industrial carbon emissions have emerged as a critical research frontier in environmental and economic studies, with scholarly attention converging on three primary domains: First, the measurement and comprehensive analysis of industrial carbon emissions have gained unprecedented prominence across multiple spatial scales, encompassing national, regional, urban and enterprise levels. Nationally, studies focus on the evolution of total industrial carbon emissions and their relationships with industrial growth and energy efficiency (Sun *et al*. 2024; Zhao *et al*.). Regionally, analyses often center on provinces with strong industrial bases, such as Sichuan, Hebei and Liaoning (Fang *et al.* 2024; Chen *et al*. 2025; Zhang *et al*. 2022), as well as key urban clusters like the Beijing-Tianjin-Hebei and Yangtze River Delta (YRD) (Wang *et al*. 2015; Zhang *et al*. 2022). At the enterprises level, empirical investigations are conducted through surveys and fieldwork (Zhao *et al*. 2024), while sectoral studies mainly concentrate on energy-intensive industries such as chemicals, steel, and power generation (Na *et al*. 2024; Xu *et al*. 2024; Bai *et al*. 2023). Second, the assessment and analysis of industrial carbon emission efficiency constitute another significant research domain. Methodologically, scholars predominantly employ radial and non-radial efficiency models, often integrated with ArcGIS spatial analysis techniques , to elucidate the spatiotemporal evolution patterns of emission efficiency across diverse geographical scales. Suo applied the three-stage DEA model proposed to evaluate the efficiency of industrial carbon emissions in western China. (Suo *et al*. 2024). Li applied the unexpected output SBM model to evaluate industrial carbon emission efficiency in the Huaihai Economic Zone from 2010 to 2020 (Li *et al*. 2023). Recent research further explores how climate transition risks affect emission efficiency in energy enterprises, revealing that such risks initially hamper efficiency, but robust innovation capabilities can buffer these negative effects, especially in the electricity sector (Wu *et al*. 2025). Third, regarding the driving mechanisms of industrial carbon emissions scholars widely recognize energy structure, economic scale, population size, and energy consumption intensity as primary determinants. Within the Chinese context specifically, researchers have increasingly examined the multifaceted impacts of international trade integration, technological advancement, and environmental regulatory frameworks on industrial carbon emissions. (Lv *et al*. 2024; Zhao *et al*. 2024; Xie *et al*. 2024). Moreover, innovation capability not only mediates the effect of digital investment on environmental performance, but also serves as a crucial buffer against climate transition risks (Wu *et al*. 2025). Digital investment, as a pivotal driver, shapes corporate environmental performance through a U-shaped trajectory mediated by technological innovation, underscoring its role in advancing green development (Jin *et al*. 2023). Additionally, Lei *et al*. (2024) utilized a three-party evolutionary game model to analyze the dynamics among government, enterprises, and environmental social organizations in green production behaviors, emphasizing the differentiated impacts of climate change on green total factor productivity across regions (Li *et al*. 2024). These findings provide actionable insights for formulating adaptive environmental regulations and promoting sustainable development.

Despite significant progress in the study of industrial carbon emissions, several critical knowledge gaps persist: First, the existing literature predominantly concentrates on macro-scale analyses at national, regional, and sectoral levels, while urban-scale investigations remain relatively scarce, largely attributable to data accessibility constraints and methodological challenges.. As the fundamental unit for implementing green industrial policies, counties require more in-depth analysis of their industrial carbon emissions and driving mechanisms. Second, contemporary research paradigms predominantly rely on attribute-based analytical approaches to investigate spatial clustering phenomena of carbon emissions across geographical units, while network-based methodologies utilizing relational data to decipher inter-regional connectivity patterns and functional roles within carbon emission networks remain underexplored. For example, Taizhou, located within the Yangtze River Delta (YRD) urban cluster, is undergoing rapid transformation. It has recently received industrial transfers from core YRD cities like Shanghai and southern Jiangsu. The number of industrial enterprises in Taizhou increased from 2,531 in 2012 to 2,861 in 2020 (Zhao *et al*. 2022; Cheng *et al*. 2023), leading to a notable rise in carbon emissions, with industry being the primary source (Li *et al*. 2020). The "Yangtze River Delta eco-green Comprehensive Development demonstration zone Land Space General Plan" highlights that such transitioning cities hold significant potential for urbanization and low-carbon transformation. To address these methodological and empirical gaps, this study adopts Taizhou City as a representative case study, implementing an enhanced gravity model framework to construct a comprehensive spatial association network of industrial carbon emissions across county-level administrative units. Subsequently, advanced social network analysis techniques are deployed to systematically uncover the structural roles, positional characteristics, and relational dynamics of constituent counties within the emergent network architecture. This aims to provide scientific support for formulating precise carbon reduction policies in Taizhou and offer exemplary insights for other transitioning cities or regions within the YRD.

2. Material and methods

2.1 Data sources

Based on the statistical standards of Taizhou City, nine counties of Taizhou were selected as the research object. Data regarding industrial energy consumption, gross industrial production and end-of-year resident population primarily derive from the Taizhou Statistical Yearbook spanning from 2016 to 2022. To eliminate price effects (Song *et al.* 2024), the GDP deflator method was adopted to uniformly convert the data into comparable price in 2015. The industrial added value data includes a total of 13 industry types, as shown in Table 1. In the production process, the IEDS in Taizhou City mainly use raw coal, coke, gasoline, diesel, heat, electricity and other energy sources. Carbon emissions were calculated following the guidelines outlined in the 2006 IPCC Guidelines for National

Greenhouse Gas Inventories. Spatial adjacency matrices and the shortest spatial distances between each county were obtained by ArcGIS 10.8. The system boundary diagram for this study is illustrated in Graphical Abstract. It is mainly divided into three parts. Part1: Analysis of spatial network structure characteristics of carbon emissions in the IEDS. Part 2: ERGS analysis. Part 3: Policy implications.

