Spatial-temporal evolution of urban low-carbon competitiveness: A case study in the Yangtze River Delta

Abstract

Low-carbon development capacity has emerged as a significant indicator of a region's overall competitiveness under the objective of emission peak and carbon neutrality. This study uses Yangtze River Delta cities as its research subjects. It builds a thorough evaluation index system of urban low-carbon competitiveness in three dimensions: carbon emissions, socio-economic factors of carbon emissions, and low-carbon technology and policy. Based on the grey correlation TOPSIS method, it then analyses the temporal evolution characteristics of low-carbon competitiveness of 41 Yangtze River Delta cities from 2000 to 2020. Its spatial-temporal evolution pattern is analysed using the LISA time path and the spatiotemporal transition approach. The findings show that: (1) The Yangtze River Delta's overall low-carbon competitiveness rises slowly, while the rank of urban low-carbon competitiveness swings visibly. (2) The spatial correlation of urban carbon emissions varies widely while that of socioeconomic factors of carbon emissions is weak. The spatial-temporal synergistic development trend of low-carbon technology and policy is obvious. (3) In the Yangtze River Delta, there are many spatiotemporal correlation kinds of low-carbon competitiveness evolution. Cities in the south and the north are part of persistent clusters of high and low values, respectively. Shanghai, Nanjing, and Hefei have not yet fully played a driving role as core cities, while Hangzhou and Ningbo are leading the low-carbon growth of nearby cities.

Keywords: Yangtze river delta; Low-carbon competitiveness; Spatial-temporal evolution; Grey correlation TOPSIS; Exploratory spatiotemporal data analysis

1 Introduction

In order to achieve low-carbon development in the region, a regional study on urban low-carbon competitiveness can aid in understanding the variations in low-carbon development between the region's cities, support the rational and effective allocation of economic, social, ecological, and technological resources at the regional level. The G20 Low-carbon Competitiveness was published in 2009 by the Climate Institute and Third Generation Environmentalism Ltd (E3G), suggesting that competitiveness assessments need to be updated to reflect the needs of future low-carbon development and that regions with strong low-carbon competitiveness will produce goods with higher profits at lower carbon emissions intensity and production costs. (The Climate Institute and E3G, 2009) China was first exposed to the idea of low-carbon competitiveness in 2011. The decoupling of national, regional, and urban economic growth from carbon emissions was the primary focus of early domestic scholars who adopted the international notion of low-carbon competitiveness (Cheng & Zhu, 2011). The academic community has come to the general conclusion in recent years that maintaining the greatest possible economic, social, and ecological benefits is the key to increasing urban low-carbon competitiveness (Chen et al., 2012). There is a dearth of assessments for the long-term low-carbon competitiveness of cities and regions, and most of the existing research on this topic is centred on business and economic development.

Urban studies define low-carbon competitiveness as the city's ongoing competitive advantage over other cities due to a favourable low-carbon development environment (Ci, 2012). Urban low-carbon competitiveness is evaluated in three dimensions: economy, society, and environment, quantified in three ways: total, efficiency, and rate of change. The economic dimension focuses on GDP and carbon productivity, the social dimension focuses on social welfare and carbon efficiency, and the environmental dimension on total and average carbon emissions (Li et al., 2015; Xu & Liu, 2014). Since 2013, domestic and foreign studies have used the DPSIR framework (five dimensions: driving force, pressure, state, impact, response) to subdivide several factors for low-carbon city evaluation: economic output, industrial structure, energy pattern, urban transport, building energy consumption, social life, ecological carbon sink, environmental governance, clean technology, policy planning (Lin et al., 2014; Li et al., 2016; Peng et al., 2022; Zhou et al., 2015). Based on this, researchers have used LMDI, STIRPAT, PCA, AHP, entropy weight, grey correlation, and TOPSIS to assess carbon emission drivers. The main findings show economic production is positively correlated with carbon emissions, energy intensity and structural improvement reduce carbon emissions, and industrial restructuring and technological progress also have a dampening effect on carbon emissions (Li et al., 2019; Shen et al., 2018; Wu et al., 2019). Low-carbon city development has also examined the relationship between urbanisation and carbon emissions. Studies show that construction land expansion and urban form characteristics affect carbon emissions, therefore spatial planning is important for carbon reduction in urbanised regions, especially city new districts (Cai & Wu, 2018; Liu & Qin, 2016). As urbanisation accelerates and urban wealth rises, consumption-based carbon emissions from housing, energy use, and transport should be given more attention than production-based emissions (Zhou et al., 2015; Harris et al., 2020). Besides, Low-carbon environmental policies also promote urban carbon reduction (Zhou et al., 2019; Sun, 2020).

Despite extensive studies on low-carbon cities, urban low-carbon competitiveness has three weaknesses. (1) Urban low-carbon competitiveness evaluation indicators are biassed toward socio-economic statistics, with insufficient analysis of urban spatial pattern characteristics in the urbanisation process, making it harder to propose low-carbon development strategies from the perspective of territorial spatial planning and governance. 2 Spatial-temporal study of urban low-carbon competitiveness is lacking. Individual scholars employ grey prediction and system dynamics models to simulate and predict low-carbon competitiveness (Yang et al., 2016). Thus, spatiotemporal evolutionary analysis methods like variation coefficient and Theil index are needed to evaluate regional disparities' temporal evolutionary characteristics (Sun et al., 2020; Huang & Li, 2017) or exploratory spatial data analysis to identify cities' spatiotemporal correlation trends (Zhang et al., 2020; Chen et al., 2022). (3) Most research units are provinces, metropolitan areas, and urban agglomerations, e.g. Li et al (2016) graded 30 Chinese provinces' low-carbon competitiveness, and Yang et al (2016) assessed the four major metropolitan agglomerations' low-carbon cities. However, empirical analysis of Yangtze Delta cities as evaluation items is limited.

This study integrates land use, urban structure and form, low-carbon policy, and technology into the current low-carbon competitiveness evaluation system to address these research gaps. It uses the grey correlation-TOPSIS model to assess the low-carbon competitiveness of 41 cities in the Yangtze River Delta from 2000 to 2020 and then uses the time series clustering algorithm, LISA time path, and spatiotemporal transition to analyse regional clustering and divergence, spatial polarisation and spillover effects. The purpose of this study is to offer a methodological guide for the thorough evaluation of urban and regional low-carbon competitiveness.

