Research on the Influencing Mechanisms of Carbon Emissions in the Typical Chinese Urban Agglomeration in the Yangtze River Delta

Wei Meng, Xu Jiangang, Qi Hongnian, Cai Zhi, Cui Hao
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Abstract Urban agglomeration plays a vital role in fostering high-quality and sustainable development in China, where urbanization rates significantly influence both urban and rural environments, generating different economic and socio-spatial impacts that, in turn, influence carbon emissions in cities. To delve into the influencing mechanisms of carbon emissions, this paper examines the spatio-temporal pattern of carbon emissions across 41 cities in the Yangtze River Delta urban agglomeration in China. It utilizes data on economic, social, and spatial factors from 2012 to 2019 and employs a spatial econometric regression model for analysis. The results indicate that carbon emissions of cities in the urban agglomeration exhibited strong spatial correlation from 2012 to 2019, characterized by relatively stable cold and hot spots, along with continuous outward spread of high-value zones. Economic and social factors demonstrate a significant positive spatial correlation with carbon emissions of a city, with weak spatial spillover effects. Spatial factors exhibit correlations with carbon emissions in both the city and neighboring cities, with strong spatial spillover effects. Moreover, the spatial layout and functional division of cities in the urban agglomeration also significantly impact the spatio-temporal pattern of carbon emissions.

Keywords economic and social factor; urban spatial factor; carbon emissions; spatial econometric analysis; urban agglomeration

1. Introduction

In recent years, climate change has become more pronounced due to the increasing severity of global warming (Grimm et al., 2008). This phenomenon has significantly affected human life, leading to disasters such as rising sea levels, droughts, floods, and hurricanes (Li et al., 2016; Li et al., 2021; Wang et al., 2022). Research indicates that the rise in carbon emissions is the main cause of global warming (Gu and Liu, 2017; Le Quere et al., 2013). According to IPCC (2022), urban settlements contribute to climate change, generating about 70% of global carbon emissions. However, cities have also played a crucial role in economic development by facilitating the concentration of population, large-scale infrastructure, and economic activities, thus promoting innovation and resource efficiency (Michail et al., 2013). Therefore, reducing carbon emissions in cities to achieve carbon-peaking goals while ensuring high-speed and stable socio-economic development has become a central concern. In September 2020, the Chinese government clearly proposed the dual carbon goals for 2030 – 2060, reflecting its resolute determination. The initial focus is on reducing carbon emissions to create a better living environment, followed by accelerating the green energy revolution to foster sustainable social and economic development in urban and rural areas. ①

With the ongoing process of urbanization, urban agglomerations have replaced individual cities and become the basic units of global competition and division of labor (He et al., 2017). The *14th Five-Year Plan* of China highlighted the importance of developing and expanding urban agglomerations to create a highly urbanized spatial pattern characterized by high density, cooperative division of labor, and comprehensive functions. Urban agglomeration is a highly integrated spatial form centered on a megacity, with three or more metropolitan areas or large cities as its core (Fang and Yu, 2017; He et al., 2021). However, the rapid development of urban agglomerations in recent years has led to increased pollution, and the continuous expansion of urban agglomerations has also led to an increasing demand for large-scale infrastructure and energy. In addition, the increase in total consumer consumption, the shift towards a more advanced consumption structure, and the rise in the proportion of urban consumption have also contributed to the increase in carbon emissions (Wang et al., 2022). Meanwhile, scholars have noticed that the spatial spillover of socio-economic factors may affect the total amount and distribution of regional carbon emissions. The spatial spillover of carbon emissions was first proposed by American economist William Nordhaus. He believed that due to the development of globalization and international trade, carbon emissions had exceeded national boundaries, so reducing the carbon emissions of one country may lead to an increase in carbon emissions from other countries (Nordhaus, 1993; Nordhaus, 2010, 2017). The significance of spatial spillover increases when close communication and cooperation networks are established among cities. In such cases, cities can benefit from lower

transaction costs and stronger factor spillovers, which can facilitate the sharing of agglomeration scale, thereby further strengthening the role of agglomeration (Camagni et al., 2015; Li and Zhang, 2021). The closer the economic and social connections between cities, the more significant this spillover effect becomes (Liu et al., 2015; Zhu and Ding, 2022).

