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Spatiotemporal Differentiation of Urban Spatial Form and Carbon Emissions in Poyang Lake City Group

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Abstract In response to the inherent requirements of low-carbon land spatial planning in Jiangxi Province and the lack of existing research, this paper explored the mechanism of spatial form elements of Poyang Lake urban agglomeration on urban carbon emissions. Based on generalized linear regression and geographically weighted regression models, this paper analyzed the spatiotemporal distribution characteristics of carbon emissions, the spatiotemporal relationship between urban form index and carbon emissions, and the spatial differentiation of the intensity of dominant factors from 63 county-level administrative units in the Poyang Lake city group from 2005 to 2020. The results showed that: ① The carbon emissions of urban agglomerations around Poyang Lake are generally increasing, and the spatial distribution of carbon emissions is characterized by high-value concentration in the middle and low-value agglomeration in pieces; ② The main driving factor for the spatial heterogeneity of carbon emissions was the expansion of built-up area; ③ Improving urban compactness and optimizing urban form could effectively reduce urban carbon emissions. The results showcased the correlation between urban spatial landscape pattern and the spatiotemporal distribution of carbon emissions, which could make the low-carbon land spatial planning in the Poyang Lake city group more reasonable and practical.

Keywords Carbon emissions, Urban spatial form, the Poyang Lake city group, Landscape pattern index, Geographically weighted regression

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Released by the Intergovernmental Panel on Climate Change (IPCC) of the United Nations in October 2018, *the Global Warming* of 1.5 ºC pointed out that as of the report, the global temperature had risen by 1 ºC compared to that of pre-industrialization, and if the global warming could not be controlled within the threshold of 1 ºC by the mid-20th century, human beings would inevitably suffer catastrophic consequences from the Earth's environment[1]. China accounted for approximately 28.8% of the world's CO_2 emissions in 2019, making it the world's largest carbon emitter, so China's goals and actions of carbon reduction play an important role in achieving the global carbon neutrality vision[2].

It is estimated that urban areas consume approximately 67% of the worlds energy and generate 71% of CO_2[3]. Research has shown that there is a high degree of consistency between urban space and carbon emission density patterns in China, making the construction of low-carbon cities an inevitable choice for China[4]. Ewing studied the relationship between urban spatial form and carbon emissions systematically for the first time, believing that urban spatial form affected residential carbon emissions through three ways: power transmission losses, impact on the housing market, and formation of urban heat island effects[5]. In China, the research on urban carbon emissions mainly focuses on the following 4 aspects: carbon emission accounting, analysis on carbon emission influencing factors, research on the relationship between carbon emissions and land use, and research on low-carbon urban development models and paths, while the research on urban spatial form and carbon emissions is mainly involved in spatial form, land use control, and spatial layout schemes[6]. In existing research, there are quite a lot of research on carbon emission efficiency at the provincial regions, city groups, and prefecture level cities, which has yielded relatively rich results. However, research on carbon emissions in small and medium-sized cities at the county level has not yet been fully conducted, and there is still a significant gap between academic research on carbon emissions in the Poyang Lake area and its inner requirements, which urgently needs to be strengthened.

The Poyang Lake city group, or the urban agglomeration around the Poyang Lake, is one of the 3 main urban agglomerations in the middle reaches of the Yangtze River, and a highly developed area in Jiangxi Province in terms of economy and urbanization. In recent years, with the rapid development of industrialization and urbanization in Jiangxi, there is a trend of rapid urban growth, wetland shrinkage, and reduced regional carbon sequestration capacity in the Poyang Lake Basin, which is gradually deviating from the original intention of China to guide the region to grow into a low-carbon city group in the central region[7]. Liu Yaobin pointed out that the spatial spillover effect of new urbanization in lake areas on carbon emission intensity is more sensitive under the spatial weight matrix of ecological security distance[8].

In this study, with the Poyang Lake city group as the research object, the correlation between carbon emissions and urban spatial forms at the county level was explored from the perspective of carbon emissions with the county (district) as the basic unit. The main influencing factors of carbon emissions were identified from the perspectives of time and space, and finally, strategic suggestions were proposed for the development of low-carbon national spatial planning in the Poyang Lake city group.