Table 1. The industrial added value data includes a total of 13 industry types

Industry ID	industry type	Industry ID	industry type
S1	Mining industry	S8	Rubber and plastic products industry
S2	Food and beverage industry	S9	Non-metallic mineral products
S3	Textile And Garment Industry	S10	Metal smelting and rolling industry
S4	Furniture and wood products industry	S11	Machine building industry
S5	Paper and cultural products industry	S12	Abandoned resource utilization industry
S6	Petroleum processing, coking and nuclear fuel processing industries	S13	Electricity, gas, and water production and supply industry
S7	Pharmaceutical chemical industry		

2.2 Measurement of the IEDS carbon emissions

Following the IPCC guidelines (Garg *et al*. 2006), the carbon emissions from the IEDS in each county of Taizhou City can be calculated according to equation 1:

$$C_{it} = \sum_{j=1}^{6} (E_{ijt} \times \alpha_j) \quad (1)$$

Where i represents each county; j represents the type of energy consumption; t represents the year; C_{it} represents the total carbon emissions for i county in t year (10^4 t); E_{ijt} represents the total amount of consumption for j type energy in t year of i county; α_j represents the carbon emission factor for j type of energy (Table 2).

Table 2. Standard coal conversion factors and carbon emission factors for various fuels

Energy source	Raw coal	Hard coke	Casoline	Diesel oil	Heat	Electricity
Conversion coefficient of standard coal /(tce/t)	0.7143	0.9714	1.4714	1.4571	0.03412	1.229
Carbon emission coefficient/(tCO_2/tce)	1.9003	2.8604	2.9251	3.0959	0.26	0.7935

Data Source: International Coal Network and General Rules for Comprehensive Energy Consumption

Calculation (GB/T 2589-2020); carbon emission factor is based on standard coal; discounted standard coal coefficient of tce/GJ for heat and tce/(MW·h) for electricity.

2.3 The gravity model for the IEDS

According to the combing of existing literature, the modified gravity model is employed to illustrate the extent of correlation between the IEDS across counties, and to establish the industrial carbon emission network relationship in Taizhou City (Zhang *et al.* 2022). The industrial carbon emission network is constructed using indicators including industrial carbon emissions, industrial added value, and end-of-year resident population. Additionally, the parameter *k* was introduced to reflect the carbon emission weight of each county, which demonstrates the gravitational relationship of the industrial carbon emissions across counties in Taizhou City. The degree of carbon emission correlation can be calculated according to equation 2:

$$F_{ij} = k_{ij} \frac{\sqrt[3]{P_i C_i S_i} \cdot \sqrt[3]{P_j C_j S_j}}{\left(\frac{d_{ij}}{s_i - s_j}\right)^2}$$

$$k_{ij} = \frac{C_i}{C_i + C_j} \qquad (2)$$

Where F_{ij} represents the spatial connection degree of carbon emissions between *i* county and *j* county; P_i and P_j respectively represent the end-of-year resident population of counties *i* and *j*, 10^4 people; C_i and C_j respectively represent the total carbon emissions of the IEDS in county *i* and *j*, 10^3 t; S_i and S_j respectively represent the industrial added value in county *i* and *j*, 10^8 CNY; d_{ij} represents the shortest spatial distance between county *i* and *j*, km; s_i and s_j respectively represent the per capita industrial added value of county *i* and *j*, CNY; *k* represents the empirical constant, reflecting the contribution rate of county *i* to the carbon emission correlation of county *j*. Equation 2 is utilized to compute the gravity matrix of the IEDS carbon emissions in Taizhou City, where the magnitude of values indicates the intensity of carbon emission gravity across counties. If each element in a row of the matrix exceeds the average value of that row, it is recorded as 1, indicating a correlation between the IEDS carbon emissions across counties. If the gravity is less than the average, it is recorded as 0, indicating no correlation. This process helps in obtaining the binarized matrix of spatial connections for the IEDS carbon emissions in Taizhou City.

2.4 The social network analysis

The study employed social network analysis to investigate the spatial network structure of the IEDS carbon emissions in Taizhou City. We characterize the overall spatial network structure of Taizhou City using three key indicators: network density, network hierarchy, and network efficiency (Shao *et al*. 2022). Additionally, three indicators were used to emphasize the individual characteristics of each county, as to degree centrality, betweenness centrality, and closeness centrality (Li *et al*. 2024).

2.5 Block model analysis

To identify the roles and functions of county in the network, we referred to Wasserman et al.'s research (Wasserman *et al*. 1994). The spatial correlation network of the IEDS carbon emissions is categorized into four blocks: "Net Benefit Block," "Net Spillover Block," "Two-way Spillover Block," and "Broker Block" based on our analysis. The "Net Benefit Block" type receives significantly more external relations than it sends out, has a high proportion of internal relations among its members, and exhibits a minimal spillover effect to other types. In contrast, the "Net Spillover Block" type sends out considerably more external relations than it receives, has a high proportion of external relations sent out by its members, and shows a greater spillover effect to other types. The "Two-way Spillover Block" type experiences both internal and external spillover effects with numerous internal relations among its members. Lastly, the "Broker Block" type has fewer internal contacts but more interactions with other external types, acting as a mediator in the network. Using UCINET software's cohesive subgroup analysis tool, we divided the provinces, autonomous regions, and municipalities directly under the Central Government in China's tourism carbon emissions network into these four types and analyzed each type based on its characteristics.

2.6 ERGM model

To further investigate the spatial impact of counties' carbon emissions on each other and to develop coordinated efforts to reduce carbon emissions, this study analyzes the factors influencing the spatial association network of carbon emissions in Taizhou. As the variables in the spatial association network are relational data presented in matrix form, there is a potential for multicollinearity among the variables, making it challenging to test their relationship using traditional multiple linear regression methods. Therefore, We employed Exponential Random Graph Models (ERGMs) to examine the key driving factors influencing the spatial correlation network of industrial carbon emissions in Taizhou City. ERGMs represent a cutting-edge statistical methodology in network science (Liu *et al*. 2024), providing more robust estimates of network formation mechanisms by accounting for the complex interdependencies inherent in network data compared to traditional Quadratic Assignment Procedure (QAP) methods (Bruner *et al*. 2022).