At present, research on the influencing mechanisms of urban agglomeration on carbon emissions can be divided into three groups. The first group focuses on the factors that influence carbon emissions during urbanization. For example, scholars have studied the impact of new urbanization in China on carbon emission intensity and explored the potential of promoting new urbanization construction to reduce carbon emission intensity for a win-win situation (Li et al., 2022). Also, Zhang and Zhao (2019) evaluated various factors affecting China's carbon emissions at the national and regional levels by categorizing China into three areas (advantageous area, potential area, and backward area) based on different levels of urbanization. Chen et al. (2020) found that population, land, and economic urbanization have a significant positive impact on carbon emissions. The second group focuses on the influencing mechanism between cities, urban agglomerations, and carbon emissions. For example, Lü et al. (2022) analyzed the relationship between multiple factors and carbon emissions to achieve a win-win situation for urban socio-economic development and carbon reduction from a spatial-temporal perspective. As the research progresses, two contrasting views have emerged in the literature. One suggested that urban agglomerations can help reduce carbon emissions through scale effects or environmental governance when they reach a certain degree of agglomeration scale (Yilmaz et al., 2021). The other suggested that urban agglomerations may intensify carbon emissions through the aggregation of factors such as population and economy or the transformation of land use (Chen et al., 2018). The third group focuses on the paths to reducing carbon emissions in urban agglomerations. It primarily involves optimizing energy technologies, government regulatory mechanisms, and spatial layouts. Firstly, the optimization of energy technologies involves upgrading industrial and energy consumption structures, promoting energy-efficient technologies, and developing low-carbon energy production technologies to reduce carbon emissions (Barido and Marshall, 2014; Rasool et al., 2022), followed by further explorations into the positive and negative impacts of advanced energy technology and industrial energy consumption structures on carbon emissions. Secondly, in the realm of government regulatory mechanisms, it is proposed that strong regulatory controls can effectively reduce urban carbon emissions (Wang et al., 2013). Thirdly, as for the optimization of spatial planning layouts, Zhang et al. (2021) suggested that the spatial layout and form of urban land use can impact carbon emissions in cities. Shi et al. (2020) coupled multiple factors to analyze the relationship between urban spatial factors and carbon emissions. Cai et al. (2021a) proposed a spatial modeling method to predict urban carbon emissions for effective planning interventions in carbon emissions reduction. These studies indicate that various urban factors have mutual correlations with carbon emissions. Therefore, enhancing our understanding of the relationships between various urban factors and carbon emissions is a key task in current research.

However, the aforementioned achievements have not fully addressed the comprehensive influencing mechanisms of multiple factors on carbon emissions of urban agglomeration. Specifically, the influence of economic, social, and spatial factors has not been fully elaborated. Also, there is limited research on the impact of urban synergy and spatial correlation. It is imperative to precisely understand the spatial-temporal differentiation of carbon emissions, explore the influencing mechanisms, and effectively guide the balanced distribution of carbon emissions among cities in the urban agglomeration. Therefore, to address the gaps in existing literature, this paper first analyzes the carbon emissions of 41 cities in the urban agglomeration in the Yangtze River Delta (YRD) in China from 2012 to 2019 using Moran's I, and examines the spatial-temporal evolution of carbon emissions using spatial autocorrelation methods. Following that, this paper employs a spatial econometric regression model to explore the influencing mechanisms of economic, social, and spatial factors on carbon emissions. The findings can provide suggestions for the integrated and sustainable development of the YRD.

2. Research data and methods

2.1 Study area and database

Currently, urban agglomeration has become the main spatial form of China's new urbanization. The YRD region, as a representative of China's urban agglomerations, has undergone a rapid urbanization process, resulting in an expanding urban scale and a sharp rise in carbon emissions. These factors have seriously affected the sustainable development of this region (Guo et al., 2014). This paper selects the YRD urban agglomeration, covering Shanghai and 40 prefecture-level cities in Anhui, Jiangsu, and Zhejiang provinces, as the study area (see Figure 1). The data used in this paper primarily comes from the *China City Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook,* and *Zhejiang Statistical Yearbook*, as well as the economic, social, and urban land statistics of each city from 2012 to 2019 published by the Bureau of Statistics. Carbon emission data

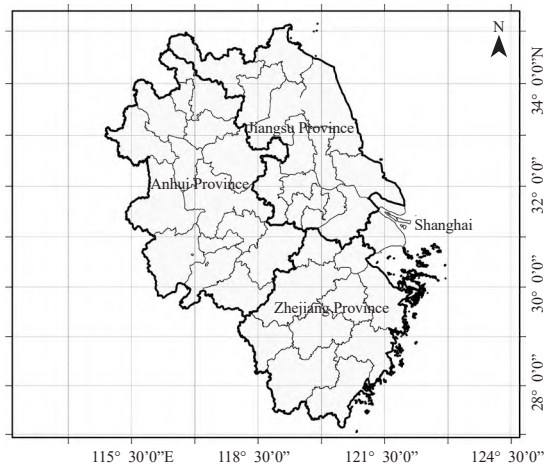


Figure 1 Study area

Source: Base map reviewed by the Ministry of Natural Resources (No. GS(2023)2767).

comes from Carbon Emission Accounts and Database (CEADs) (Shan et al., 2022). The data is standardized to minimize errors.

2.2 Research methods

2.2.1 Analysis method

American geographer Tobler (1970) introduced the phenomenon of spatial effects early on and proposed the first law of geography: everything is related to everything else, but near things are more related than distant things. This law laid the foundation for spatial quantitative analysis. As research progressed, the academic community has gradually recognized the existence of spatial correlation and spatial dependence between spatial elements (Raper, 2009), which has been gradually applied to geographic information (Liu et al., 2022), environmental science (Shaikh et al., 2021), economic geography (Li et al., 2022), urban and regional planning, sociology (Yu et al., 2020), and other fields. The spatial econometric regression model is usually used to study the relationship between the dependent and independent variables in spatial data. The purpose of this paper is to explore the relationship between multiple influencing factors and carbon emissions in the urban agglomeration, and thereby conclude the spatial-temporal influencing mechanisms of carbon emissions. So, it selects the spatial econometric regression model as the research method, in which the dependent variable is carbon emissions and the independent variables include economic, social, and spatial factors. Compared with traditional multiple regression analysis, this study incorporates spatial correlation analysis, i.e., the influence of spatial independent variables and spatial error terms on dependent variables, which can help figure out spatial patterns including aggregation and dispersion, assess the degree of spatial autocorrelation, thereby providing a deeper spatial understanding (Liu et al., 2022).