2 Methodology

2.1 Study area

The scope of the Yangtze River Delta is the study area, as defined in the State Council's 2019 Outline of Integrated Regional Development of the Yangtze River Delta, which includes Shanghai City, Jiangsu Province, Zhejiang Province, Anhui Province, and 41 prefecture-level cities. The Yangtze River Delta is a crucial strategic location for China's economic and social development with a total area of 350,000km2, a resident population of 235 million, and a total GDP of 24% of China. The Yangtze River Delta, however, accounts for one-fifth of all of China's carbon emissions, making it one of the areas with the highest energy consumption per unit of land area in the country. Cities around the Yangtze River have comparatively high per-person carbon emissions (Figure 1). In order to meet the goals of carbon peak and carbon neutrality, the Yangtze River Delta is under increased strain and challenges.

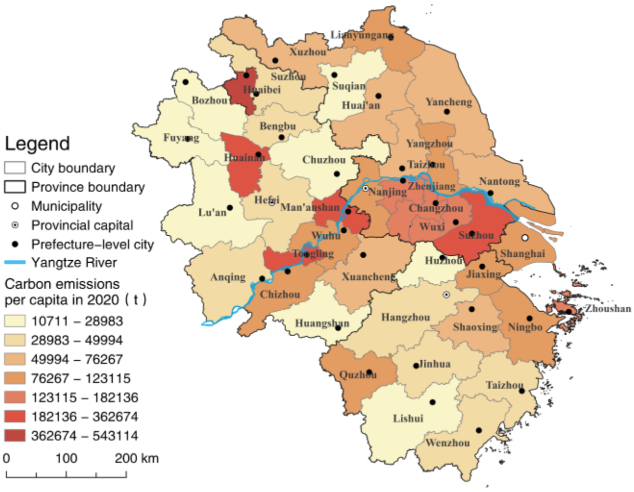

Figure 1. **Study area and spatial distribution of per capita carbon emissions in the Yangtze River Delta in 2020.**

2.2 Indicator system and data sources

In this study, the criterion layer of the indicator system contains carbon emissions, socioeconomic factors, and low-carbon technology and policy. The factor layer contains carbon emission intensity, land carbon sources and sinks, low-carbon space, low-carbon production, low-carbon living, low-carbon technologies and low-carbon policies. A total of 21 specific indicators are selected to create a low-carbon competitiveness evaluation index system for cities in the Yangtze River Delta (Table.1).

2.2.1 Indicators

The selection of indicators is based on three principles: Reliability, representativeness and data availability.

(1) Reliability: Numerous studies have established a strong association between the indicators and urban low-carbon development.

(2) Representativeness: The indicators should be as complete as feasible in their evaluation of urban low-carbon competitiveness, considering not only all sources of carbon emissions but also all variables that affect carbon emissions.

(3) Data accessibility: In order to prevent significant errors brought on by the interpolation of missing values, the evaluation's thoroughness and data integrity are both taken into account as far as is practical.

Table 1. **index system of low-carbon competitiveness and index weight.**

Criterion layer	Factor layer	Indicator layer and weights	Calculation formula/statistical methods	Meanings of indicator
Carbon emissions A	Carbon emission intensity A1	Carbon emission intensity (t/¥) A11 **0.0727**	$A11 = A1/Y$	Reflecting the economic efficiency of urban carbon emissions, i.e. carbon emissions per GDP. A1 is the total socio-economic carbon emissions and Y is the city's GDP.
		Decoupling Index A12 **0.0866**	$A12 = \frac{\Delta A1/A1}{\Delta Y/Y}$	Reflecting the elasticity of urban carbon emissions change relative to GDP growth. A1 is the total socio-economic carbon emissions and Y is the city's GDP, where the value of A1 < 0 indicates absolute decoupling; ∈ (0,1) interval indicates relative decoupling; > 1 indicates negative decoupling (Shuai et al., 2019).
		Carbon emissions per unit area of land (t/km^2) A13 **0.0563**	$A13 = A1/S$	Reflecting the spatial efficiency of urban carbon emissions, i.e. the number of carbon emissions per unit built-up area. S is the city's built-up area.
		Carbon emissions per capita (t/10,000 people) A14 **0.057**	$A14 = A1/P$	Reflecting the average carbon emissions of the city's residents. P is the total population of the city.
	Land carbon sources and sinks A2	Carbon source of land use (kg) A21 **0.064**	$A21 = \sum F_i \times A21i$	Reflecting the number of carbon emissions in the city's arable and construction land. The carbon emission factors for arable land and construction land are 0.0422kg/(m²-a) (Shuai et al., 2019) and 5.58kg/(m²-a) (Yuan & Tang, 2019) respectively.
		Carbon sink of ecological land (kg) A22 **0.0373**	$A22 = \sum G_i \times A22i$	Reflecting the amount of carbon sink in the city's ecological land. woodland, The carbon emission factors for woodland, grassland, water area and unutilized land are 0.06125, 0.0021, 0.00248 and 0.0005 kg/(m^2・a) respectively.
Socio-economic factors of carbon emissions B	Low carbon space B1	Dominance index B11 **0.0445**	$B11 = S_{max}/S$	Reflecting the concentration of built-up areas in the city. S_{max} and S are the maximum and total area of the city's built-up areas respectively.
		Compactness index B12 **0.0363**	$B12 = 2\sqrt{\pi S_{max}}/P_{max}$	Reflecting the shape regularity degree of space form of the city's built-up areas. S_{max} and P_{max} are the maximum area and maximum perimeter of the built-up area respectively.

		Fragmentation index B13 **0.0409**	$B13 = N/S$	Reflecting the fragmentation of the city's built-up areas. N is the number of built-up area patches of the city.
	Low carbon production B2	Industrial structure rationalization B21 **0.059**	$B21 = \sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right)\ln\left(\frac{Y_i/Y}{L_i/L}\right)$D	Reflecting the level of coordination between industries and the effective use of resources in the city
		Industrial structure optimization B22 **0.0613**	$B22 = Y_3/Y_2$	Reflecting the service orientation in the city's economic structure
	Low carbon living B3	Number of bus rides per capita (times/year) B31 **0.0318**	Total number of bus passenger traffic / total population at the end of the year in the municipal district	Reflecting the situation of public transport travelling of the city's residents
		Urban housing area per capita (m^2) B32 **0.0402**	Urban housing area per capita index in local statistical yearbooks	Reflecting carbon emissions induced by urban residents in the city (Wang &Shi, 2009)
		Rural housing area per capita (m^2) B33 **0.0381**	Rural housing area per capita index in local statistical yearbooks	Reflecting carbon emissions induced by rural residents in the city (Wang &Shi, 2009)
		Average household electricity consumption (billion kWh/household) B34 **0.0747**	Electricity consumption by urban and rural residents/total number of households	Reflecting the carbon emissions induced by domestic electricity use per household in the city (Peng & Zhu, 2010)
Low-carbon technology and policy C	Low carbon technology C1	Number of low-carbon enterprises in the year C11 **0.0785**	Counting by the search criteria based on the name or business scope of the enterprise containing any of the keywords "low carbon", "energy saving", "emission reduction" and "new energy" and its paid-up capital scale being ¥10 million or more (Shi et al., 2010)	Reflecting the city's strength of the technology and equipment to support the development of a low-carbon economy
		Number of low-carbon technology patent disclosures in the year C12 **0.0415**	Counting by the search criteria based on the patent name or the abstract of the patent specification containing any of the keywords "low carbon", "energy saving", "emission reduction" and "carbon emission" and according to the date of a patent disclosure and the applicant's city (Liu et al., 2021)	Reflecting the city's ability to low carbon technology innovation
	Low carbon policy C2	Number of local normative documents at the provincial level C21 **0.0194**	Counting by the search criteria based on the policy title containing any of the keywords "energy saving", "low carbon", "emission	Reflecting policy attention given to the city's low-carbon development by provincial government departments