The industrial carbon emission spatial network structure results from the synergistic interaction between internal industrial development and external socio-economic dynamics. Changes in the intensity of driving factors promote the reorganization and optimization of spatial network structures. According to relevant studies, the factors affecting the spatial connection of carbon emissions of YRD city cluster are investigated and analyzed from the seven dimensions (Table 3) (Yuan *et al*. 2022; Liu *et al*. 2022; Dai *et al*. 2022). In this paper, the mean values of variables from 2015 to 2021 are selected, and difference matrices of explanatory variables are constructed, with carbon emission spatial correlation matrix as the explained variables. The Z-Score standardization method is applied to standardize each matrix, thereby eliminating the interference of explanatory variable dimension on the regression structure.

The ERGM model is as follows equation 3:

$$P(Y = y \mid \theta) = \frac{\exp\{\theta^{T} s(y)\}}{C(\theta)} \qquad (3)$$

where the dependent variable y represents the network. P(Y=y|θ) denotes the probability of observing network y given the parameter θ. θ is the parameter vector, s(y) is the vector of sufficient statistics, and c(θ) is the normalizing constant. The model characterizes the intrinsic mechanisms of network formation through both structural network effects (edges) and nodal attribute effects.

Table 3. Factors affecting the spatial association network of carbon emissions

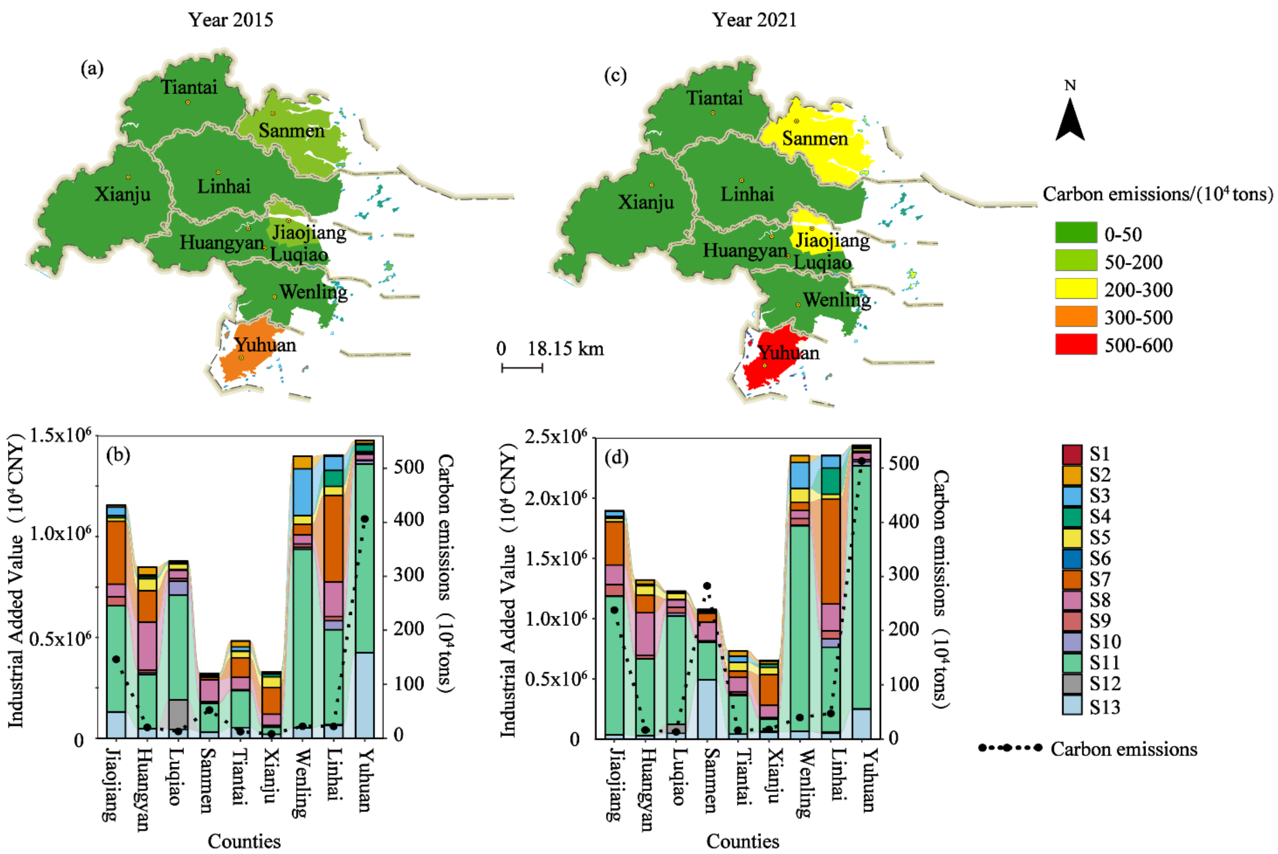
Factors	Variables	Measure
Carbon intensity	CI	Absolute value of difference in ratio of carbon emissions to regional GDP between counties
Industrial structure	IS	Absolute value of difference in ratio of industrial added value to regional GDP between counties
Urbanization level	UL	Absolute value of difference in ratio of urban population to resident population at year-end between counties
Technology development	TD	the number of granted patents between counties
Opening-up level	OL	Absolute value of difference in ratio of total import and export volume to regional GDP between counties
Informatization	IN	the number of Internet broadband access users between counties
Geographical adjacency	GA	If the two counties are neighboring, it is noted as 1; otherwise, noted as 0

Energy intensity	EI	Absolute value of difference in ratio of energy consumption to regional GDP between counties