2.2.2 Factor selection

(1) Economic and social factors

In order to understand the influence of urban economic and social development on carbon emissions, we reviewed a large number of journal papers that used spatial econometric analysis (Guo et al., 2022; Wang et al., 2013; Wang et al., 2017; Gu et al., 2022), and finally select a set of socio-economic variables, including level of affluence (per capita GDP), level of social consumption (total retail sales of consumer goods), level of industrialization (secondary industry's share of GDP), level of service industry (tertiary industry's share of GDP), population density, population in the municipal area by the end of the year, proportion of employees in tertiary industry , and number of employees in health and social security industries.

(2) Urban spatial factors

In the process of urban land development and utilization, population and industries aggregate spatially in response to various economic and social activity demands, forming functional zones and spatial structures of the city. These different types of land are the spatial factors of the city, which affect the carbon cycle of the urban ecosystem and compose the most significant human causes of the sharp increase in carbon emissions, second only to the burning of fossil fuels (Quay et al., 1992). Land use pattern and its changes directly or indirectly affect the intensity of natural and anthropogenic carbon emissions, and further influence the process and rate of regional carbon cycling (Zhao et al., 2010). Accordingly, this paper uses statistical data from the *China City Statistical Yearbook* for five periods (2012, 2014, 2016, 2018, and 2019), and selects five most commonly used factors based on previous research on urban spatial factor analysis (Fang et al., 2015; Jia et al., 2020; Wang et al., 2017), to quantify urban spatial factors, namely, built-up land area, construction land area, residential land area, green area, and road area.

2.2.3 Spatial econometric regression model

The common spatial econometric models include the Spatial Lagged Model (SLM), Spatial Error Model (SEM), and the Spatial Durbin Model (SDM). Based on the LM test results, this paper determines that the model suitable for this study is the Spatial Durbin Model. The Hausman test shows that this model is suitable for adding fixed effects, and further verification through the Wald test and LR test confirms that the Spatial Durbin Model is the optimal choice. The formula for the Spatial Durbin Model is:

$$\gamma = X\beta + WX\delta + \varepsilon \quad (1)$$

In which, γ is matrix of dependent variables, X is an $n \times k$ matrix of independent variables, β is the matrix of parameters to be estimated, W is the spatial weight matrix, δ is the spatial coefficient, and ε is the matrix of random disturbance terms.

2.2.4 Spatial autocorrelation analysis

Spatial autocorrelation analysis includes Moran's I and hot spot analysis (Getis-Ord G_i*), which can measure the spatial correlation of carbon emissions. The formula for Moran's I is:

$$\text{Moran's } I = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} \omega_{ij} (y_i - \overline{y})(y_j - \overline{y})}{\sum_{i=1}^{N} (y_i - \overline{y})^2} \quad (2)$$

In which, N represents the number of spatial units, S_0 represents the sum of all elements, y_i represents the observed value of the variable y in spatial unit i, $\overline{y}$ is the mean value, and ω_{ij} represents the elements in the matrix.

Hotspot analysis is used to analyze the spatial aggregation of carbon emissions in different cities. The calculation formula is as follows:

$$G_i^* = \frac{\sum_{j=1}^{t} w_{i,j} x_j - \overline{X} \sum_{j=1}^{t} w_{i,j}}{S \sqrt{[t \sum_{j=1}^{t} w_{i,j}^2 - (\sum_{j=1}^{t} w_{i,j})^2] / (t - 1)}} \quad (3)$$

In the formula, the statistical result of G_i* is the Z-score. A positive value indicates a hotspot, while a negative value indicates a cold spot. x_j represents the attribute value of spatial unit j; $w_{i,j}$ represents the spatial weight between spatial units i and j; t is the number of spatial units; $\overline{X}$ is the mean value; S is the standard deviation.

3. Analysis of research results

3.1 Analysis of the spatio-temporal distribution and influencing mechanisms of carbon emissions

3.1.1 Global correlation characteristics

This paper uses Moran's I to examine the spatial correlation between the carbon emissions and economic, social, and urban spatial factors of 41 cities in the YRD from 2012 to 2019. The results are presented in Table 1. It can be seen that the I values for all 41 cities are greater than 0, and the P-values indicate relatively strong correlations, proving that there is mutual influence among cities in the urban agglomeration. Specifically, the spatial correlation is more significant in 2018 and 2019, but weaker from 2012 to 2016. Moreover, in terms of the temporal variation of the values, Moran's I value of urban carbon emissions shows an upward trend, indicating an overall rise in spatial dependence. It means that in recent years, production activities among cities in the urban agglomeration have become more interconnected. Thus, when one city's carbon emissions increase, so do those of closely linked cities.

By analyzing the spatial distribution characteristics of carbon emissions (see Figure 2), it is evident that Shanghai consistently has the highest carbon emissions compared to other cities in the urban agglomeration. Before 2018, Shanghai served as the main core of carbon emissions, with Nanjing, Hangzhou, and Suzhou as secondary cores. After 2018, emissions from Shanghai, Hangzhou, and Suzhou spread to neighboring cities. Additionally, the carbon emissions of Hefei, Ningbo, Wuxi, Changzhou, and Xuzhou have also gradually increased, despite that Hefei and Xuzhou are not geographically adjacent to higher-emission cities (such as Shanghai, Nanjing, Hangzhou, and Suzhou). It is worth noting that the spatial distribution pattern of carbon emissions basically presents a hierarchical relationship from metropolitan areas to urban agglomerations. For example, the cities of Shanghai, Nanjing, Suzhou, Hangzhou, Hefei, and Ningbo have higher carbon emissions, which constitute the main skeleton and form six major metropolitan areas of the YRD urban agglomeration, and play vital roles in the integration and high-quality development of the YRD region.