	Number of local work documents at the provincial level C22 **0.0144**	reduction", "ecology", "environmental protection", "sustainable", "energy consumption" and "carbon emission" and the document being "currently valid" (Luo & Zhu, 2014)	
	Number of local normative documents at municipal level C23 **0.0282**		Reflecting policy attention given to the city’s low-carbon development by the city government department
	Number of local work documents at municipal level C24 **0.0174**		

Notes: F_i and G_i are the carbon emission and carbon sink factors of the i-th land type. Y and L are the GDP and total employment of the city in the year, Y_i and L_i are the added value of the i-th industry in the year. Total socio-economic carbon emissions A1 includes five main types of human activities: energy consumption, industrial processes, population respiration, wastewater treatment and waste incineration (Hu et al., 2016), and S_{COD} is taken as70g (person/day) (Cai, 2012) in the references.

The main component used to gauge a city's low-carbon competitiveness is its carbon emissions sub-dimension, which takes two factors into account: carbon emissions intensity and land carbon sources and sinks. The unit carbon emissions in terms of economy, space, and population, as well as the extent to which carbon emissions are decoupled from the economy—where carbon emissions are computed based on human socioeconomic activities—are all included in the carbon emissions intensity layer. The land carbon sources and sinks layer shows how much carbon is emitted overall as a result of urban land usage, including how much is emitted from construction and agricultural land as well as how much is sucked up by ecological land.

The socio-economic factors sub-dimension, which is separated into three factor indicator layers: low-carbon space, low-carbon production, and low-carbon living, depicts the entire low-carbon index of cities in three aspects: spatial shape, production structure, and social life. The low-carbon space layer reflects the concentration and compactness of the entire and central built-up area of the city. Research indicates that the more concentrated, regular, and compact the built-up area of the city is, the lower the carbon emissions generated (Wang et al., 2017; Ou et al., 2019). The two factor indicator layers of the low-carbon production layer—industrial structure rationalisation and industrial structure optimization—reflect the industrial structure's degree of low carbonization. Industrial structure rationalisation measures the coupling between factor input structure and output structure. The higher the coupling degree, the more effectively resources are used, and the greater the degree of low carbonization. Industrial structure optimization reflects the orientation of the industry toward services because the tertiary industry emits less carbon than the secondary industry (Wang et al., 2019). The low-carbon living layer reflects residents' receptivity to low-carbon lifestyles. Studies indicate that the growth of the housing area is a significant contributor to the rise in energy consumption (Wang & Shi, 2009). Therefore, this study incorporates the urban housing area per capita and rural housing area per capita in the indicator system in addition to the two indicators of the number of bus rides per capita and the average household electricity consumption.

The low-carbon technology and policy sub-dimension, which is made up of two factor layers—low-carbon technology and low-carbon policy—reflects a city's capacity to control carbon emissions through energy-saving technological advancements and environmental legislation. The low-carbon policy layer represents the policy attention given to low-carbon development at the province and local levels, whereas the low-carbon technology layer measures technological innovations in terms of the number of low-carbon-related enterprises and patents. Based on the research of Ling Shi et al. (Shi et al., 2010), search for low-carbon enterprises, low-carbon technology patents, and low-carbon policies using the keywords "low carbon", "energy saving," "new energy," etc. and use annual values rather than cumulative values over time.

2.2.2 Data sources

Data sources for indicator system in this study include statistical yearbook data, land use data, spatial boundary data and internet big data. The data sources are shown in Table 2.

Table 2. List of data sources.

Data name		Data time frame	Data sources
Statistical Yearbook Data		2000-2020	*China Urban Construction Statistical Yearbook*, *China City Statistical Yearbook* and Statistical Yearbooks of needed provinces and cities
Land use data		2000,2005,2010,2015, 2020	Institute of Geographic Sciences and Resources, Chinese Academy of Sciences http://www.resdc.cn
Spatial boundary data	Urban built-up area	2000,2005,2010,2015, 2018	Global Urban Boundary Dataset from Tsinghua University http://data.ess.tsinghua.edu.cn/gub.html
	Urban built-up area boundary	2000-2018	40-Year (1978–2017) human settlement changes in China reflected by impervious surfaces from satellite remote sensing, Tsinghua University http://data.ess.tsinghua.edu.cn/urbanChina.html
	Urban administrative district boundaries	2021	Resource and Environment Science and Data Centre, Chinese Academy of Sciences http://www.resdc.cn
Internet Big Data	Enterprise Big Data	2000-2020	https://www.qcc.com/web/search/advance
	Patent Big Data		https://www.baiten.cn/
	Policy Big Data		https://www.pkulaw.com/

2.3 Methods

2.3.1 Grey correlation TOPSIS

As the urban low-carbon competitiveness is influenced by the multi-dimensional synergy of economic, social and environmental dimensions, the traditional TOPSIS method can hardly reflect the nonlinear structure of its internal factors. However, when combined with the grey correlation method, it can more accurately measure the proximity of the evaluation object to the ideal solution (Yuan, 2014). Therefore, urban low-carbon competitiveness in the Yangtze River Delta is measured in this study using he grey correlation TOPSIS approach. The same formula is used to determine the scores for the indicator system's criteria layer.

（1）indicator weights

① The raw data were nondimensionalized using range standardization method. By combining the AHP approach with the entropy weight method, the weights are calculated while considering the significance of the indicator attributes as well as the facts reflected in the data. This method has been employed frequently in the literature, hence the specific mathematical procedure will not be given here (Wu et al., 2017).

