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Spatiotemporal Pattern and Driving Factors of Carbon Emissions in Guangxi Based on Geographic Detectors

Qianru Guo, Xiuting Lai, Yanhong Jia * and Feili Wei *

Guangxi Key Laboratory of Environmental Processes and Remediation in Ecologically Fragile Regions, College of Environment and Resources, Guangxi Normal University, Guilin 541000, China; 13077710120@163.com (Q.G.); hawkweed123@163.com (X.L.)
* Correspondence: j-913@163.com (Y.J.); weifeili@pku.edu.cn (F.W.)

Abstract: Analysis of the spatiotemporal distribution pattern and driving factors of carbon emissions has been a focus of research in recent years. However, at the county level, analyses of the driving factors of carbon emissions are still relatively few. This study selected the Guangxi Zhuang Autonomous Region as the research subject, selecting the normalized difference vegetation index (NDVI), nighttime light index (NLI), gross domestic product (GDP), and population density (POP) as driving factors. Based on the geographic detector method, the spatiotemporal distribution pattern and driving factors of carbon emissions at the county level in Guangxi were investigated. The results show the following: (1) There are significant regional differences in the degree of change in carbon emissions. From 2005 to 2020, the total carbon emissions in Guangxi show an upward trend, presenting a "high in the south and low in the north" distribution characteristic, gradually forming a high-level region in the capital city of Nanning, the city of Liuzhou, and some coastal cities (such as the cities of Qinzhou, Beihai, and Fangchenggang) as the core of carbon emissions; (2) NDVI, NLI, GDP, and POP have a relatively high impact on the carbon emission pattern in Guangxi, and the impact of human activity intensity on carbon emissions is higher than that of the influencing factors of NDVI; (3) The interaction between NDVI, NLI, GDP, and POP has a significant impact on the carbon emission pattern. The aforementioned results can provide decision-making suggestions for the social and economic development of Guangxi, as well as the formulation of carbon sequestration policies.

Keywords: carbon emissions; geographic detectors; driving factors; carbon sink

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1. Introduction

Currently, carbon emissions are an important factor causing global climate change, and studying the factors that determine carbon emissions to reduce greenhouse gas emissions has become an important measure for countries around the world to alleviate global warming [1]. According to related data, CO_2 emissions caused by human activities account for over 80% of total CO_2 emissions [2], and carbon emissions from land use change account for about 1/3 of the total carbon emissions obtained by humans [3]. Up until 2020, China's carbon emissions were 9.89×10^9 tons, accounting for 30.9% of the world's total carbon emissions, making it the country with the largest global carbon emissions [4]. In order to address issues of climate change and achieve sustainable development, the Chinese government proposed the "dual carbon" goal in 2020, which was to achieve a carbon peak by 2030 and carbon neutrality by 2060. This article is based on the Guangxi Zhuang Autonomous Region and conducts research on the spatiotemporal differences and driving factors of carbon emissions in counties. This study aims to provide a theoretical basis for optimizing land use structure and formulating scientific and targeted emission reduction strategies in Guangxi.

Recently, studies on carbon emissions carried out by scholars from home and abroad have mainly focused on the analysis of spatiotemporal differences in carbon emissions and

the influencing factors of carbon emissions. From the perspective of research scale, this study mainly concerns the spatiotemporal patterns of carbon emissions at the national, provincial, and municipal levels [5–10], with less research on the spatiotemporal patterns of carbon emissions at the county level [11]. In terms of studying the spatiotemporal patterns of carbon emissions, most scholars at home and abroad use the methods of Moran index, Gini coefficient, and Thiel coefficient to analyze the regional differences and agglomeration effects of carbon emissions, as well as the evolution of spatial patterns [12–16]. Scholars such as Zhang et al. analyzed the trend of changes in the Moran index and believed that the overall carbon emissions from land use in the three provinces in northeast China show a significant positive correlation [12]. Domestic scholars such as Yan et al. found, through methods such as the Gini coefficient and Thiel coefficient, that there are significant differences in carbon emission intensity among different provinces, cities, and autonomous regions in China, and the differences gradually expand with the passage of time [13]. In terms of studying the influencing factors of carbon emissions, by using geographic detectors, geographic weighted regression models (GWRs), LMDI factor decomposition methods, and STIRPAT model methods, scholars have explored the impact of economic growth, energy structure, urbanization, industrial structure, population size, and other factors on carbon emissions [17–22]. Scholars Shi et al. applied the LMDI model to analyze the contribution rate of driving factors such as economic growth and population size to carbon emissions [19]. Scholars Li et al. used geographic detector analysis to investigate the driving factors of carbon emissions from agricultural land at the provincial level. The results show that the main driving factors of carbon emissions from agricultural land are gradually shifting from population and mechanization levels to economic factors [22].