This paper uses hotspot analysis to figure out the spatial-temporal aggregation characteristics of carbon emissions in the urban agglomeration. And it verifies the results using land cover data of the YRD region (Yang and Huang, 2021) in the 30 m annual land cover datasets and its dynamics in China from 2012 to 2019 and Google Earth image data (see Figure 4). As can be seen from Figure 3, carbon emissions of the YRD urban agglomeration show a significant positive spatial aggregation from 2012 to 2019. High carbon emissions were centered on Shanghai in the early stage, and later a new pattern was formed that high carbon emissions centered on Shanghai in the east and low-value dual aggregations in Chizhou in the southern part and Bengbu in the northern part of Anhui Province on the west. Looking at the temporal change of carbon emissions and the dynamic evolution of

Table 1 Global Moran's I and P-value of carbon emissions in the YRD urban agglomeration

Year	2012	2014	2016	2018	2019
Moran's I	0.0815	0.1106	0.1005	0.3244	0.3223
P-value	0.1140	0.0676	0.0892	0.0001	0.0001

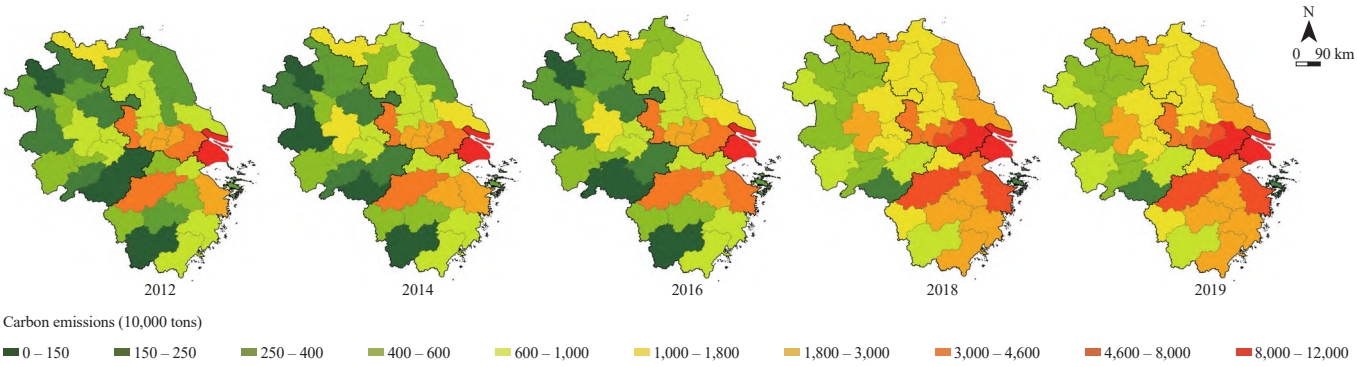


Figure 2 Spatial pattern of carbon emissions in the YRD urban agglomeration from 2012 to 2019
Source: Base map reviewed by the Ministry of Natural Resources (No. GS(2023)2767). Carbon emission data from China Carbon Accounting Database (CEADs), available at: <https://www.ceads.net/>.

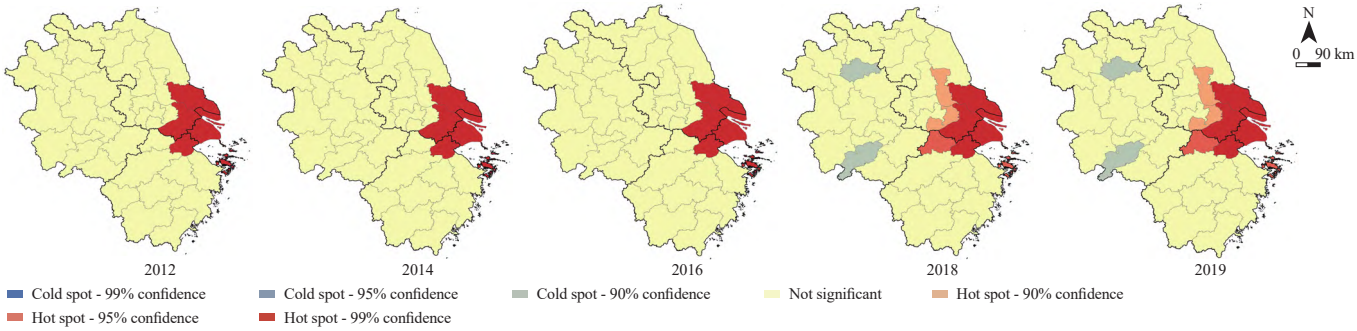


Figure 3 Spatio-temporal aggregation of carbon emissions in the YRD urban agglomeration from 2012 to 2019
Source: Base map reviewed by the Ministry of Natural Resources (No. GS(2023)2767).