② Combination weights via the linear weighting approach.

$$w_j = \mu\alpha_j + (1-\mu)\beta_j \tag{1}$$

Where α_j, β_j are the weights of each indicator derived from the AHP and entropy weight methods respectively. The value of variation coefficient μ is usually assigned as 0.5.

（2）weighted normalization matrix

$$V_{ij} = (w_j x'_{ij})_{m\times n} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & u_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \tag{2}$$

where m, n are the number of cities and indicators respectively, the same below.

（3）The positive-ideal and negative-ideal solution

Positive-ideal solutions:

$$v_j^+ = \left(\max v_{ij} \mid j = 1,2,3,\cdots,n\right), \qquad V^+ = (v_1^+, v_2^+, v_3^+, \cdots, v_n^+) \tag{3}$$

Negative-ideal solutions:

$$v_j^- = \left(\min v_{ij} \mid j = 1,2,3,\cdots,n\right), \qquad V^- = (v_1^-, v_2^-, v_3^-, \cdots, v_n^-) \tag{4}$$

where v_j^+ is the positive-ideal solution of the j-th indicator, v_j^- is the negative-ideal solution of the j-th indicator.

（4）Grey correlation coefficient

① The formula of the grey correlation coefficient ρ_{ij}^+ between the j-th indicator of the i-th evaluation object and its positive-ideal solution is as follows:

$$\rho_{ij}^+ = \frac{\min\limits_{1\le j\le n}\min\limits_{1\le i\le m}\left| v_{ij}^+ - v_{ij} \right| + \xi \max\limits_{1\le j\le n}\max\limits_{1\le i\le m}\left| v_{ij}^+ - v_{ij} \right|}{\left| v_{ij}^+ - v_{ij} \right| + \xi \max\limits_{1\le j\le n}\max\limits_{1\le i\le m}\left| v_{ij}^+ - v_{ij} \right|} \tag{5}$$

where $\min\limits_{1\le j\le n}\min\limits_{1\le i\le m}\left| v_{ij}^+ - v_{ij} \right|$ is the minimum difference, and $\max\limits_{1\le j\le n}\max\limits_{1\le i\le m}\left| v_{ij}^+ - v_{ij} \right|$ is the maximum difference. ξ is the distinguishing coefficient, the value of which is usually assigned as 0.5. The differences between the grey correlation coefficients are larger when is ξ smaller. The grey correlation coefficient matrix of each evaluation object with its positive ideal solution is:

$$\rho^+ = \begin{bmatrix} \rho_{11}^+ & \rho_{12}^+ & \cdots & \rho_{1n}^+ \\ \rho_{21}^+ & \rho_{22}^+ & \cdots & \rho_{2n}^+ \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{m1}^+ & \rho_{m2}^+ & \cdots & \rho_{mn}^+ \end{bmatrix} \tag{6}$$

② The formula of the grey correlation coefficient ρ_i^+ between the i-th evaluation object and its positive-ideal solution is as follows:

$$P_i^+ = \frac{\sum_{j=1}^{n} \rho_{ij}^+}{n}, (i = 1,2,\cdots,m) \tag{7}$$

Similarly, the grey correlation coefficient ρ_i^- between the i-th evaluation object and its negative-ideal solution:

$$P_i^- = \frac{\sum_{j=1}^{n} \rho_{ij}^-}{n}, (i = 1,2,\cdots,m) \tag{8}$$

To calculate the grey relative similarity degree, which is expressed as:

$$C_i = \frac{P_i^+}{P_i^- + P_i^+}, (i = 1,2,\cdots,m) \tag{9}$$

where C_i The range of values $\in$ [0,1]. Ranking cities' levels of low-carbon competitiveness through time based on the value of C_i. Higher the grey relative similarity degree of the city is, the Higher the urban low-carbon competitiveness is, and vice versa.

2.3.2 Exploratory spatiotemporal data analysis

Traditional exploratory spatial data analysis (ESDA) is restricted to analyzing cross-sectional features for spatial patterns and regional differences of geographical observation variables. Exploratory spatiotemporal data analysis (ESTDA), which Rey et al. (2010) proposed, is a collection of spatial data analysis methods including global and local spatial autocorrelation analysis (Moran's I), LISA time path and spatiotemporal transition, and integrating time and space dimensions. In this study, ESTDA is used to analyze the spatiotemporal pattern evolution characteristics of the urban low-carbon competitiveness in the Yangtze River Delta.

(1) Spatial autocorrelation

The global spatial autocorrelation index (Global Moran's *I*) is used to determine the spatial agglomeration of low-carbon competitiveness in the region, as shown in the following equation:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{10}$$

where n is the total number of cities, the y_i and y_j represent the low-carbon competitiveness levels of the i-th city and the j-th city during the period, respectively. W_{ij} is the spatial weight matrix, and different spatial weight matrices reflect different spatial correlation rules. With reference to the already published literature, this study chose the geographic distance weight matrix and employed the inverse of the distance between the government coordinates of the cities. The 1-hour city economic circle was considered as the distance threshold of spatial correlation between cities and was taken as 250km according to the design speed for high-speed rail set by the State Railway Administration of China (Wu et al., 2017).

(2) LISA time path

LISA time path shows the moving tracks of the spatial units' coordinates in the Moran scatterplot over the past years, which can reveal the spatiotemporal interactions, rivalries, and collaborations between cities (Rey, 2004). The movement of coordinates can be represented by the vector $[(y_{i,1}, yL_{i,1}), (y_{i,2}, yL_{i,2}), \ldots, (y_{i,t}, yL_{i,t})]$, where $y_{i,t}$ denotes the Z-score standardization value of the i-th city's low-carbon competitiveness in the year t while $yL_{i,1}$ denotes that of the neighboring cities' low-carbon competitiveness (the spatial lag). the geometric indicators of LISA time path include relative length Γ_i, tortuosity $\triangle_i$ and movement direction θ_i (Rey, 2001).

$$\Gamma_i = \frac{n \times \sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}{\sum_{i=1}^{n}\sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}, \quad \triangle_i = \frac{\sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}{d(L_{i,1}, L_{i,T})}, \quad \theta_i = \arctan\frac{\sum_{t=1}^{T}\sin\theta_{i,t}}{\sum_{t=1}^{T}\cos\theta_{i,t}} \tag{11}$$

where T is the number of the time series' intervals, N is the total number of cities, and L is the LISA coordinate of the i-th city in the year t, i.e. $(y_{i,1}, yL_{i,1})$. The moving distance between the coordinates of the i-th city in years t and t+1 is expressed as $d(L_{i,t}, L_{i,t+1})$. A higher value of $\triangle_i$ implies that the i-th city has a more dynamic evolutionary process impacted by spatial interaction. θ_i indicates the average movement direction of the i-th city. A win-win situation is indicated by a value between 0° and 90°, a lose-lose situation by a value between 180° and 270°, and a win-lose situation by a value between 90° and 180° and a value between 270° and 360°, respectively.