In summary, research methods related to carbon emissions have gradually developed and matured and significant progress has been made. However, most of the existing research is focused on economically developed regions such as East China [23–26], North China [27–29], and Southeast China [30–32]. There is relatively little research on the driving factors of carbon emissions at the county level in the Southwest region, which has superior natural conditions and great economic development potential. Therefore, for this study, we selected Guangxi Zhuang Autonomous Region as the research goal, comprehensively utilizing spatial autocorrelation analysis and geographic detectors to explore the spatiotemporal characteristics, spatial correlations, and influencing factors of carbon emissions at the county level in the years of 2005, 2010, 2015, and 2020; the purpose of this study is to provide a systematic basis for formulating more targeted and scientific policies to achieve the "dual carbon" goals in the Guangxi Zhuang Autonomous Region.

The geodetector used in this study is an efficient spatial analysis method that can measure the spatial distribution variability of geographic elements, explain the degree of influence of factors on the spatial distribution pattern of geographic elements, and, at the same time, analyze the interaction between variables. In the study of the spatial pattern of carbon emissions in Guangxi, this geodetector can better explain the spatial stratified heterogeneity of carbon emissions. Compared with other methods, the geodetector is able to analyze the importance of different factors on the carbon emission pattern in Guangxi and explore the influence of the interaction between urbanization factors and natural factors on the spatial pattern of carbon emission, which makes the research results more reliable. The innovation of this study lies in revealing the nonlinear correlation between carbon emissions and influencing factors based on geographic detector methods, providing a theoretical basis for the formulation of carbon emission policies under the "carbon peak and carbon neutrality goals".

2. Data Sources and Methods

2.1. Research Area

Guangxi Zhuang Autonomous Region is located in the southwest of China (Figure 1), where it is seated at the southeast edge of the Yunnan–Guizhou Plateau on the second step of China's terrain, in the west of the hills of Guangdong and Guangxi (104°26′ E −112°04′ E,

20°54′ N−26 °24′ N), with a total area of 236,700 km^2. Guangxi is situated at the junction of subtropical and tropical regions, with a subtropical monsoon climate. The climate is warm and humid, with abundant rainfall. The annual average temperature is around 20 °C, and the annual precipitation ranges from 1000 to 2000 mm; the terrain is complex and diverse and is mainly divided into mountainous and hilly areas. According to "the 2023 Guangxi Statistical Yearbook", the total GDP of Guangxi in 2022 was CNY 2630.87 billion with a year-on-year increase of 2.9% across a permanent population of 50.47 million, exhibiting an urbanization rate of 55.65%. In recent years, with the increasing development of urbanization, the proportion of construction land in land use in Guangxi has gradually increased, while the proportion of arable land has gradually decreased. On the other hand, along with the development of the economy and the improvement of people's living standards, people's awareness of protecting forest land and water has gradually increased, so the proportion of forest land and water has become relatively stable. Meanwhile, the proportion of grassland and unused land is relatively small.