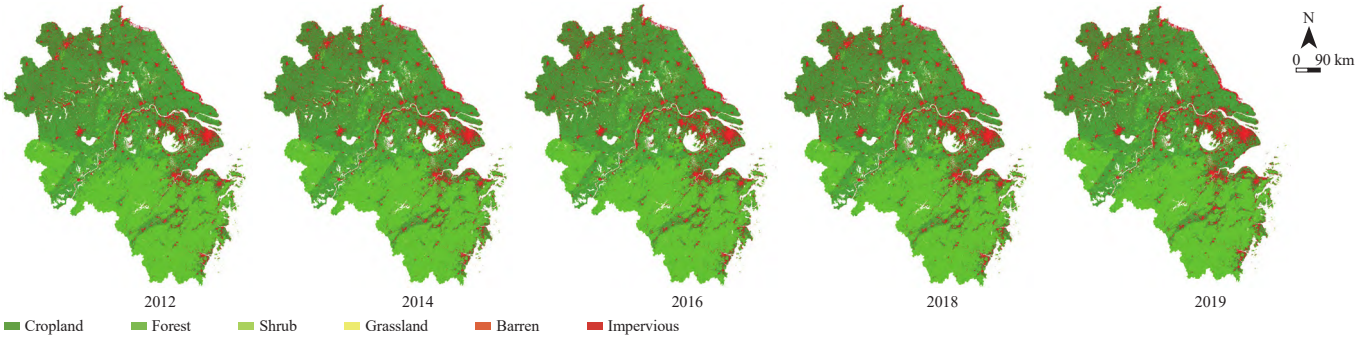


Figure 4 30 m annual land coverage datasets and its dynamics in the YRD urban agglomeration from 2012 to 2019
Source: Data from China Land Cover Dataset and Google Earth.

land use coverage data, it can be found that the built-up areas in the YRD urban agglomeration were mainly expanding outwards around Shanghai. While the built-up areas in Anhui Province, the southern part of Zhejiang Province, and the northern part of Jiangsu Province were expanding outwards based on the original land use. Although the carbon emissions were increasing in each city, the high-value aggregation was still mainly centered on the core range of the Shanghai metropolitan area. It shows that the spatio-temporal aggregation of carbon emissions generated by the socio-economic construction activities centered on Shanghai has a greater impact on the surrounding areas than the three provincial capital cities in the YRD have on their adjacent areas. Moreover, the high-value aggregation of carbon emissions has a diffusion effect. For example, Shanghai contributed to the rapid growth of carbon emissions in the southern Jiangsu Province

and northern Zhejiang Province, thereby causing the high-value aggregation area of Suzhou, Nantong, and Jiaxing bordering Shanghai to expand to the periphery, and reach Shaoxing, Wuxi, and Taizhou in 2018. Anhui Province, which is considered a low-value area of carbon emissions, exhibits a multi-point aggregation feature, indicating that the economic construction activities of Anhui were not closely connected with other provinces and cities in the YRD, and the overall carbon emissions were relatively low. Therefore, the ecological advantages of Anhui Province can be utilized to make it a core carbon sink, thereby enhancing the sustainable development of the YRD region. The overall spatial pattern of carbon emissions indicates that there are strong economic and social ties between the Jiangsu Province, Zhejiang Province, and Shanghai, while Anhui Province has not yet been able to fully integrate into the urban agglomeration. There is still a large room for improvement in the integrated development.

3.1.2 Local correlation characteristics

Through local spatial correlation analysis based on data from 2012 to 2019 (see Figure 5), it can be found that most cities in the YRD urban agglomeration located in the low-low[②] cluster until 2016, and the spatial correlation was not significant. After 2016, the number of cities located in "high-high" cluster is increasing. Therefore, it is evident that the spatial aggregation degree of carbon emissions of each city in the urban agglomeration has increased annually, and there is a significant positive spatial correlation. Cities with higher carbon emissions witnessed higher carbon emissions in their neighboring cities, and cities with lower carbon emissions also witnessed lower carbon emissions in their neighboring cities.

3.2 Analysis on influencing factors of carbon emissions in the YRD urban agglomeration

3.2.1 Influence of socio-economic factors

According to the preliminary results of the Spatial Durbin Model (see Table 2), enhancing the level of socio-economic development in a city will significantly increase its carbon emissions. This suggests that industry, population aggregation, and consumption level are the main factors affecting carbon emissions, while the impact on neighboring cities is relatively small. Given that the coefficient for the direct effect of socio-economic factors is significantly positive, it means that an increase in the socio-economic factors in the city will increase its carbon emissions. Specifically, the direct effect coefficients of factors such as the level of affluence (per capita GDP), level of industrialization, population in the municipal area, and the proportion of tertiary industry employees in the city are more likely to affect the city's carbon emissions, and all show positive correlations. In addition, the correlation coefficient of the population in the neighboring cities is -0.506**, implying that an increase in the population of neighboring cities will lead to a reduction in the city's carbon emissions. This could be attributed to the frequent internal economic activities and specific regional division of labor in the YRD urban agglomeration as one of China's most developed regions. Specifically, if a city's population increases, it will undertake more division of labor in the region, and attract more industries and talents, thereby the urban energy consumption will increase. As a result, the energy consumption demand of the neighboring cities will decrease to a certain extent due to the transfer of industry and population.