1 Study area and data sources

1.1 Overview of the study area

The study area is consistent with the scope of *the Plan for Poyang Lake Ecological City Group* (2015–2030) approved by the State Council, covering 63 counties and districts with a regional area of 92 300 km^2. In 2020, with a population of 32.517 9 million, the Poyang Lake city group had a regional GDP of 1,752.55 billion yuan, which accounted for 68.21% of the regional GDP of Jiangxi Province.

The study area is one of the earliest areas in China to carry out low-carbon construction pilot projects: Nanchang City was included in the first batch of national low-carbon pilot cities as early as 2010, Jingdezhen City was included in the

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second batch in 2012, and Gongqing City, Ji'an City, and Fuzhou City were included in the third batch in 2017. The low-carbon city pilot policy has played its role in reducing carbon emissions, that is, the construction of low-carbon cities is effective, which provides empirical evidence for further expanding the pilot scope of low-carbon cities and provides useful reference to improve environmental policies for carbon reduction in China[9].

1.2 Data sources

The research data included the administrative division data in 2005, as well as carbon emission data and land use data for the same period in the study area in 2005, 2010, 2015, and 2020. Due to the approval of the establishment of county-level Communist Youth cities by the government in 2010, as well as administrative adjustments made in counties such as Honggutan District and Lushan District in the later period, the administrative division data from 2005 were used and relevant carbon emission data were processed. The carbon emission data from 2005 to 2017 were sourced from the China Carbon Emission Accounts and Datasets, and the carbon emission data for 2020 were calculated using interpolation method. CEADs used Particle Swarm Optimization Backpropagation (PSO-BP) algorithm to match and unify DMSP/OLS and NPP/VIIRS satellite data, which reversed the carbon dioxide emissions data based on fossil energy consumption in 2 735 counties in China from 1997 to 2017[10]. Land use data were sourced from the European Aviation Safety Agency (http://maps.elie.ucl.ac.be/CCI/viewer/index.php), which consisted of 22 types of land use, including farmland (10), shrubs (120), urban built-up areas (190), and water bodies (210). The land use types in urban built-up areas were used to extract the urban landscape pattern indices [11], and which were preprocessed by ArcGIS Pro on four phases of land use image data and completed in FRAGSTATS.

2 Study methods

2.1 Selection of urban form and landscape pattern index

There are three methods for measuring urban spatial form: aesthetic degree measurement, form measurement, and indicator measurement[12]. As a highly concentrated information of landscape pattern, the landscape pattern index is a simple quantitative indicator reflecting the composition and spatial configuration characteristics of landscape structure[13]. Urban form can be characterized by multiple indicators. Based on relevant references, 4 dimensions of indicators were ultimately selected to characterize urban form, namely urban scale, urban compactness, urban centrality, and urban complexity[14].

Table 1 Elements of urban spatial form

Urban form	Index	Description
Urban scale	Total class area (CA)	Referring to the area of the urban built-up area
Urban compactness	Proximity mean area (PROX_MN) Class cohesion index （COHESION）	Standing for the fragmentation or sparsity degree of the patch
Urban centrality	Euclidean distance mean (ENN_MN) Largest patch index (LPI)	Measuring the spatial connectivity value between urban patches
Urban complexity	Edge density (ED)Landscape shape index (LSI) Area-weighted mean shape index (SHAPE_AM)	Referring to the irregularity of patch types and the complexity of land use boundaries

2.2 Correlation analysis between urban form and carbon emissions

2.2.1 Generalized linear regression (GLR). Generalized linear regression is a kind of data mining tool in ArcGIS Pro that sets conditions such as multicollinearity and significance to screen models that pass all necessary conditions for OLS diagnosis, thereby generating combinations of all possible explanatory variables. By evaluating all possible combinations of candidate explanatory variables, the opportunity to find the best model can be increased, thereby determining the explanatory variable indicators.

2.2.2 Geographically weighted regression (GWR). The geographically weighted regression (GWR) model was proposed in 1996, which is an extension of the generalized linear regression model by embedding the geographic location of data into regression parameters[15].

$$Y_i = \beta_0 (\mu_i, v_i) + \sum_{j=1}^{p} \beta_j (\mu_i, v_i) X_{ij} + \varepsilon_i$$

Where, Y_i is the total carbon emissions of city i (Mt); $\beta_j (\mu_i, v_i)$ (j=0, 1, ..., p) is a spatial geographic location function; (μ_i, v_i) is the spatial location of city i; X_{ij} is the value of the j^{th} urban landscape pattern index in city i; j is the number of urban form indices; ε_i is the residual.