3. Results and Discussion

3.1 Spatial distribution characteristics of the IEDS carbon emissions

The industrial added value and the IEDS carbon emissions in each county in Taizhou City in 2015 and 2021 are illustrated in Figure 1. The industrial added value in Taizhou City shows an increasing trend, with an average annual growth rate of 7.54% from 2015 to 2021. Meanwhile, the IEDS carbon emissions also show an upward trend. Compared to 2015, the IEDS carbon emissions in Taizhou City increased by 4.8129 million tons in 2021. Among these, the IEDS carbon emissions increased by 44.65% from 2015 to 2018. This is closely related to the rapid development of industry in Taizhou City during the same period. The industrial development has consumed a significant amount of resources and energy, thereby increasing carbon emissions. From 2019 to 2020, industrial carbon emissions decreased, which can be attributed to the impact of COVID-19 on various types of enterprises during this period. With the gradual recovery of industrial development, carbon emissions in Taizhou City increased rapidly in 2021. From the spatial distribution, the total carbon emissions of the IEDS in Taizhou City generally exhibit an east-high and west-low distribution pattern (Figure 1a, 1c). Except for Jiaojiang County, Sanmen County, and Yuhuan County, whose Industrial carbon emissions remain in a continuous fluctuating growth, others remain relatively stable. The ranking of total carbon emissions in each county is as follows: Yuhuan County, Sanmen County, Jiaojiang County, Linhai County, Wenling County, Xianju County, Huangyan County, Tiantai County, and Luqiao County. The highest total amount of industrial carbon emissions are in Yuhuan County and Sanmen County, accounting for 67.19% of the city's total. This suggests that the electricity, gas, and water production and supply industry significantly impact industrial carbon emissions in the region. Particularly in Sanmen County, the significant increase in carbon emissions is attributed to the transfer of energy-intensive industries such as electricity and heat supply (Figure 1b, 1d). Therefore, it is necessary to further optimize the industrial structure, shift away from the traditional model of relying on non-renewable resources for industrial development, and improve energy utilization efficiency. In the future, with the rapid growth of the industrial economy in Taizhou City, carbon emissions will continue to rise, making it imperative to accelerate emission reduction efforts.



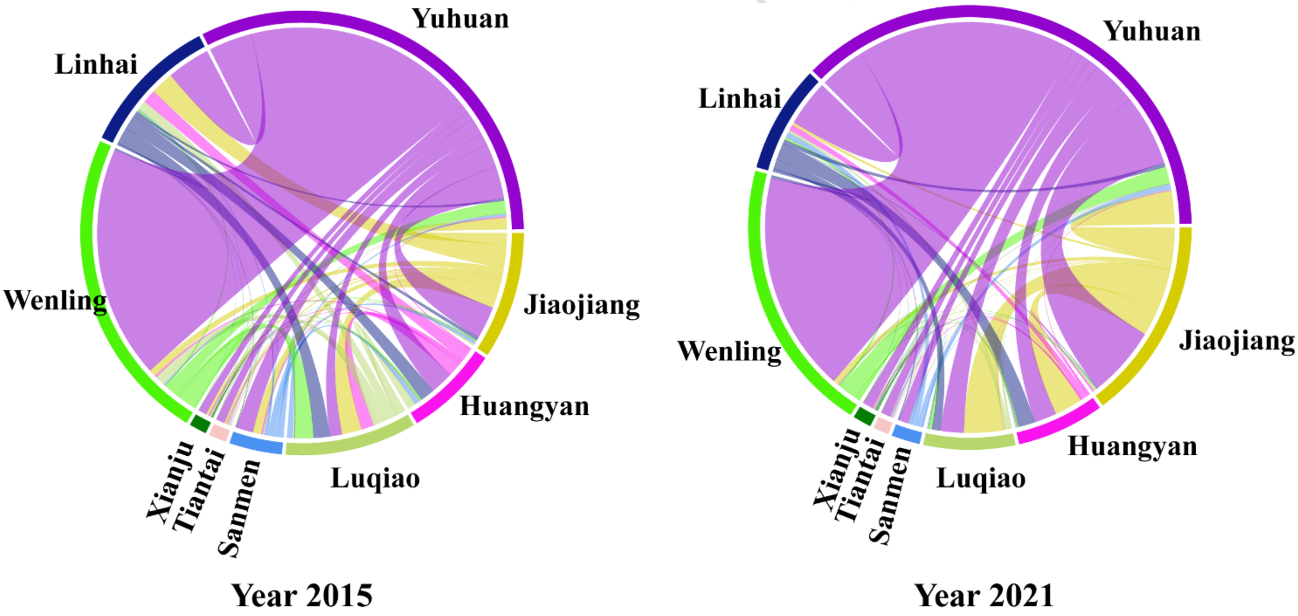
Notes: The boundary of the base map of Taizhou City has not been modified at all. The review number of the map is Zhe S (2023) 38

Figure 1. Spatial Distribution of Carbon Emissions from the IEDS in Taizhou in 2015 and 2021

3.2 Spatial correlation network

3.2.1 Evolution trend of spatial association network of the IEDS carbon emission

A chord diagram was utilized to visually represent the spatial connection intensity of carbon emissions among nine counties and districts in Taizhou City (Figure 2). The spatial correlation intensity of carbon emissions is significantly influenced by spatial proximity. The spatial correlation intensity between adjacent counties is higher, as evidenced by the relationships between Yuhuan County and Wenling County, as well as between Jiaojiang County and Luqiao County. This phenomenon can be primarily attributed to the interconnections between neighboring administrative regions. As a result, the cost associated with connecting and cooperating between regions will decrease, leading to a higher intensity of carbon emission connections in industrial exchanges and transfers. Consequently, this promotes the spatial linkage of industrial carbon emissions across regions. Furthermore, it is worth noting that counties and cities with close spatial connections are predominantly represented by Yuhuan County. Notably, Yuhuan County exhibits the highest average spatial correlation strength with other counties and cities, due to its reputation for low-efficiency and high industrial added value machinery within the manufacturing industry. Its advanced technology level has a radiating effect on other regions, positioning it as a "leader" within the space network structure. From a geographical perspective, the areas with closely connected carbon emissions are primarily situated in the southern part of Taizhou City, with relatively limited impact in the northern region. From an economic perspective, the central nodal areas consist of counties with high industrial added value and significant social influence, such as Yuhuan County, Wenling County, and Jiaojiang County (Figure 1b, Figure 1d). Moreover, it should be noted that the strength of spatial correlation in Taizhou City is not limited to traditional geographical proximity, exhibiting evident spatial spillover and intricate network characteristics in the cross-regional spatial network.