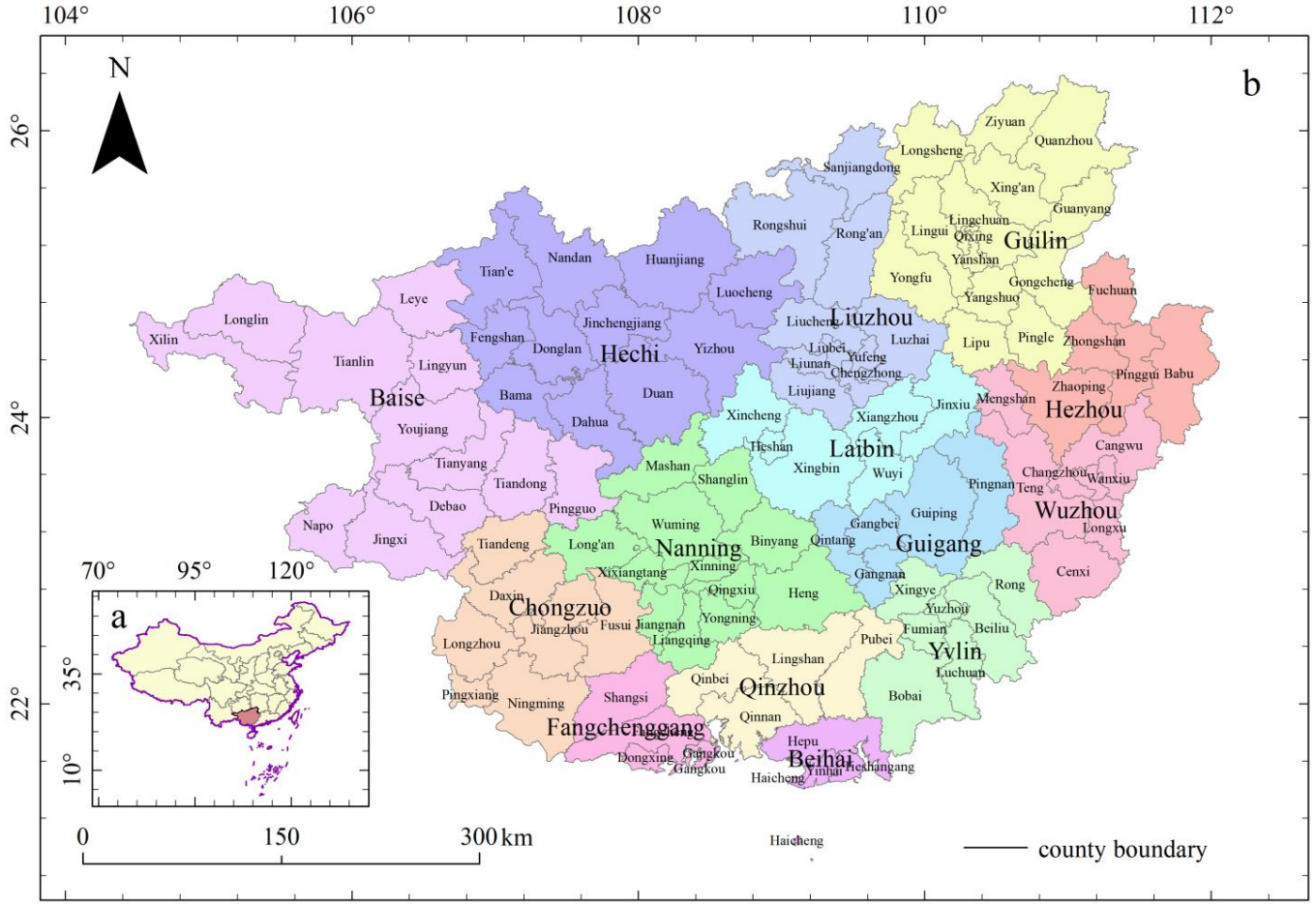


Figure 1. County-level administrative divisions in Guangxi ((**a**) is the location of Guangxi in China, (**b**) is the administrative division of Guangxi).

2.2. Data Sources

The level of urbanization and economic development have a positive impact on carbon emissions, and there are significant regional differences in these impacts [33]. Carbon emissions are mainly concentrated in urban areas where human activities are relatively localized. Land use change is also an important factor that affects the carbon cycle of terrestrial ecosystems, and its impact on carbon emissions is mainly reflected in the reduction in vegetation area, significant expansion in arable land, and increase in building land area [34]. Based on the existing research, for this study, we selected gross domestic product (GDP)

as the indicator for evaluating economic development [35], population density per square kilometer (POP) as the indicator for evaluating population development [36], normalized difference vegetation index (NDVI) as the indicator for measuring ecological environment and vegetation cover area [37], and nighttime light index (NLI) to reflect the impact of the urbanization process and human activity intensity [38], in order to analyze the impact of human activities and land use changes during urbanization on county-level carbon emissions. The data sources involved in the study are as follows.

The carbon emission data from various districts and counties in Guangxi come from the China Carbon Accounting Database (https://www.ceads.net.cn, accessed on 1 June 2023). Among them, the carbon emission data in 2020 are based on the data from 2000 to 2017, which were linearly interpolated and corrected based on the economic development level and urban impermeable area of each county. The nighttime lighting data were collected using DMSP-OLS sensors and NPP-VIIRS sensors, with a spatial resolution of 1 km. The kilometer-grid POP data and GDP data were sourced from NASA's Socio Economic Data Center (http://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-Rev10, accessed on 1 June 2023)) with a spatial resolution of 1 km. The vector data of the administrative divisions in Guangxi were sourced from the National Geographic Information Resource Catalog Service System (www.webmap.cn, accessed on 1 June 2023).