3 Results and analysis

3.1 Spatial and temporal distribution characteristics of carbon emissions

As is shown in Fig.1, the carbon emissions of the Poyang Lake Ecological city group increased from 72.83 million tons in 2005 to 205.10 million tons in 2020, an increase of 181.61%. The spatial and temporal distribution of carbon emissions in the Poyang Lake city group showed significant differences, with high values concentrated in the central region while low values fragmented and clustered.

In 2005, Nanchang County had the highest carbon emissions in the Poyang Lake city group, with a total carbon emissions of 5.46 million tons, followed by 4.25 million tons in the Qingshan Lake area. During the same period, the total carbon emissions in most regions were below 2 million tons, with an average of 1.16 million tons and a minimum of 0.14 million tons in Tonggu County, indicating significant regional differences.

In 2010, the total carbon emissions showed a central clustering feature, with Nanchang County having the highest total carbon emissions. The total carbon emissions of Xinjian County, Qingshanhu District, Fengcheng City, and Yushui District rose rapidly, all exceeding 4 million tons. The maximum carbon emissions were 8.09 million tons, and the minimum were 0.25 million tons, with an average of 1.77 million tons. In 2010, the total carbon emissions increased from 72.83 million tons in 2005 to 111.40 million tons, with a growth rate of 52.96%. The main reason was the comprehensive promotion of industrialization and urbanization, as well as the rapid development of high-energy consuming and high emission industries.

In 2015, the distribution of total carbon emissions was relatively stable compared to that of the past decade, with the total carbon emissions in the jurisdiction of Yichun, Jiujiang, and Fuzhou reaching over 4 million tons, while there was no significant change in other regions. The maximum carbon emissions were 9.95 million tons, and the minimum were 0.15 million tons, an average of 2.16 million tons. In 2015, the growth rate of total carbon emissions decreased, with a year-on-year increase of 22% compared to 2010. Studies showed that the economy of the Poyang Lake Ecological city group was gradually transitioning towards a low-carbon economy, which had greatly slowed down the growth rate of carbon emissions[16].

In 2020, the total carbon emissions of the Poyang Lake city group distributed unevenly, which concentrated in one core area but sparsely distributed in multiple areas. The areas with high values of total carbon emissions were Nanchang County, Qingshanhu District, and Xinjian District; the urban areas of Jiujiang, Jingdezhen, Shangrao, Yichun, Pingxiang, Xinyu, and Fuzhou, as well as Gao'an, Fengcheng, and Guixi, were the second highest;

the total carbon emissions in other areas were all below 4 million tons, making them low value areas.

3.2 Analysis of regression model results

The dependent variable of the regression model was the carbon emission data of the Poyang Lake city group in 2005, 2010, 2015, and 2020, with 8 landscape pattern indices from 4 dimensions as independent variables. Generalized regression analysis was conducted in stages, and considering the multicollinearity and significance judgments between variables, the indicators were screened to establish a unified regional carbon emission generalized linear regression model (Table 2). Finally, CA, PROX_MN, ENN_MN, and SHAPE_AM were selected as the 4 indicators. The regression analysis results showed that the values of $AdjR^2$ were all above 0.65, with a high fitting degree of 90% in 2020, and the values of VIF were all within 5; in 2010, the multicollinearity was as low as 1%, and at least one P-value was significant in the four stages; in 2015, three indicators showed significant differences. Therefore, the simulation results were generally ideal.

The impact of different landscape pattern indices on carbon emissions varied within the same time period[17]. In 2005, the 3 indicators of CA, PROX_MN, and SHAPE_AM affected the total carbon emissions: CA had a positive correlation with carbon emissions, while PROX_MN and SHAPE_AM had a negative correlation, and ENN_MN had no effect on the total carbon emissions. In 2010, there was only 1 factor affecting carbon emissions, CA, and its impact on carbon emissions was positively correlated, meaning that the total amount of carbon emissions increased synchronously with the CA value. In 2015, there were 4 factors, namely CA, PROX_MN, ENN_MN, and SHAPE_AM, affecting carbon emissions. PROX_MN was negatively correlated, meaning that the total carbon emissions decreased with the increase of PROX_MN value, while the other 3 factors were positively correlated. The total carbon emissions in 2020 were influenced by 4 factors, with CA, ENN_MN, and SHAPE_AM showing a positive correlation with carbon emissions, while PROX_MN showed a negative correlation. The results indicated that the carbon source was in the dominant position of construction land[18].