Notes: The contact area between the arc and the circle signifies the degree or proportion of inter-county relationships, while the thickness of the arcs for counties indicates the strength of spatial linkage in carbon emissions.

Figure 2. Spatial connection strength of carbon emission from the industrial enterprises above designated size in Taizhou

3.2.2 Overall network characteristics of spatial association network of the IEDS carbon emission

The relationship matrix was utilized to compute the overall network structure characteristic indicators of Taizhou City from 2015 to 2021 (Table 4). The results show that the spatial correlation network of the IEDS in Taizhou City has strengthened over time, while the degree of network correlation has remained moderate. The network density has gradually increased to 0.3611. However, the network density between counties and districts remains low, indicating the continued need for regional cooperation to promptly achieve the dual carbon goals. The network correlation degree from 2015 to 2021 is 1. This indicates that the spatial network structure is stable in Taizhou City, and the overall spatial correlation and spillover effects between counties and cities are common, exceeding the influence of geographical proximity. The network efficiency gradually decreased from 0.6786 to 0.6429, indicating that the number of connections in the carbon emission network structure of Taizhou City continues to increase, and the stability of the spatial network structure has been improved. The network hierarchy gradually decreased from 0.6452 to 0.5588, indicating a reduction in status differences among Taizhou's counties. However, the phenomenon of regional development imbalance still exists. Therefore, it is still urgent to strengthen the inter-regional cooperation in emission reduction.

Table 4. Evolution trend of the overall network of Carbon Emissions from the IEDS in Taizhou

Year	2015	2016	2017	2018	2019	2020	2021
Density	0.3194	0.3056	0.3194	0.3056	0.2917	0.3472	0.3611
Connectedness	1	1	1	1	1	1	1
Hierarchy	0.6452	0.6774	0.6774	0.6774	0.6774	0.5588	0.5588
Efficiency	0.6786	0.6786	0.6429	0.6786	0.6786	0.6786	0.6429

3.2.3 Individual network characteristics of spatial association network of the IEDS carbon emission

A detailed analysis of the network structural characteristics was undertaken across different regions of Taizhou City, focusing on the 'centrality' of nodes within the spatial network and their interrelationships. This approach aimed to assess the impact of each county on surrounding regions. From 2015 to 2021, Yuhuan County, Linhai County, and Luqiao County consistently ranked high in centrality. The year 2021 was used as a reference for centrality analysis (Figure 3). Generally speaking, Yuhuan County exhibited higher centrality index values than other regions, suggesting its dominant network position and greater potential for carbon emissions. Luqiao County closely follows, indicating that the spatial network is primarily centered around Yuhuan County and Luqiao County, influencing the spatial distribution of carbon emissions in Taizhou City. Linhai County ranks slightly below Yuhuan County and Luqiao County, playing an important role in connecting distant areas such as Tiantai County, Xianju County, and Sanmen County.