2.3. Methods

2.3.1. Local Spatial Autocorrelation Analysis

Local spatial autocorrelation mainly uses the local Moran I index and the local Getis OrdGi* index to reflect the degree of spatial aggregation of attribute variables within the local region. The calculation formula for the local Moran I index is

$$I_i = Z_i \sum_j W_{ij} Z_i$$

In the formula, I_i represents the index for local Moran's I, while Zi and Z_j stand for the normalized variance values of carbon emissions in regions i and j. When the index is greater than 0, this indicates a positive spatial correlation between local spatial units and adjacent spatial units, manifested as "high high" or "low low" clustering. When the index is less than 0, this indicates a negative spatial correlation between local spatial units and adjacent spatial units, manifested as "low high" or "high low" clustering.

The calculation formula for the Getis OrdGi* index is

$$G*_i = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{[n \sum_{j=1}^{n} w^2{}_{i,j} - (\sum_{j=1}^{n} w_{i,j})^2]}{n-1}}}$$

In the formula, the G_i* statistical index is the z-score. When the z-score is greater than 0 and higher, the high-value clustering of the target object's attributes becomes closer, forming hotspots; if the z-score is less than 0, the lower it is, the closer the low-value clustering of the target object's attributes becomes, forming a cold spot [39].

2.3.2. Geographic Detector

Geographic detectors are an effective method for detecting spatial heterogeneity. The principle of this method is to measure the explanatory power of each independent variable on the dependent variable by comparing the spatial distribution consistency of the independent variable and the dependent variable [40]. Geographic detectors mainly consist of four parts: risk detectors, factor detectors, ecological detectors, and interaction detectors [41]. The core of this study uses factor detectors to study the explanatory power of various driving factors on carbon emissions and to explore the impact of the interaction between factors on carbon emissions through interaction detectors. This can help us better understand the impact of the interaction between factors on carbon emissions. Factor

detection was mainly used to measure the degree of explanation of the impact of different driving factors on carbon emissions, measured using q values. The calculation formula is

$$q = 1 - \frac{\sum_{h=1}^{L} Nh\delta^2 h}{n\delta^2}$$

In the formula, h = 1, 2,. . ., L is the stratification of a certain driving factor X, i.e., classification or partition; N_h and n represent the number of units in layer h and the entire region, respectively; ${\delta^2}_h$ and δ^2 demonstrate the variance in the Y values for layer h and the entire region, respectively; and q stands for the explanatory power of a driving factor on carbon emissions, with a range of [0, 1]. The closer the q value is to 1, the stronger the explanatory power of driving factor X on the dependent variable Y, and vice versa.

Interaction detection was used to measure the interaction between each driving factor X and evaluate whether the joint action of the two factors increased or weakened the explanatory power of the dependent variable. The interaction relationship between the two factors is shown in Table 1.

Table 1. Types of interaction between two factors.

Interaction Type	q Value Relationship
Nonlinear attenuation	$q(X_1 \cap X_2) < \mathrm{Min}(q(X_1), q(X_2))$
Single-factor nonlinear attenuation	$\mathrm{Min}(q(X_1), q(X_2)) < q(X_1 \cap X_2) < \mathrm{Max}(q(X_1), q(X_2))$
Double-factor enhancement	$q(X_1 \cap X_2) > \mathrm{Max}(q(X_1), q(X_2))$
Independent	$q(X_1 \cap X_2) = q(X_1) + q(X_2)$
Nonlinear enhancement	$q(X_1 \cap X_2) > q(X_1) + q(X_2)$

The geographic detector requires the input variable as the categorical variable, which means that continuous data need discretization processing. The natural break point method reduces the difference within the same hierarchy, increasing the size of different hierarchical differences in terms of the natural clustering method. The natural clustering method narrows the average layer in discrete minimum variance and maximizes the average discrete maximum variance. The natural clustering method is widely used in the classification of variables for a geographical detector. Therefore, in this study, we adopted the natural break point method of ArcGIS 10.2 to categorize the data. We divided the continuous data of each factor into seven categories. The consistent stratification method was applied for each influence factor in order to ensure that the effect of the impact factor on the change in carbon emissions was explored under the same stratification conditions, which guarantees the comparability of results.