3.3 Characteristics of spatiotemporal relationship changes in urban form and landscape pattern

Correlation analysis was made to the urban carbon emissions and spatial form of the Poyang Lake city group during the research period, in both temporal and spatial dimensions. The research results were as follows:

The class area (CA), that is, the total area of a certain patch class, characterizes the urban form from the dimension of urban scale, and the larger the value, the larger the urban built-up area. The urban scale increased stably, with the built-up area of the city increasing from 89 089 hm^2 in 2005 to 213 516 hm2 in 2020, an average growth rate of 139.65%. The impact of CA on carbon emissions was highly significant, showing a positive significant feature in all 4 periods, that is, the carbon emissions of the counties increased with the increase of CA value. Taking Nanchang County, a city with high total urban carbon emissions, as an example, its CA value was among the top in the same period, indicating that the increase in the scale of urban construction areas was not conducive to carbon reduction.

The proximity mean area (PROX_MN) is the sum of the patch areas divided by the square of the minimum distance between all patch edges and the center patch edge of a certain patch type. It reflects the average distance between patches and the center patch, and the smaller the distance, the higher the overall clustering degree of the patch[19]. The overall trend of urban compactness increased gradually, with some regions maintaining the same or slightly decreasing PROX_MN values. During the 3 periods, PROX_MN showed a significant negative correlation, indicating that carbon emissions at the county level decreased with the increase of PROX_MN values. Wang et al. used the panel data model to establish the relationship between carbon dioxide emissions and urban form index of 9 major cities in the Pearl River Delta, finding that a more concentrated and compact urban form was accompanied by less carbon dioxide emissions, and a relatively loose development model reduced the economic efficiency of CO_2[20]. A compact urban spatial form could reduce urban carbon emissions and achieve the development path of low-carbon cities[21].

The Euclidean mean distance (ENN_MN) refers to the shortest straight-line distance between the target patch and its nearest neighboring patches of the same type. It reflects the spatial connectivity value between urban patches, and the smaller the nearest neighbor distance of the average urban patch, the lower the differentiation degree and the higher the centrality. The overall urban centrality declined significantly from 2005 to 2010, with significant changes observed in areas such as Duchang County, Tonggu County, Wannian County, and Wanzai County, while there was little change in the other 3 periods. Taking Duchang County as an example, during the period from 2005 to 2010, the decrease in ENN_MN was the largest, reaching 50.25%, but it had no significant effect on the carbon emissions. The correlation reached the significant level only after 2015, indicating that the carbon emissions increased with the decrease of urban centrality. At the initial stage of development in functional areas such as county new areas and development zones, although the urban centrality was reduced, the effect on carbon emissions was not significant since the population did not reach the scale and there were relatively few living and production activities. With the cultivation and improvement of new areas and development zones, as well as the increase in life and production activities, the effect of centrality on carbon emissions became significant, which fell behind the changes of urban centrality.

Area-weighted mean shape index (SHAPR_AM) reflects the complexity of patch shape and the shape characteristics and possible evolutionary trends of landscape spatial structure[22]. The increase in SHAPR_AM value indicates that urban boundaries become complex and irregular with urbanization development. The SHAPR_AM values showed no significant changes during the 4 periods, and the trend of change varied among cities. The complex and irregular urban boundaries reduced the accessibility of public services and infrastructure, and increased commuting time and distance, thus leading to an increase in carbon emissions.

Table 2 Test results and related parameters of the regression model

Year	AdjR2	AICc	JB	K (BP)	VIF	SA	Model
2005	0.65	118.66	0	0.03	1.94	0.79	− SHAPE_AM − PROX_MN*** + CA***
2010	0.70	158.69	0.00	0.00	1.00	0.21	+ CA***
2015	0.84	145.99	0.00	0.06	3.25	0.21	+ SHAPE_AM − PROX_MN*** + ENN_MN** + CA***
2020	0.90	173.81	0.11	0.01	3.34	0.58	+ SHAPE_AM − PROX_MN*** + ENN_MN + CA***