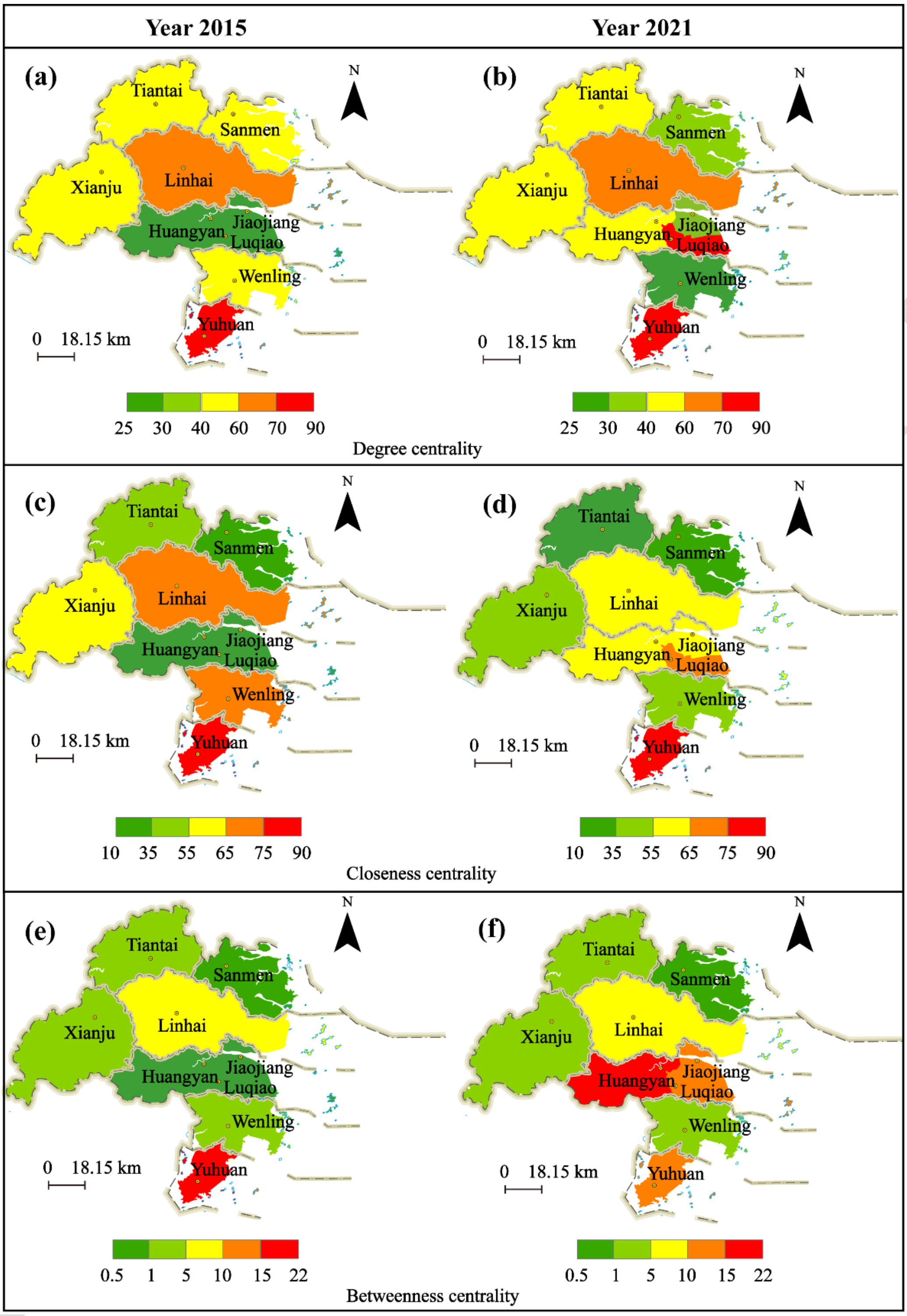


Figure 3. Spatial pattern of average degree centrality, betweenness centrality and closeness centrality of the IEDS carbon emissions network in Taizhou City from 2015 to 2021

3.2.4 Block model analysis

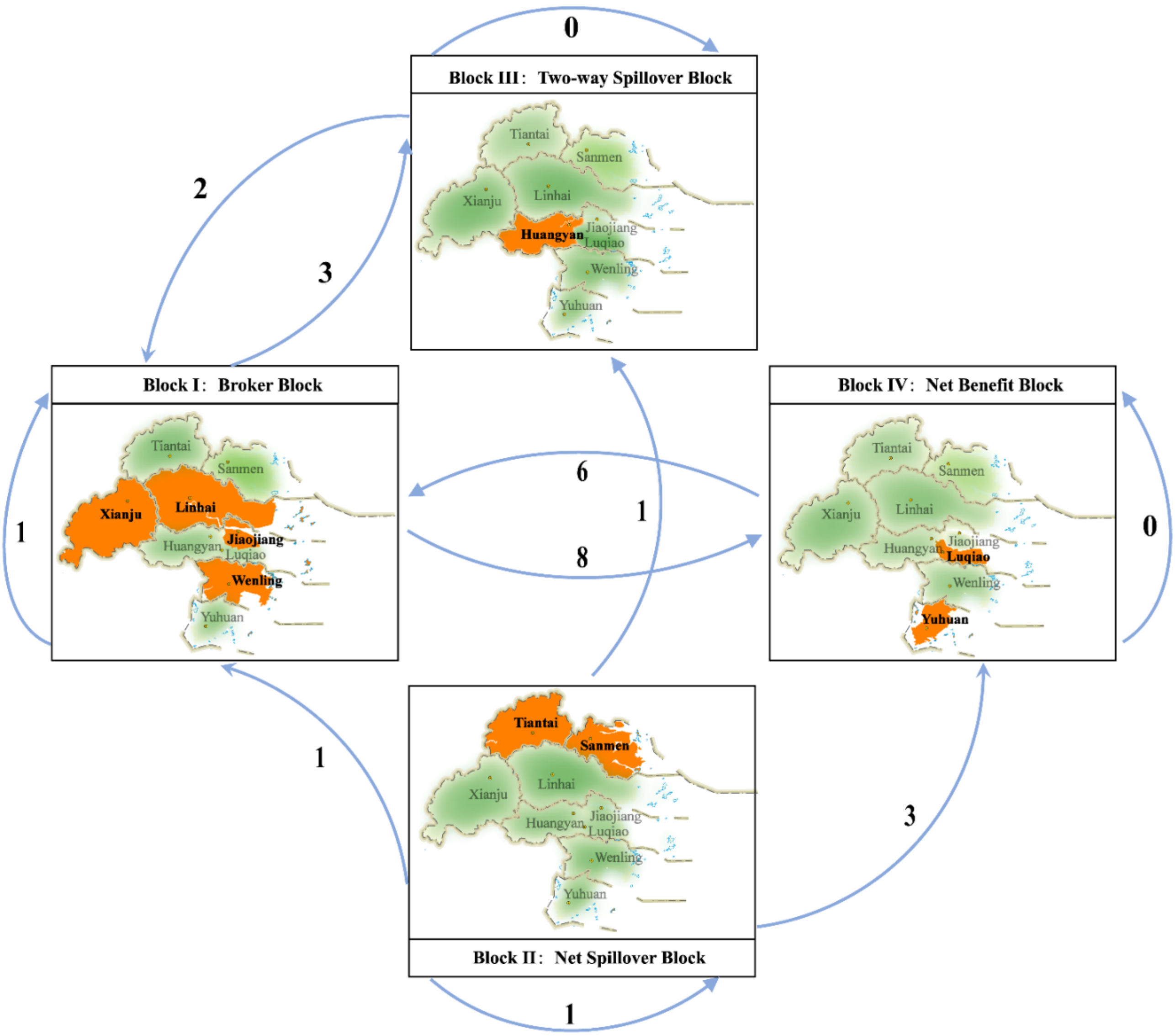
Using the CONCOR (Convergent Correlations) conjugate gradient method, with the maximum split density set to 2 and the convergence criterion of 0.2, the 9 counties in Taizhou City are clustered into

4 clusters. The density values between groups are obtained simultaneously, enabling comprehensive analysis within each group. Our objective is to elucidate the specific roles of each county in the carbon emission network in Taizhou City. Block I consists of four counties, including Jiaojiang County, Xianju County, Wenling County, and Linhai County. Block II consists of two counties, including Sanmen County and Tiantai County. Block IIII consists of one county in Huangyan County. Block IV consists of two counties, including Luqiao County and Yuhuan County.