2.4 Analytical framework

The research framework is shown in Figure 2. First, the impact mechanism of carbon emission driving and response forms the basis of the framework for evaluating low-carbon competitiveness. Second, the Yangtze River Delta's 41 cities' low-carbon competitiveness is ranked using the Grey correlation TOPSIS approach from 2000 to 2020. Furthermore, temporal clustering is used to categorize different types of urban low-carbon competitiveness in the Yangtze River Delta based on level disparities and evolutionary trend characteristics. Finally, exploratory spatiotemporal data analysis is employed to reveal the dynamic evolution of the global and local spatial correlation patterns of low-carbon competitiveness in the Yangtze River Delta.

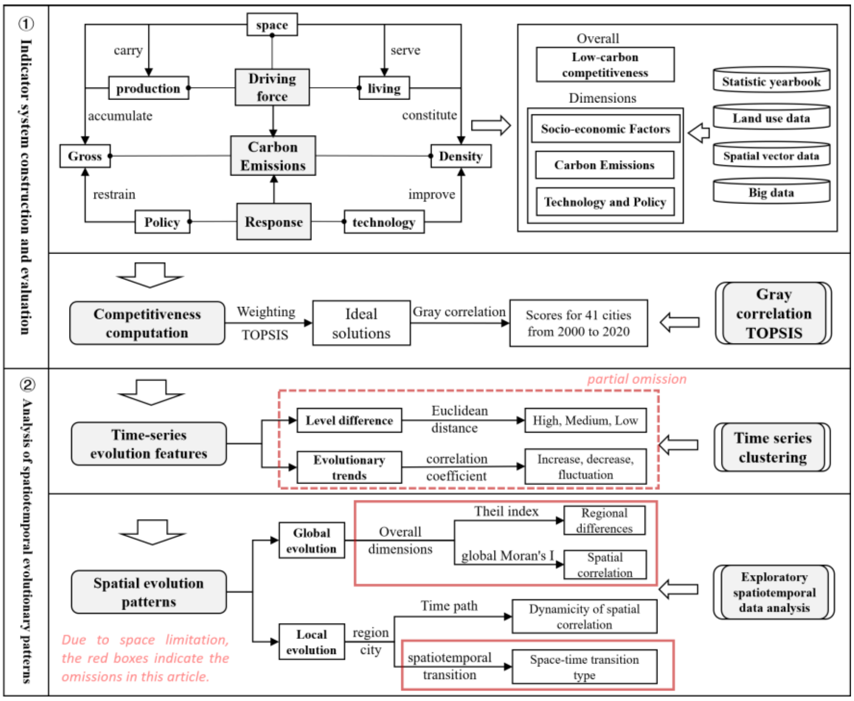

Figure 2. The framework of low-carbon competitiveness evaluation and spatial-temporal evolution in the Yangtze River Delta.

3 Result

3.1 Time-series evolution features of low-carbon competitiveness in the Yangtze River Delta

Considering the visualization effect, data from five time points, 2000, 2005, 2015 and 2000, are selected for presentation in this study.

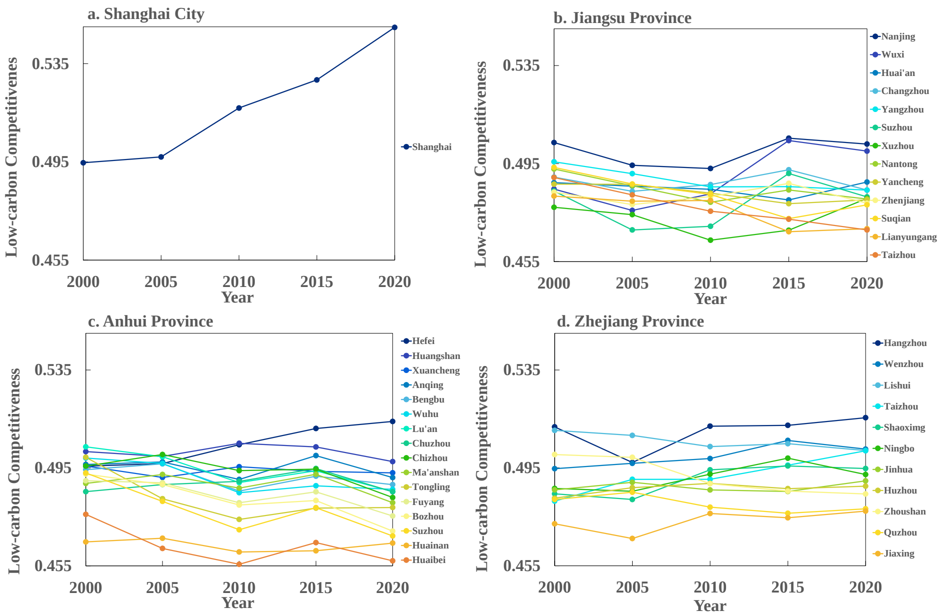

Figure 3. Evolution of low-carbon competitiveness in the Yangtze River Delta.

Figure 3 depicts the overall evolution of the Yangtze River Delta's urban low-carbon competitiveness. Some of the cities exhibit an increasing trend in low-carbon competitiveness, with Shanghai leading the way, followed by Wuxi, Hefei, and Hangzhou. Comparing the three provinces, except for a few cities, the overall low-carbon competitiveness of Zhejiang Province's cities is superior to that of the other two provinces. The disparities in low-carbon competitiveness across cities in Jiangsu Province are minor, whereas those in Zhejiang Province are greater and those in Anhui Province are the greatest.

To further examine the various development trends of low-carbon competitiveness in the Yangtze River Delta, this study used the K-Medoids algorithm for time series clustering with the aid of the space time pattern mining tool in ArcGIS Pro 2.8.4. This study selected the following two clustering basis. Urban low-carbon competitiveness in the Yangtze River Delta is divided into three levels using Euclidean distance, and its evolutionary pattern is divided into three types using correlation coefficient: increasing trend, fluctuating trend, and decreasing trend (Figure 4.).