3.2.2 Influence of spatial factors

The preliminary results from the Spatial Durbin Model (see Table 3) show that the area of various types of land use in a city significantly influences carbon emissions in both the city itself and neighboring cities. As shown in the table, a city's construction land area, green area, and road area are more likely to affect its carbon emissions. Among them, construction land area and road area show positive correlations, while green area shows a negative correlation. This indicates that the expansion of urban land scale affects carbon emissions, while the increase in green area can reduce them. It is worth noting that an increase in the built-up area of neighboring cities will increase the carbon emissions of this city, while an increase in the construction land area and road area of neighboring cities will reduce the carbon emissions of this city. This is probably because the built-up area includes not only urban construction land in the central city but also non-agricultural area in the suburban and the fringe area. These two areas are much more likely to generate economic and social activities with neighboring cities, thereby bringing about greater energy demand. In terms of construction land and road area, if a city exhibits

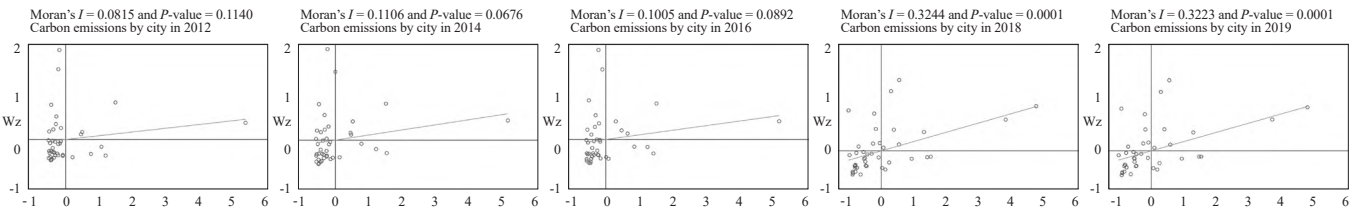


Figure 5 Scatterplot of local Moran's *I* from 2012 to 2019

Table 2 Results of spatial regression modeling of social and economic influencing factors

Variable	SDM	Direct effect	Indirect effect	Total effect
Level of affluence	0.162***	0.164***	0.0465	0.210**
	(0.0593)	(0.0604)	(0.103)	(0.0827)
Level of social consumption	0.0265	0.0216	0.315	0.337
	(0.141)	(0.138)	(0.325)	(0.335)
Level of industrialization	0.187*	0.195**	0.0404	0.235*
	(0.0964)	(0.0939)	(0.142)	(0.133)
Level of service industry	-0.00275	0.00547	0.128	0.133
	(0.122)	(0.124)	(0.164)	(0.124)
Population density	-0.0165	-0.0157	0.255	0.239
	(0.0830)	(0.0794)	(0.161)	(0.159)
Population in the municipal area	0.746***	0.749***	-0.509**	0.240
	(0.114)	(0.114)	(0.242)	(0.271)
Proportion of employees in the tertiary industry	0.0489	0.0513*	0.0713	0.123***
	(0.0300)	(0.0307)	(0.0486)	(0.0399)
Number of employees in health and social security industries	0.181	0.177	0.196	0.373
	(0.143)	(0.137)	(0.300)	(0.318)
WX-affluence	0.0367	– –	– –	– –
	-0.10	– –	– –	– –
WX-social consumption	0.314	– –	– –	– –
	(0.305)	– –	– –	– –
WX-industrialization	0.0459	– –	– –	– –
	(0.145)	– –	– –	– –
WX-service industry	0.140	– –	– –	– –
	(0.162)	– –	– –	– –
WX-population density	0.249	– –	– –	– –
	(0.155)	– –	– –	– –
WX-population in the municipal area	-0.506**	– –	– –	– –
	(0.248)	– –	– –	– –
WX-proportion of employees in the tertiary industry	0.0713	– –	– –	– –
	(0.0468)	– –	– –	– –
WX-number of employees in health and social security industries	0.155	– –	– –	– –
	(0.304)	– –	– –	– –
R-squared	0.896	– –	– –	– –
Log-likelihood	323.1556	– –	– –	– –

Note: ***, **, and * indicate that the variable is significant at the 1%, 5%, and 10% level of significance, respectively. WX- indicates the correlation coefficient of the influence on neighboring cities.

rapid growth in these dimensions over a specific period, it suggests that, relative to neighboring cities, this city is expanding more quickly and has a higher level of development. Spatially, this expansion may exert a certain siphon effect on surrounding cities, potentially reducing their carbon emissions to some extent.

4. Discussion

4.1 Significant correlation between economic and social factors and carbon emissions

The above analysis shows that the urban economic and social factors have a significant positive spatial correlation with carbon emissions in the city but no significant impact on neighboring cities. The economic and social factors within a city can affect carbon emissions through various approaches. For example, as the city's wealth and population increase, the purchasing power and usage rate of motor vehicles also increase, resulting in higher carbon emissions. In addition, a higher share of the secondary industry output value in a city's GDP indicates that the city's economic growth is more dependent on industrial development, leading to higher carbon emissions as well. Comparatively, the influence of economic and social factors on the carbon emissions of neighboring cities is limited, possibly because the carbon generated by economic and social activities is mostly consumed locally and cannot be transferred quickly. Additionally, this paper demonstrates that the increase in tertiary industry employees will also raise local carbon emissions to a certain extent, as the rise in tertiary sector workers reflects a surge in demand for services and energy consumption (Kuang et al., 2022).