3.4 Changes in the spatiotemporal relationship between urban form index and carbon emissions

As is shown in Fig.2, CA index was positively correlated with the carbon emissions of the Poyang Lake city group, indicating that the scale of construction land was also one of the main factors promoting the growth of carbon emissions from land use in districts and counties[23]. The areas with high values of the CA regression coefficient in 2005 were concentrated in the northeast of the Poyang Lake city group, such as some counties and districts in Jiujiang City, Jingdezhen City, and Shangrao City. The low value areas were mainly Jing'an County, Nanchang County, and Yingtan City, with regression coefficients ranging from 0.000 85 to 0.000 9 for most counties and districts. In 2010, the regression coefficients in regions such as Jinxian, Linchuan, Chongren, and Fengcheng increased significantly; In 2015, the impact of class area index on carbon emissions increased in the eastern and northern regions; In 2020, the regression coefficients for most cities ranged from 0.000 9 to 0.001 0, and the impact of class area index on carbon emissions significantly increased.

As is shown in Fig.3, there was a negative correlation between PROX_MN and carbon emissions in the Poyang Lake city group, indicating that increasing urban compactness could reduce carbon emissions. In 2005, the areas with high absolute PROX_MN values were concentrated in Jiujiang County, Ruichang County, and Xunyang District, while the low value areas were distributed in the southern part of the Poyang Lake city group; In 2010, counties and districts in Pingxiang and Yingtan became low value areas, and the impact of PROX_MN on urban carbon emissions gradually decreased; In 2015, the regression coefficients for most cities were ranged from −0.06 to −0.04, showing a spatial distribution trend of gradually decreasing from the eastern and central regions to the western regions; In 2020, the impact of PROX_MN on carbon emissions in the Poyang Lake city group weakened, and some counties and districts had positive regression coefficients, suggesting that the two were closed to a decoupling state.

As is shown in Fig.4, ENN_MN showed a significantly positive correlation with carbon emissions, indicating that the development of a single urban core was beneficial for reducing carbon emissions. It was further speculated that the urbanization rate of the Poyang Lake city group was not high, which did not reach the stage of development of large urban clusters to reduce carbon emissions. In 2005, the regression coefficients for most cities were between 0.01 and 4.00, indicating a relatively low overall impact. In 2010, the impact of ENN_MN on carbon emissions became stronger in cities in the central and eastern regions, such as Shangrao, Jingdezhen, Yingtan, Fuzhou, and Jiujiang. In 2015, the impact of ENN_MN on carbon emissions gradually increased, with regression coefficients ranging from 8.00 to 12.00 for more than half of the cities. In 2020, the impact of ENN_MN on carbon emissions gradually increased westward from the districts of Shangrao, Yingtan, and Jingdezhen cities.