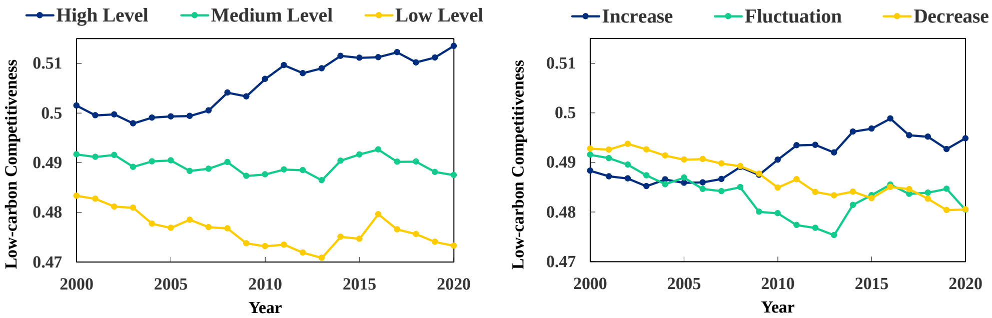

Figure 4. Average time series of low-carbon competitiveness clusters based on Euclidean distance (left) and correlation (right).

The results of the two time-series clustering were integrated to classify the time-series evolution types of urban low-carbon competitiveness in the Yangtze River Delta (Table 3.). Among the cities with high levels of low carbon competitiveness, all cities are on a stable upward trend, except Lishui, which is gradually going downhill. Most cities with medium levels of low carbon competitiveness are on a stable or fluctuating upward trend, while Bozhou, Nantong and Jinhua show a gradual decline or fluctuating downward trend in low carbon competitiveness. Most of the cities with low levels of low carbon competitiveness are in northern Jiangsu and northern Anhui, with cities such as Jiaxing, Suzhou, Zhenjiang and Huainan showing a gradual upward trend.

Table 3. Classification of low-carbon competitiveness development in the Yangtze River Delta.

	High level	Medium level	Low level
Increasing trend	Shanghai, Hangzhou, Hefei, Huangshan, Wenzhou	Chuzhou, Nanjing, Changzhou, Wuxi, Huzhou, Ma'anshan Shaoxing, Ningbo, Zhoushan, Taizhou	Jiaxing, Suzhou, Zhenjiang, Huainan
Fluctuating trend	/	Fuyang, Bengbu, Xuancheng, Huai'an, Wuhu, Anqing, Lu'an	Tongling, Huaibei, Xuzhou, Suizhou, Yancheng
Decreasing trend	Lishui	Bozhou, Nantong, Chizhou, Jinhua, Yangzhou	Quzhou, Taizhou, Suqian, Lianyungang

3.2 Spatial evolution patterns of low-carbon competitiveness in the Yangtze River Delta

LISA time path can depict the evolution of the region's local spatial structure and spatial dependence directions. Figure 5. illustrates the spatial distributions of the relative length, tortuosity, and movement direction of urban low-carbon competitiveness and its three sub-dimensions in the Yangtze River Delta, where the relative length and tortuosity values are divided into five classes using the natural breakpoint method.

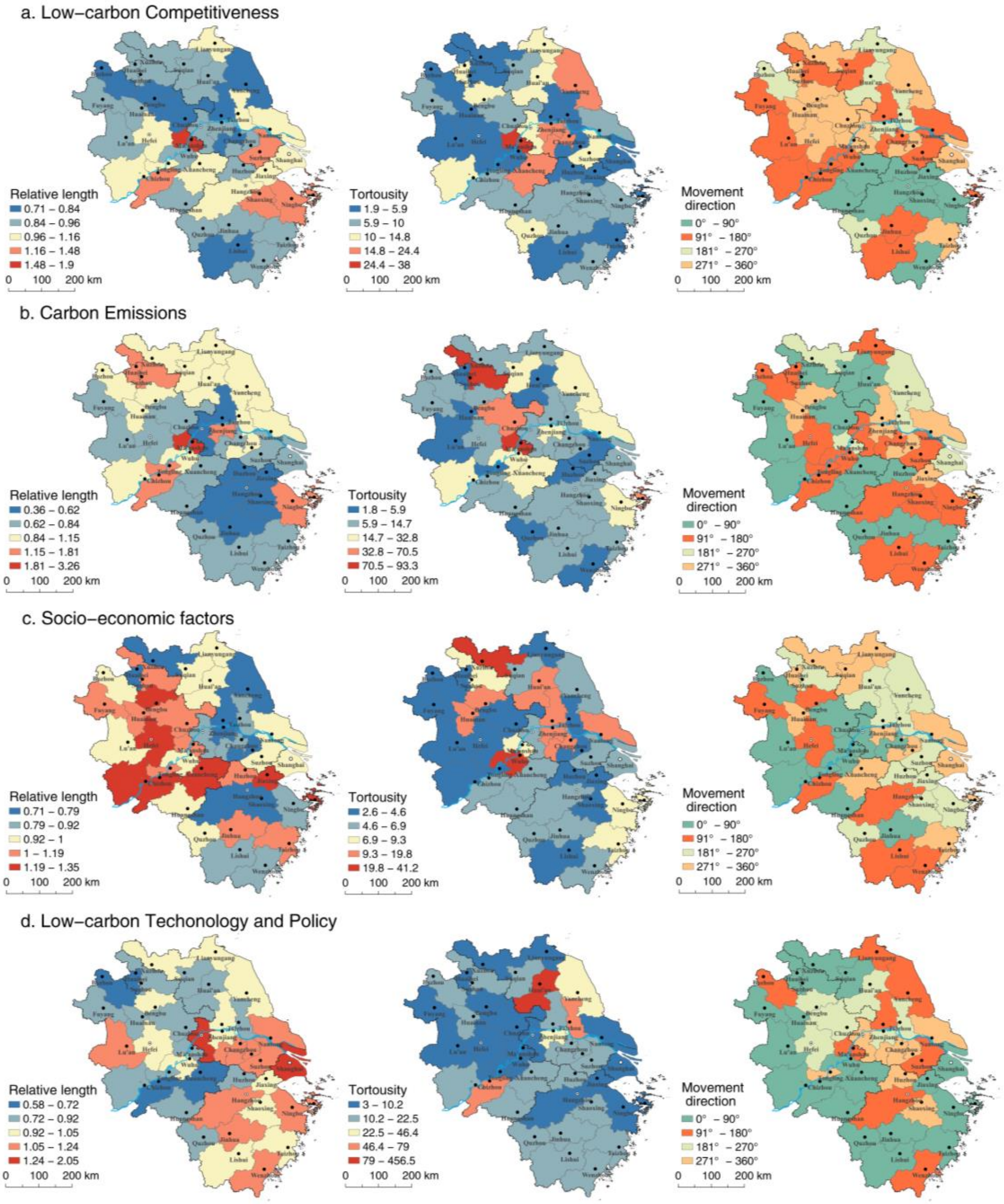

Figure 5. Spatial distribution of time path features of low-carbon competitiveness and subdimensions in the Yangtze River Delta.