4.2 Significant correlation between spatial factors and carbon emissions both in the city and its neighboring cities

The analysis results indicate that spatial factors are significantly

Table 3 Results of spatial regression modeling of urban spatial influencing factors

Variable	SDM	Direct effect	Indirect effect	Total effect
Built-up land	-0.354**	-0.0853	3.427***	3.341***
	(0.141)	(0.156)	(0.627)	(0.716)
Construction land	1.829***	1.511***	-3.966***	-2.455**
	(0.258)	(0.264)	(0.901)	(1.024)
Residential land	-0.319	-0.204	1.220	1.016
	(0.262)	(0.267)	(0.915)	(1.030)
Green space	-0.675***	-0.659***	0.358	-0.301
	(0.131)	(0.148)	(0.609)	(0.711)
Road	0.454***	0.397***	-0.714**	-0.316
	(0.0694)	(0.0721)	(0.286)	(0.325)
WX-built-up land	2.089***	– –	– –	– –
	(0.332)	– –	– –	– –
WX-construction land	-3.076***	– –	– –	– –
	(0.516)	– –	– –	– –
WX-residential land	0.800	– –	– –	– –
	(0.524)	– –	– –	– –
WX-green space	0.526*	– –	– –	– –
	(0.305)	– –	– –	– –
WX-road	-0.604***	– –	– –	– –
	(0.149)	– –	– –	– –
R-squared	0.897	– –	– –	– –
Log-likelihood	360.8141	– –	– –	– –

Note: ***, **, and * indicate that the variable is significant at the 1%, 5%, and 10% level of significance, respectively. WX- indicates the correlation coefficient of the impact of the factor of this city on neighboring cities.

correlated with carbon emissions in both the city and neighboring cities. Not only does the scale of factors affect carbon emissions, but they also spatially coincide with areas where carbon emissions are aggregated. This suggests that urban land use will affect carbon emissions by undertaking various spatial functions and behaviors. For example, the increase in urban construction land will generate a large number of construction activities, thereby increasing carbon emissions. Transportation connects different cities and has a certain spillover effect on carbon emissions of the city and its neighboring cities. Urban green space can absorb carbon and release oxygen, which effectively alleviates the heat island effect and the overall energy consumption of the city (Zhao and Liu, 2010). The analysis results of this paper also demonstrate its effectiveness in reducing urban carbon emissions. Additionally, referring to the land use changes during the same period, it can be found that the expansion of construction land in the YRD urban agglomeration occurred both outward and along the Yangtze River and other important river systems. The land use changes within the scope of the six major metropolitan areas of the YRD are the most obvious, which can affect the carbon emissions and its aggregation characteristics.

4.3 Spatial layout and functional division in the urban agglomeration affect the spatio-temporal characteristics of carbon emissions

In the context of globalization, the division of labor among global cities is leading to different spatial characteristics of carbon emissions in cities with different functions. The analysis in this paper shows that the total carbon emissions of the YRD urban agglomeration continued to increase from 2012 to 2019, but the growth rate gradually slowed down. And the total carbon emissions of each city vary significantly in space, generally showing a spatial distribution pattern centered on Shanghai and spreading outwards. This proves that cities in the urban agglomeration are often interdependent, and economic activities and population flows between cities will lead to cross-border use of energy and resources, thereby raising carbon emissions. The role of a city determines its economic and social connections with other cities, which in turn affects the spatial spillover effect of carbon emissions. For example, the carbon emissions of Shanghai are much higher than other cities, and the carbon emissions of most cities in Jiangsu Province are higher than those in Zhejiang Province and Anhui Province. This indirectly suggests that there is still potential for enhancing the coordinated development of the YRD urban agglomeration. The functional allocation of each city is still not perfect, and the functions of some cities are relatively concentrated. Improving the coordination level of the YRD urban agglomeration will effectively promote the high-level, high-quality, and sustainable development of the urban agglomeration.

Although Nanjing, Hangzhou, and Hefei are all provincial capitals, this analysis shows that Shanghai still plays a dominant role in the

YRD urban agglomeration, leading to a central aggregation pattern of carbon emissions. Shanghai is a global city in the YRD urban agglomeration, characterized by significant industrial and population concentrations. The concentration and expansion of both population and urban construction land facilitate the rapid development and upgrading of industries. These chain reactions have led to increased carbon emissions, resulting in a continuous spillover effect in recent years.

4.4 Planning optimization strategies

Firstly, cities in carbon emission hotspot areas should optimize regional cooperation governance and industrial service level to promote low-carbon city development. The purpose of regional cooperation for the low-carbon development of urban agglomerations is not only to promote regional economic development, but also to control carbon emissions of the urban agglomeration. The analysis results of this paper show that the service level and technical level of the city have a suppressive effect on the level of carbon emissions. Therefore, it is recommended to promote the development of high-tech industries and optimize industrial structure to increase the added value. For example, cities like Shanghai and Suzhou can promote energy-saving buildings, improve transportation efficiency, encourage enterprises to adopt energy-saving technologies, promote intelligent energy systems, etc. They can also promote the development of low-carbon industries such as the service industry and information technology, so as to reduce the proportion of high-carbon industries.