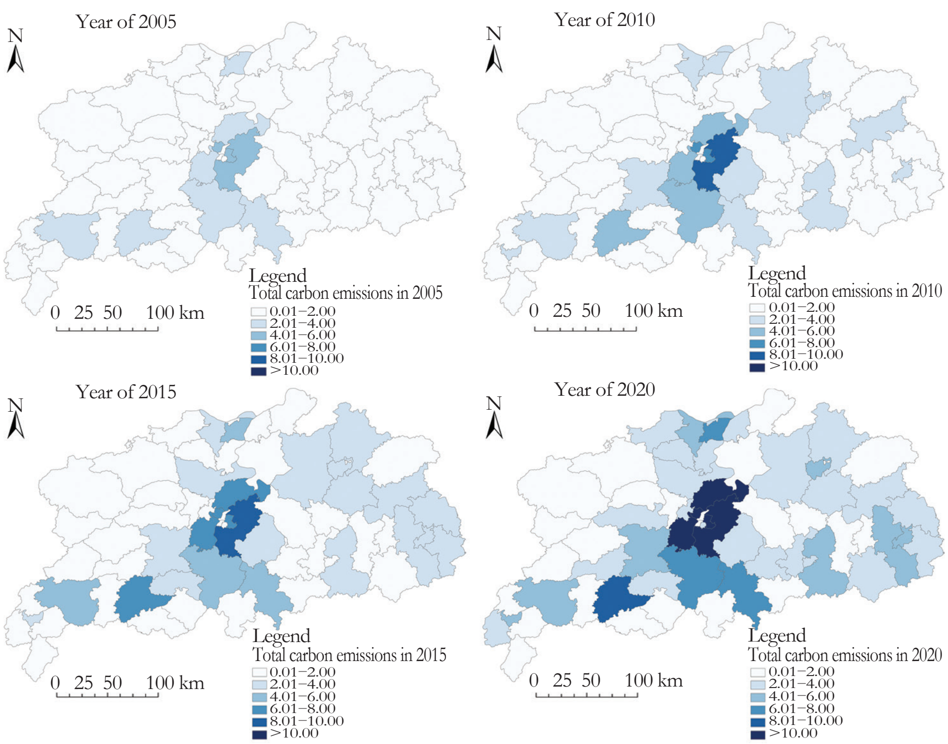

Fig.1 Spatial distribution of carbon emissions in the Poyang Lake urban agglomeration from 2005 to 2020

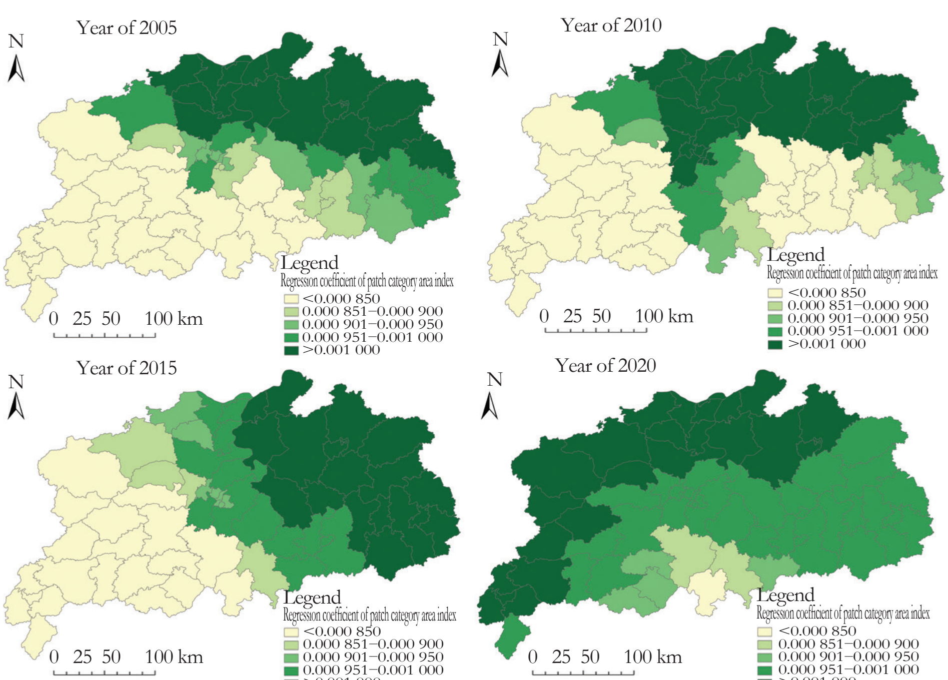

Fig.2 Spatial distribution of regression coefficients for class area (CA) index in the Poyang Lake city group

As is shown in Fig.5, SHAPE_AM showed no significant positive or negative correlations. The spatial characteristics showed that in 2005, there was a transition from negative values to positive values from the eastern to western regions. In 2010, the spatial distribution of SHAPE_AM was imbalanced: Fuliang and Wuyuan counties were the areas with high values of positive correlation, while the areas with high values of negative correlations included Pingxiang County, Linchuan, Chongren, and Jinxian. In 2015, the regression coefficients for most cities were between 0.01 and 0.30, indicating a significant impact. In 2020, SHAPE-AM showed an overall positive correlation in the east and a negative correlation in the west.