During the study period, the relative length of urban low-carbon competitiveness in the Yangtze River Delta tends to decrease from the central region to the north and south regions, indicating that cities in the central area of the Yangtze River Delta have a more dynamic local spatial structure of low-carbon competitiveness than those in the north and south regions. The tortuosity tends to decrease from the centre to the periphery, and Nanjing and its nearby cities have the highest tortuosity values, indicating that the low-carbon competitiveness of this region is undergoing a more dynamic spatial change process. In terms of movement direction, the coevolutionary trend is apparent in the cities of Zhejiang Province, indicating that spatial integration is rather robust there, but it is less evident in the cities of Anhui and Jiangxi Provinces.

Comparing the spatial distribution of the relative lengths of different sub-dimensions, the relative length of carbon emissions exhibits a spatial distribution of "high in the north and low in the south," indicating that the local spatial structure of carbon emissions is more dynamic in the northern region than in the southern region, whereas the local spatial structure variations of socio-economic factors and low-carbon technology and policy exhibit spatial distributions of "high in the west and low in the east" and "high in the east and low in the west", respectively.

In the Yangtze River Delta, the average tortuosities of each sub-dimension are as follows: low-carbon technology and policy (26.04) > carbon emissions (15.84) > socio-economic factors (8.40), indicating that the stability of the local spatial structure in the direction of spatial dependence increases sequentially. High values of tortuosity in each dimension are predominantly observed in Jiangsu and Anhui provinces, indicating that the local spatial dependence direction of these two provinces is more dynamic in all sub-dimensions than that of Zhejiang province.

In terms of the spatial distribution of movement direction, 26 cities in the Yangtze River Delta exhibit positive or negative co-evolution trends in the low-carbon technology and policy sub-dimension (i.e. movement directions of 0°-90° and 180°-270°), indicating a stronger spatial spillover effect; whereas the carbon emissions dimension displays a lose-win or win-lose situation (i.e. movement directions of 90°-180° or 270°-360°), indicating a stronger spatial polarization effect in this dimension.

Using a combination of time-series clustering and spatiotemporal evolution features analysis, the seven types of urban low-carbon competitiveness spatiotemporal evolution in the Yangtze River Delta were determined (Table 4.). The "High-Synergism" type of cities, which have maintained a stable high-value agglomeration throughout evolution, are located in southern Zhejiang and southwest Anhui. In addition, other cities with a high level of low-carbon competitiveness are mostly metropolises such as Shanghai, Nanjing, Hangzhou, Hefei, and Ningbo, although they have varied spatial influences on the neighboring areas. Hangzhou and Ningbo, the type of "High-Spillover" city, have developed a strong spatial interaction with their neighbouring cities, such as Huzhou, Shaoxing, and Jinhua, and have increased the low-carbon competitiveness of the corresponding kind of "Medium-Progress" cities. Nevertheless, Shanghai, Nanjing, and Hefei still belong to the "High-Centrality" type, and the low-carbon competitiveness of their neighbouring cities, such as Nantong, Zhenjiang, and Chuzhou, has slowed over the years, indicating that the three major cities have not yet been able to produce significant and positive spillover effects on their peripheral cities, the "Medium-Stagnation" type. “Low-Depression” cities include Suzhou and Quzhou, which are like "depressions" located in high-value agglomeration zones. Northern Anhui and northern Jiangsu are home to the "Low-Solidity" kind of cities, which maintain a steady low-value agglomeration.

Table 4. spatiotemporal correlation type of low-carbon competitiveness evolution in the Yangtze River Delta.

Spatiotemporal type	City name	Spatiotemporal correlation evolutionary patterns
High-Synergism	Huangshan, Chizhou, Anqing, Wenzhou, Lishui	Consistently sustaining its own and neighbouring cities' low-carbon competitiveness at a high level.
High-Spillover	Hangzhou, Ningbo	Gradually increasing its low-carbon competitiveness and leading the synergistic development of neighbouring cities.
High-Centrality	Shanghai, Hefei, Nanjing	Gradually increasing its low-carbon competitiveness yet failing to

		stimulate development in neighbouring cities.
Medium-Progress	Shaoxing, Taizhou, Jinhua, Huzhou, Wuxi Changzhou, Xuancheng, Maanshan	Gradually increasing in its low-carbon competitiveness driven by cities with high-level low-carbon competitiveness
Medium-Stagnation	Nantong, Taizhou, Yangzhou, Zhenjiang, Chuzhou Bengbu, Huainan, Bozhou, Liu'an, Wuhu, Zhoushan	Decreasing or remaining stagnant in its low-carbon competitiveness and not being led by cities with high-level low-carbon competitiveness
Low-Depression	Suzhou, Quzhou, Jiaxing, Tongling	Consistently maintaining low-levels low-carbon competitiveness surrounded by cities with high-level low-carbon competitiveness
Low-Solidity	Huabei, Fuyang, Suizhou, Xuzhou, Lianyungang Suqian, Huai'an, Yancheng	Consistently maintaining its own and neighbouring cities' low-carbon competitiveness at a low level.

High-Synergism cities and Low-Solidity cities are distributed in the southwest and northeast of the Yangtze River Delta, respectively, as shown in Figure 6. The majority of "Medium-Progress" cities are positioned south of the Yangtze River. The "Medium-Stagnation" and "Low-Depression" are predominantly spread along the Yangtze River, with a concentration to the north.

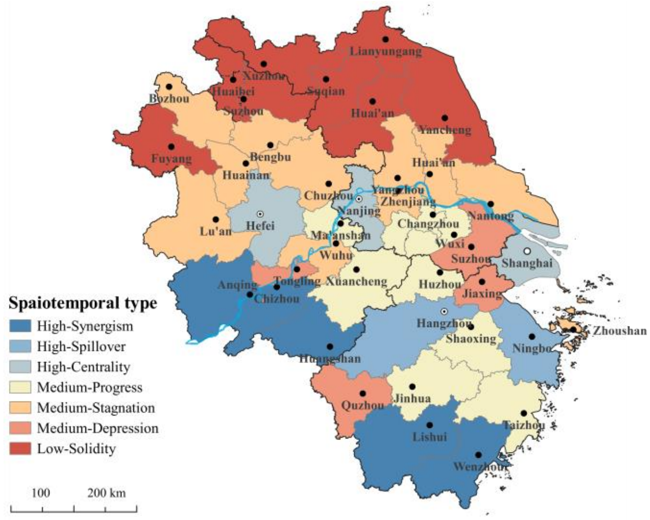

Figure 6. Distribution of spatiotemporal correlation types of urban low-carbon competitiveness in the Yangtze River Delta.