The number of members and correlations within each block are identified, as shown in Table 5. As show in Table 5, By analyzing the spatial network structure and spillover relationships of carbon emissions, Taizhou exhibits a total of 26 spatial network relationships. Among these, there are two intra-Module relationships, accounting for 7.69% of the total, while there are 24 inter- Block relationships, accounting for 92.31%. This indicates a discernible spillover effect of carbon emissions in Taizhou, with regional spillover being the predominant factor. Block I exhibits 12 spillover relationships, with 9 originating from other Blocks and 1 internal to the Block. The expected proportion of internal relationships is 37.5%, which is higher than the actual proportion of 8.33%, suggesting that Block I plays a " Broker Block " role in facilitating spillover relationships within and beyond the Block boundaries. Block II has 6 spillover relationships, with no inflows from other Blocks and 1 internal relationship. The expected proportion of internal relationships is 12.5%, whereas the actual proportion is 16.67%, suggesting that Block II plays a "Net Spillover Block" role. The Block typically show significant carbon emission overflow effects due to substantial energy output. Block III shows 2 spillover relationships, with 4 spillover relationships from other Blocks and no internal relationships, suggesting that Block III plays a "Two-way Spillover Block" role. Block IV exhibits 6 overflow relationships, with 11 overflow relationships from other Blocks and no internal relationships, also classifying it as a " Net Benefit Block " Block. Block III and IV are characterized by significant industrial value-added areas. They are positioned dominantly in the network, typically receiving spillover effects from other Blocks within the network. For a comprehensive depiction of the correlations among the four blocks, we generated visual representations of their spatial correlation relationships using the data from Table 5. These correlations are displayed in Figure 4.

Table 5. The spillover effects of the spatial correlation plates of the industrial enterprises above designated size carbon emission in Taizhou

Block	Accepted relationships		Overflow relationships		Expected internal relationships	Actual internal relationships
	Inside	Outside	Inside	Outside		
Block I	1	9	1	11	37.5	8.33
Block II	1	0	1	5	12.5	16.67
Block III	0	4	0	2	0	0
Block IV	0	11	0	6	12.5	0



Notes: The yellow shading on the map denotes the geographic locations of the counties and municipalities within each plate.

Figure 4. Block model analysis

To enhance the depiction of how industrial carbon emissions propagate across Blocks, we constructed a network density matrix based on the spatial structure of carbon emission networks as compared to the overall density (0.3611) shown in Table 4. If the network density of the Blocks is higher than 0.3611, the corresponding density value in the matrix is assigned as 1, and otherwise 0, so that the network density matrix is transformed into an image matrix (Li *et al*. 2024). Blocks with network densities exceeding 0.3611 indicate more significant carbon emission spillover effects. As shown in Table 6, it is apparent that Block II exhibits internal correlations with Block III and IV, as well as receiving spillover relationships from them. This suggests its dependence on energy inputs from other Blocks, since its own resources are insufficient to meet local demand. Additionally, Block I and II show no direct associations with Block III and IV. The correlation between regions should be strengthened to fully leverage the regional advantages of each Blocks and further enhance the spatial correlation of the IEDS carbon emissions in Taizhou City.

Table 6. Spatial correlation module division and density value of the industrial enterprises above designated size carbon emission in Taizhou

	Density matrix				Image matrix			
Block	Block I	Block II	Block III	Block IV	Block I	Block II	Block III	Block IV
Block I	0.083	0.000	0.750	1.000	0	0	1	1
Block II	0.125	0.500	0.500	0.750	0	1	1	1
Block III	0.500	0.000	/	0.000	1	0	0	0
Block IV	0.750	0.000	0.000	0.000	1	0	0	0

3.3 ERGM analysis

To explore the influencing factors of the spatial correlation network of carbon emission in the IEDS, we aim to identify and analyze the key driving factors through the formation mechanism of the carbon emission spatial correlation network using the ERGM. The ERGM utilizes the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to assess model fit, with smaller AIC and BIC values indicating better model fit. The standardized ERGM coefficients and their significance levels are presented in Table 7. The model converged successfully with excellent goodness-of-fit indicators (AIC=59.0, BIC=80.6), demonstrating superior explanatory power. The ERGM results revealed a distinct hierarchical structure among the influence factors, with four variables achieving extremely high significance ($p<0.001$), three variables showing high significance ($p<0.01$), and one variable demonstrating negligible influence.

The ERGM results revealed a hierarchical structure among influence factors. Carbon intensity emerged as the strongest negative inhibitor with a coefficient of -18.245, indicating that regions with higher carbon emission intensity are significantly less likely to form network connections. This suggests a "carbon isolation" phenomenon where high-emission areas become disconnected from regional cooperation networks. Energy intensity showed the strongest positive effect (14.567), suggesting that energy-intensive regions are more likely to form collaborative networks, possibly reflecting integration demands of energy supply chains and energy security cooperation drivers. Opening-up level exhibited a significant positive coefficient of 12.834, confirming the role of economic openness in promoting network formation. Technology development showed a negative coefficient of -11.567, revealing a competition effect where technologically advanced regions may reduce connections with less advanced areas. Among moderately significant factors, industrial structure (8.432) and geographical adjacency (7.234) showed positive effects, while urbanization level (-6.789) demonstrated negative influence. Informatization level showed negligible influence (-0.892, p=0.486).

Table 7. ERGM correlation analysis results of spatial correlation of carbon emissions in the IEDS and its influencing factors

Variable	β-coefficient	Std Dev	p-value
CI	-18.245***	2.985	0.001
IS	8.432**	1.196	0.006
UL	-6.789**	0.901	0.002
TD	-11.567***	1.618	0.001
OL	12.834***	2.715	<0.001
IN	-0.892	0.518	0.486
GA	7.234**	0.85	0.003
EI	14.567***	2.456	<0.001

Notes: 1)Significance levels: *** p<0.001; ** p<0.01; * p<0.05. 2) variables are shown in Table 3.

4. Discussion

The findings of this study align with previous research highlighting the spatial heterogeneity of carbon emissions in industrial clusters (Yu *et al*. 2024), yet provides novel insights through county-level analysis and ERGM methodology. Our results reveal three key mechanisms governing inter-county carbon emission networks that challenge conventional assumptions about regional cooperation.