Secondly, it is recommended to optimize the development pattern of urban economic, social, and spatial factors, while coordinating resources and production factors across all cities within the region. Carbon emissions, as well as economic, social, and spatial factors, all exhibit strong spatial aggregation, and the impact of spatial factors on carbon emissions shows a certain spillover effect. The analysis results reveal a lack of coordination among economic, social, and spatial development of the YRD urban agglomeration. Specifically, the northern and southern parts of Anhui Province exhibit lower level of economic and social development. Therefore, the governments of the three provinces and one city should actively promote and enhance broader cooperation and exchanges between cities, accelerate the flow of various production factors in the region, and reduce carbon emissions of each city in the region, thereby promoting sustainable development. At the same time, it is important to optimize the land use layout of each city in the region through controlling urban scale and the expansion of construction land. This approach helps prevent excessive urbanization, which often results in a significant increase in carbon emissions. It is also recommended to consider the job-housing balance in the city by implementing a reasonable land use layout and optimizing the distribution of living, working, and entertainment facilities. The existing high-energy-consuming industrial parks should be transformed into industrial parks with reasonable industrial gradients and optimized ecological environment. Furthermore, we should also actively explore various forms of low-carbon land use, such as the governance of hollow villages and the development and remediation of unused land, etc.

Thirdly, attention should be paid to the economic development gap between different cities, social resource disparities, and the similarities and differences in land use. Different development policies should be formulated in accordance with the characteristics of each city to achieve high-level and sustainable development of the YRD urban agglomeration. In the low-low cluster shown in the above analysis, the government should provide policy support for the local economic and social development, encourage sustainable development, and strengthen the spatial spillover effect of green development on neighboring areas. For the high-high cluster, the government should relieve some functions to the outside and control the excessive energy consumption. For example, Anhui Province has a lower carbon emission level and can serve as a key functional area for achieving carbon neutrality in the YRD by enhancing ecological development efforts and developing carbon sink capacity. Meanwhile, the southern part of Jiangsu, the northern part of Zhejiang, and Shanghai can be designated as key functional areas for carbon peaking in the YRD, by controlling the carbon emissions of this region and evacuating some economic and social production and construction functions to the peripheral areas, etc.

5. Conclusion

In response to the challenges posed by global climate change, different sectors have devised and tested a series of energy-saving and emission-reduction strategies and technologies. The public is also increasingly concerned about the impact of urban spatial factors and the level of socio-economic development on carbon emissions. Based on this, this study attempts to empirically quantify the influencing mechanisms of economic, social, and spatial factors on the spatio-temporal characteristics of carbon emissions in China's mega-urban agglomeration. The results indicate a significant spatial correlation in carbon emissions within the YRD urban agglomeration between 2012 and 2019, and the hot and cold spot areas are relatively stable. The city's affluence level, industrialization level, service level, population, and land use (construction land, road land, and green space) have a greater impact on carbon emissions than other factors and show positive

correlations. This indicates that controlling carbon emissions requires addressing corresponding economic and social factors. According to the new urbanization development policy, China's megacities will continue to control the population scale and promote stable and healthy urbanization. Further urbanization will be more difficult for China's major cities. However, it should be noted that China is still a developing country and still needs to vigorously develop the economy (Guo et al., 2022; Shi et al., 2020). Although the government has promised to achieve emission reduction targets by reducing emission intensity, under the current scenario, it is not feasible to reduce carbon emissions at the expense of future economic growth, which means that the contradiction between economic development and sustainable development must be coordinated. Therefore, it is necessary to coordinate the development of regional urban functions, optimize the spatial development pattern of cities, and develop emerging low-carbon industries in urban agglomerations to reduce carbon emissions. In addition, this paper has not yet considered the coupling impact of various complex factors such as the transportation and information network between cities on carbon emissions. Also, this study is based on statistical data of administrative division, but it is unclear whether the real linkage effect between regions is bounded by administrative divisions. Additionally, urban agglomeration is a complex system, and urban carbon emissions are often affected by multiple aspects. Whether the carbon emission influencing mechanisms mentioned in this paper has universal significance needs to be continuously figured out in subsequent research. C

Notes:

① On Sept. 22, 2020, President Xi Jinping made a statement at the general debate of the 75th session of the United Nations General Assembly that China aimed to reach CO_2 emissions peak before 2030 and achieve carbon neutrality before 2060. In January 2023, the State Council Information Office released a white paper on *China's Green Development in the New Era.*

② The term "high-high cluster" is used to describe regions where both the focal city and its surrounding cities exhibit high data values. This is typically observed in regions with a high level of economic activity. In contrast, the term "low-low cluster" is used to describe regions where both the focal city and its surroundings display low data values. In this study, this indicates regions with minimal carbon emissions. Both of these statistical concepts are used in the analysis of spatial autocorrelation.

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Authors

Wei Meng, PhD Candidate, School of Architecture and Urban Planning, Nanjing University, Nanjing, P. R. China.

Xu Jiangang (corresponding author), Professor, Doctoral Supervisor, School of Architecture and Urban Planning, Nanjing University, Nanjing, P. R. China. Email: xjg129@sina.com

Qi Hongnian, Professor-Level Senior Engineer, National Registered Planner, School of History, Nanjing University, Nanjing, P. R. China.

Cai Zhi, Lecturer, School of Tourism and Urban-Rural Planning, Zhejiang Gongshang University, Hangzhou, P. R. China.

Cui Hao, Senior Engineer, Jiangsu Oriental Architectural Design Company, Nanjing, P. R. China