4 Conclusion and discussion

4.1 Conclusion

This study evaluates the spatiotemporal evolution characteristics of low-carbon competitiveness of 41 cities in the Yangtze River Delta from 2000 to 2020 based on grey correlation TOPSIS and exploratory spatiotemporal data analysis, and analyses the regional differences, evolutionary trends, and dynamic spatial correlation patterns of urban low-carbon competitiveness in the Yangtze River Delta, with the following findings in particular:

(1) In terms of time series evolution, Carbon emissions, socioeconomic factors, and low-carbon technology and policy in the Yangtze River Delta demonstrate a stable, fluctuating downward, and fluctuating upward trend, respectively. The regional differences in the dimensions of carbon emissions, low-carbon technology and policy, and socioeconomic factors are bigger than those in the dimension of socioeconomic factors. The average regional low-carbon competitiveness

is Shanghai > Zhejiang Province > Jiangsu Province > Anhui Province, with Shanghai, Hangzhou, and Hefei advancing more rapidly while Huainan, Huabei, and Xuzhou lagging.

(2) The carbon emissions dimension has the strongest spatial correlation in terms of spatial evolution, followed by the low-carbon technology and policy dimension. Southern Zhejiang and southwest Anhui are steady high-value regions, whereas northern Jiangsu and northern Anhui are consistent low-value regions. Hangzhou and Ningbo have led the synergistic growth of most nearby cities, while Shanghai, Nanjing, and Hefei's positive spillover effects have not yet benefited the majority of neighbouring cities, except a few cities such as Wuxi and Xuancheng.

4.2 Discussion

This study assesses the evolution of the Yangtze River Delta's urban low-carbon competitiveness along three dimensions: carbon emissions, socio-economic factors, and low-carbon technology and policy. The carbon emission dimension determines the fundamental level of low-carbon competitiveness, and the significant spatial aggregation of this dimension influences the spatial pattern of regional low-carbon competitiveness, which is "high in the south and low in the north"; whereas the instability in the spillover direction and scope of the core cities' low-carbon technology and policy dimension drives the dynamic spatial pattern evolution of low-carbon competitiveness. Regional low-carbon competitiveness finally develops three spatial interactions: agglomeration effect, diffusion effect, and polarisation effect, followed by seven types of spatiotemporal evolution, as shown in Figure 7. The thickness of the arrows in the graphic represents the magnitude of each dimension's influence on the spatiotemporal evolution of low-carbon competitiveness.

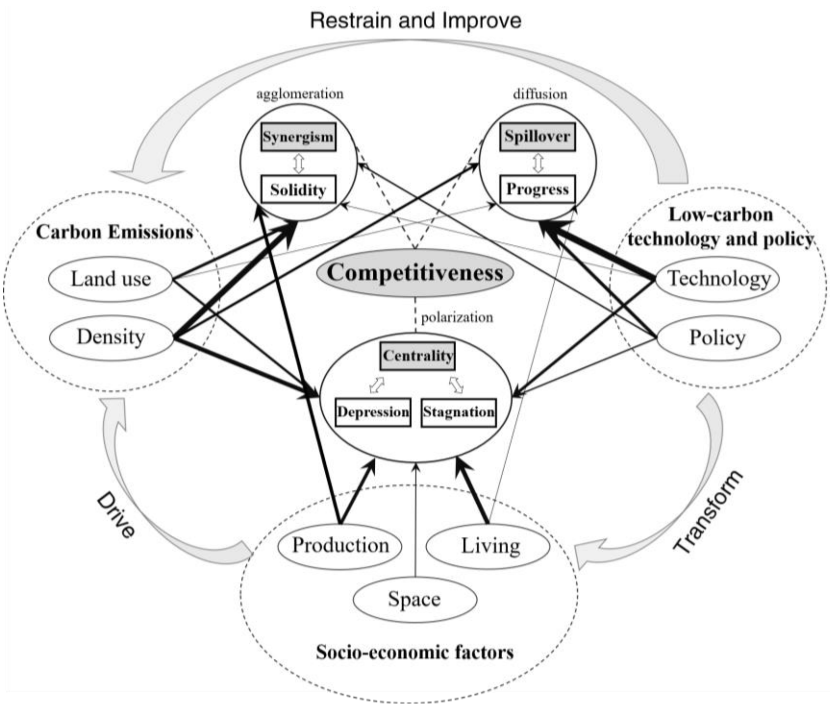

Figure 7. Impact mechanism of the spatiotemporal evolution of the low-carbon competitiveness in the Yangtze River Delta

The following is a summary of the mechanisms impacting the saptiotemporal evolution of low carbon competitiveness. (1) Carbon emissions per capita, density, and industrial structure rationalisation in the carbon emissions and socio-economic factors dominate the agglomeration effect. For example, northern Anhui and northern Jiangsu, where high energy-consuming industries drive economic development, have formed a "Low-Solidity" agglomeration area, while the cities in southern Anhui and southern Zhejiang have a smaller amount of production-based carbon emissions due to their city orientation, and the ecological and environmental management of regional collaborations further promote the generation of "High-Synergism" agglomerations. (2) The diffusion effect is predominantly influenced by the low-carbon technology and policy dimension. Some core cities promote their neighbouring cities' low-carbon competitiveness through low-carbon firm migration, energy-saving technology spillover, and low-carbon regulations. (3) The polarisation effect is largely impacted by the socio-economic factors dimension, where low-carbon technology and policy have yet to show positive effects. Thus, core cities may reduce the low-carbon competitiveness of their bordering cities by transferring carbon emissions from high-energy-consuming businesses or syphoning low-carbon technology resources. In "Medium-Stagnation" and "Low-Depression" cities, consumption-based carbon emissions of the low-carbon living dimension, such as per capita housing area and per household electricity consumption, further hinder low-carbon competitiveness improvement.

The key to enhancing the Yangtze River Delta's low-carbon competitiveness in the future lies in breaking the "Matthew effect" and the "core-periphery" spatial pattern and further optimising regional integration strategies. Regionally, we should expand intergovernmental collaboration, construct an integrated low-carbon industrial system and carbon emission management mechanism, unify territorial planning for green growth, and promote a low-carbon lifestyle. To create a leading demonstration area, cities like Hangzhou and Ningbo can vigorously promote energy-saving and strategic developing enterprises. To reduce the transfer of high-energy-consuming enterprises, northern Jiangsu and northern Anhui should develop environmental regulating regulations with adjacent cities. Shanghai, Nanjing, and Hefei should increase the spatial spillover effect of technology, talent, and capital to support neighbouring cities' green innovation and environmental governance.

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