First, the pronounced 'carbon isolation' effect ($\beta = -18.245$, $P<0.001$) demonstrates that environmental performance has become a critical determinant of regional integration, contrasting with traditional proximity-based cooperation models. High-emission counties face systematic exclusion from collaborative networks, potentially driven by environmental regulatory pressures and competitive disadvantages in attracting clean technology partnerships (Wang *et al*. 2024). This finding suggests the need for targeted policy interventions to prevent marginalization of high-carbon regions while incentivizing their low-carbon transitions.

Second, the energy-environment paradox-whereby energy intensity promotes connectivity ($\beta= 14.567$, $P <0.001$) despite potential environmental costs-illuminates complex resource dependencies in regional development. Energy-intensive regions form stronger networks through supply chain integration demands and energy security imperatives, consistent with previous studies (Song *et al*. 2024; Guan *et al.* 2023). This presents opportunities for leveraging energy cooperation frameworks to promote broader environmental coordination.

Third, contrary to traditional spillover theories, technological development exhibits a negative effect ($\beta=-11.567$, $P < 0.001$), revealing competitive dynamics where technologically advanced counties strategically limit connections with less advanced areas. This competition effect may arise from intellectual property concerns and preferences for collaborating with similarly advanced partners, necessitating technology-sharing mechanisms to overcome these barriers (Wei *et al.* 2024).

However, several limitations warrant acknowledgment: First, the relatively short temporal span (2015-2021) may limit the generalizability of findings, particularly given potential structural disruptions from the COVID-19 pandemic during 2020-2021, which could have altered traditional inter-county collaboration patterns and industrial production networks. Specifically, the 2020 pandemic disrupted traditional industrial networks through supply chain interruptions, mobility restrictions, and emergency production adjustments, evidenced by the notable network density increase to 0.3472 in 2020 compared to 0.2917 in 2019. Second, the omission of environmental regulation intensity as a driving factor represents a significant analytical gap, as regulatory heterogeneity across counties likely influences carbon emission spatial correlations through compliance costs and policy-induced technological adoption patterns. Third, while the gravity model effectively quantifies spatial connections, it cannot fully elucidate the qualitative mechanisms underlying these relationships, such as informal institutional arrangements, political economy factors, and social capital dynamics that may drive or constrain inter-county cooperation. Fourth, the county-level analysis, while providing valuable sub-regional insights, may overlook intra-county heterogeneity and enterprise-level variations that could influence network formation mechanisms. Future research should incorporate multi-dimensional regulatory indicators, extend temporal coverage to capture long-term structural changes, and integrate mixed-methods approaches to better understand the qualitative dimensions of spatial carbon emission networks.

5. Conclusion and policy implications

Through the application of an enhanced gravity model coupled with social network analysis, this study systematically investigates the spatial network architecture of industrial carbon emissions across nine counties in Taizhou City over the period 2015-2021, thereby elucidating critical insights for regional carbon governance and strategic policy development.

5.1 Conclusion

(1) Network Evolution and Structure

The spatial correlation network governing industrial carbon emissions in Taizhou has demonstrated progressive strengthening over the study period while exhibiting remarkable structural stability (network correlation degree = 1). Notably, network density increased to 0.3611, concomitant with a hierarchical reduction from 0.6452 to 0.5588, signifying diminishing status disparities among counties. However, persistent developmental imbalances necessitate enhanced inter-regional collaborative mechanisms.

(2) Spatial Roles and Connectivity

Yuhuan County and Luqiao District have emerged as pivotal network actors, functioning as critical intermediary nodes that facilitate spatial carbon emission interconnections. The eastern economically advanced regions—namely Yuhuan, Wenling, and Jiaojiang—occupy strategically central network positions, whereas their less economically developed counterparts (Sanmen, Tiantai, Xianju) are relegated to peripheral positions. Through comprehensive block analysis, four functionally distinct roles were delineated: Broker Blocks (encompassing Jiaojiang, Xianju, Wenling, and Linhai), Net Spillover Blocks (comprising Sanmen and Tiantai), Two-way Spillover Blocks (represented by

Huangyan), and Net Benefit Blocks (including Luqiao and Yuhuan).

(3) Key Driving factors

The ERGM analysis unveiled a hierarchical constellation of influence patterns, with carbon emission intensity functioning as the most potent negative inhibitor (β = -18.245), while energy intensity emerged as the predominant positive driver (β = 14.567). These findings substantiate a distinctive "carbon isolation" phenomenon, wherein high-emission regions experience systematic disconnection from collaborative networks, contrasting sharply with energy-intensive regions that forge enhanced cooperative linkages through supply chain integration mechanisms.

5.2 Policy Implications

Based on the distinct network roles identified, four targeted strategic interventions emerge for achieving dual-carbon objectives:

(1) For Net Spillover Blocks (Sanmen and Tiantai): implement differentiated carbon tax mechanisms that account for their energy output characteristics, establishing carbon pricing structures that incentivize emission reductions while maintaining their spillover functions within the regional energy supply chain;

(2) For Net Benefit Blocks (Luqiao and Yuhuan): design technology transfer incentive programs that leverage their dominant network positions, creating innovation hubs that facilitate knowledge diffusion to peripheral counties through preferential R&D funding and tax credits for collaborative green technology development;

(3) For Broker Blocks (Jiaojiang, Xianju, Wenling, and Linhai): establish coordination mechanisms that utilize their intermediary roles effectively, developing cross-regional carbon trading platforms and emission monitoring systems that capitalize on their strategic network positions to facilitate inter-county carbon flow optimization;

(4) For Two-way Spillover Blocks (Huangyan): implement balanced regulatory frameworks that support both emission reduction and technology absorption capabilities, fostering bidirectional knowledge exchange through specialized green innovation incubators.

The findings provide scientific foundation for formulating coordinated carbon reduction strategies in transitioning regions and offer valuable insights for similar industrial clusters pursuing low-carbon transformation within China's dual-carbon framework.

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