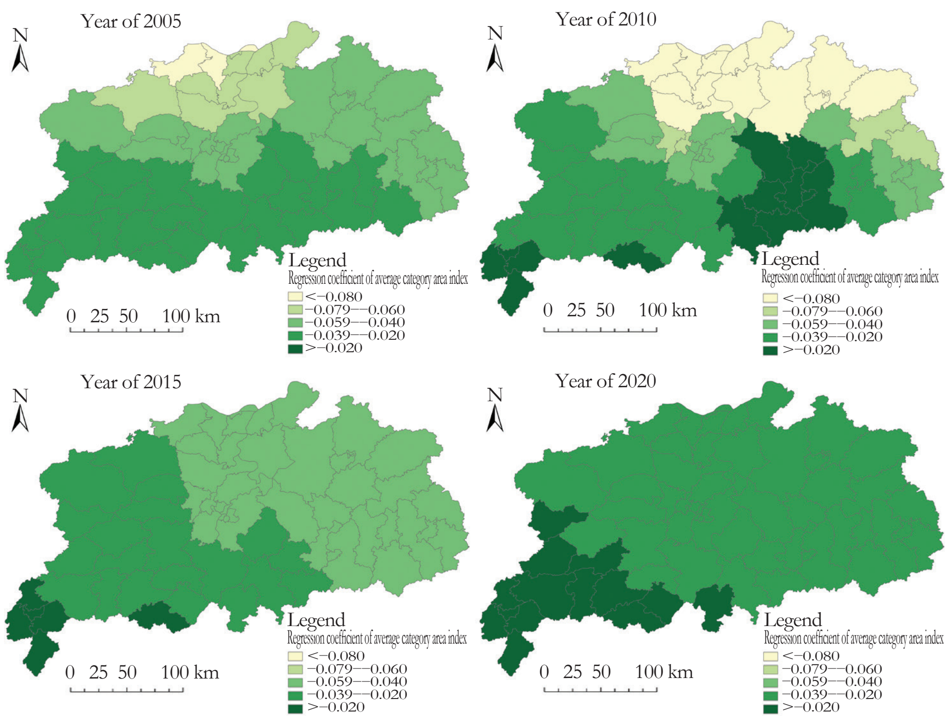

Fig.3 Spatial distribution of regression coefficients for the proximity mean area (PROX-MN) index of the Poyang Lake city group

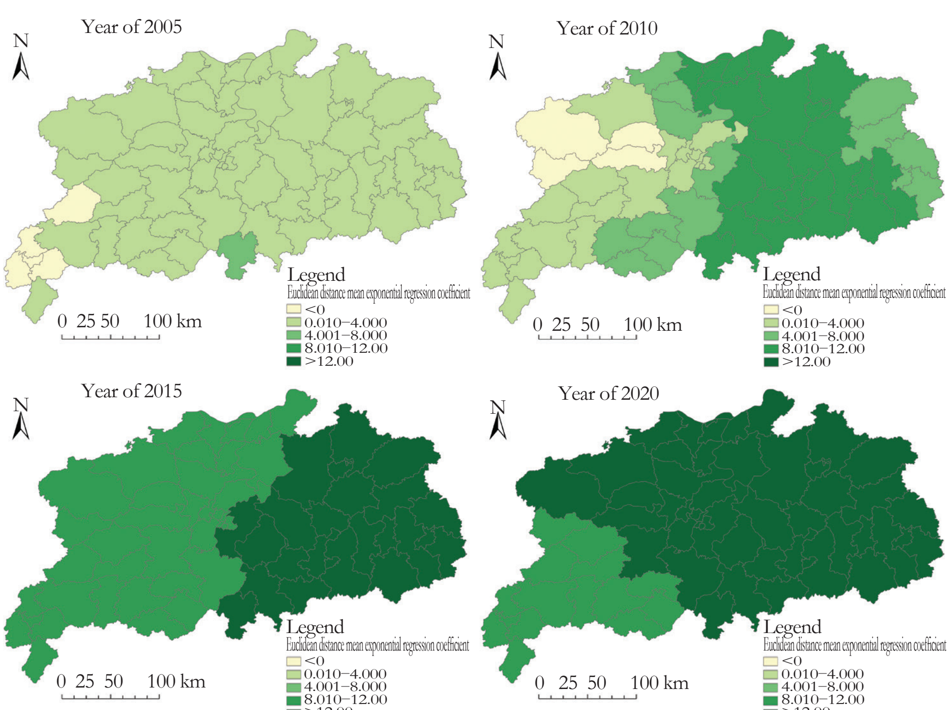

Fig.4 Spatial distribution of regression coefficients for the Euclidean distance mean (PROX-MN) index in the Poyang Lake city group

4 Conclusion and outlook

At present, most low-carbon national land spatial planning in China is still in the conceptual stage, and there is still a long way to go in terms of how to achieve carbon reduction goals through planning spatial structure (morphological indicators and related schemes). Therefore, based on generalized linear regression and geographically weighted regression models, analysis was made to the spatiotemporal distribution characteristics of carbon emissions, the spatiotemporal relationship between urban form index and carbon emissions, and the spatial differentiation of the intensity of dominant factors from 63 county-level administrative units in the Poyang Lake city group from 2005 to 2020. The following conclusion has been drawn:

(1) From 2005 to 2020, the overall carbon emissions of the Poyang Lake city group showed an increasing trend, and the areas with high carbon emissions were concentrated in the central region while the areas with low values were fragmented and clustered. The growth rate of total carbon emissions was relatively high from 2005 to 2010, mainly due to the comprehensive promotion of industrialization and urbanization, as well as the rapid development of high-energy consuming and high emission industries. The gradual decrease in the growth rate of total carbon emissions from 2010 to 2020 indicated that the economy of the Poyang Lake Ecological City Group was gradually transitioning towards a low-carbon economy.

(2) The main driving factor for the spatial heterogeneity of carbon emissions was the expansion of built-up area. The geographically weighted regression model was used to analyze the significance of spatial form factors in various cities, and the results showed the the scale of urban built-up areas had a significant impact in all 4 periods, indicating that the expansion of urban built-up area was the main factor leading to carbon emissions.

(3) Improving urban compactness and optimizing urban form could effectively reduce urban carbon emissions. Compact cities could reduce urban carbon emissions through mixed land use, improved community living circle configuration, and convenient public transportation systems.

County level small and medium-sized cities are the "main battlefield" for future urbanization development, so conducting research on the

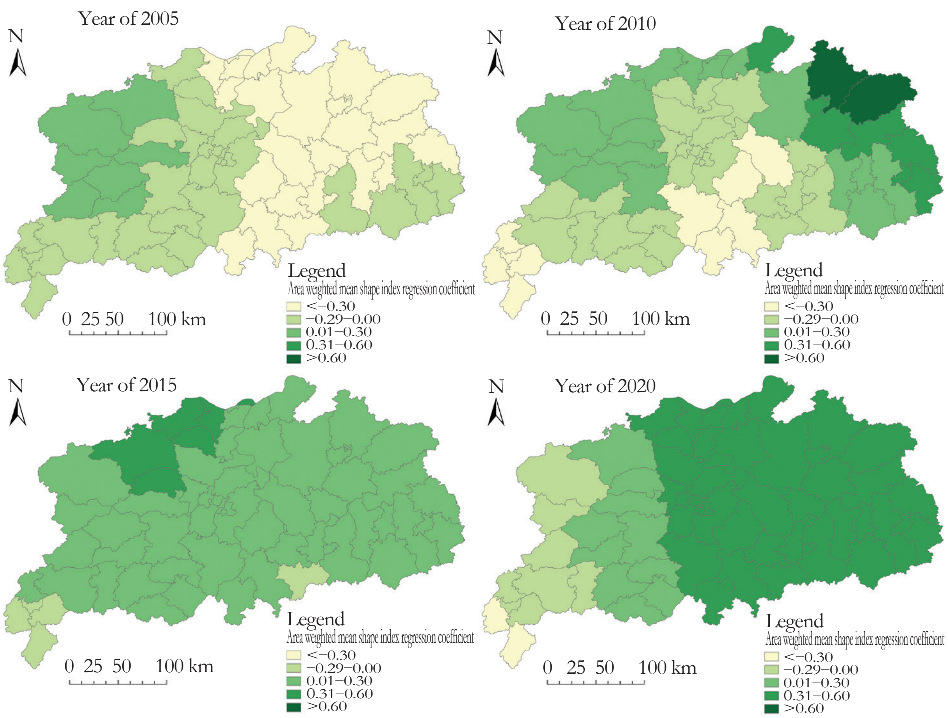

Fig.5 Spatial distribution of egression coefficients for the area weighted mean shape (SHAPE_AM) of the Poyang Lake city group

impact of urban spatial form on carbon emission efficiency can provide a new approach for low-carbon development of small and medium-sized cities at the current stage[24]. This study only discussed the impact of various urban forms in the Poyang Lake city group on carbon emissions from 2005 to 2020. Further research is needed to explain the spatiotemporal heterogeneity of the decoupling state of urban form indices and the range of urban form indices. Research has shown that controlling the scale of urban built-up areas and optimizing urban morphology can effectively reduce urban carbon emissions, and in the process of urban development, cities should improve their land use efficiency and internal connectivity and regularity.

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