3. Results and Analysis

3.1. Temporal and Spatial Distribution Characteristics of Carbon Emissions in Guangxi

In order to analyze the degree of change in carbon emissions, the carbon emissions of various districts and counties since 2000 were fitted to obtain the change rate (slope) of carbon emissions in different regions of Guangxi, so as to express the significant degree of change in carbon emissions. We visualized the slope of carbon emissions using ArcGIS10.2 software and adopted natural breakpoint classification to classify the slope into five categories, as shown in Figure 2. In the past 15 years, the carbon emissions of various districts and counties in Guangxi have shown an upward trend, but the degree of change in carbon emissions in different regions has changed significantly. The region was studied with Youjiang District, Tiandong County, Pingguo County, Wuming District, Binyang County, Qintang District, Gangbei District, Guiping City, Pingnan County, Teng County, Cangwu County, and Pinggui District as the boundary. Most of the districts and counties in the north of the boundary have relatively low changes in carbon emissions, with only the districts and counties under Liuzhou City and surrounding areas having relatively high slopes; the slope of carbon emissions in most districts and counties south of

the boundary is relatively high, especially in the surrounding districts and coastal counties in the city of Nanning, where the degree of change is the most severe.

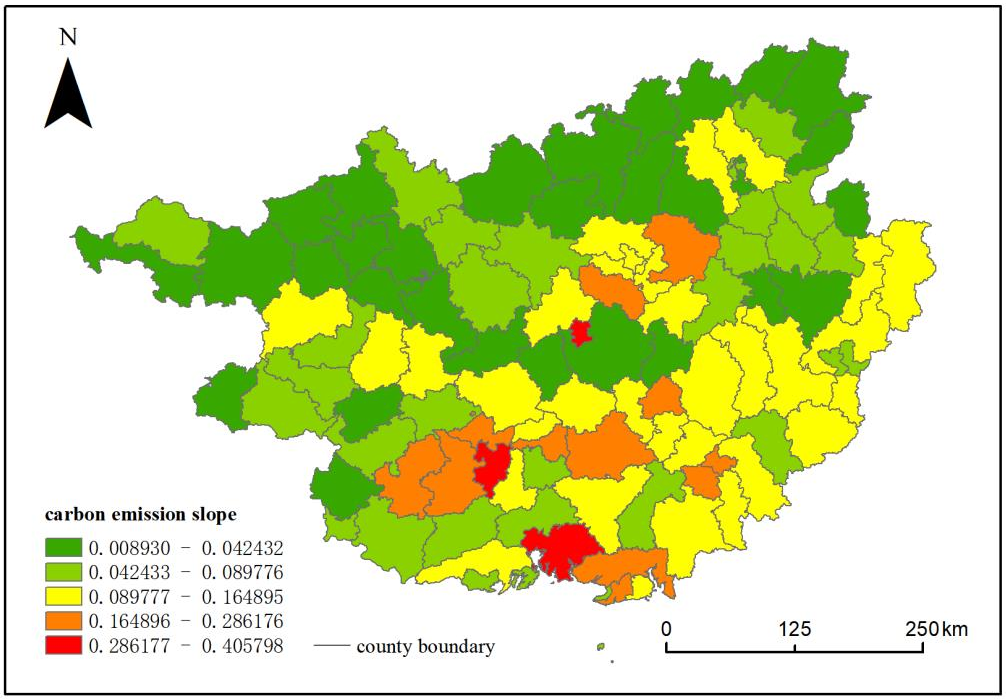


Figure 2. Spatial pattern of changes in carbon emissions in Guangxi.

The total carbon emissions of Guangxi in 2005, 2010, 2015, and 2020 were 101.39 t, 162.49 t, 206.11 t, and 266.39 t, respectively, showing an overall upward trend (Figure 3). From Figure 3, it can be seen that, in 2005, the carbon emission levels of most districts and counties were relatively low, with carbon emission values below 1.60 tons. Only a few scattered areas in the central and southern regions had higher carbon emissions. In 2010, the carbon emissions in the central and southern regions showed significant changes, with southern districts and counties such as Wuming District, Binyang County, Guiping City, Gangbei District, Hengzhou City, Qingxiu District, Jiangnan District, and Xixiangtang District achieving an increase in carbon emissions levels. The degree of change in the northern and western regions is relatively low, and low levels of carbon emissions are still maintained. In 2015, the carbon emission levels of southern districts and counties further improved, initially showing differences in carbon emission patterns between the north and the south, presenting a spatial distribution pattern of higher carbon emissions in the southern regions and lower carbon emissions in the northern regions. In 2020, the spatial pattern of high carbon emissions in the south and low carbon emissions in the north was further strengthened. The southern region formed a high-value contiguous area around cities in the Beibu Gulf of Guangxi, while the northern edge region did not experience significant changes in carbon emissions in the past 15 years and still maintained a relatively low level of carbon emissions.

Based on the analysis of the trend in carbon emissions and the spatiotemporal distribution pattern of carbon emissions, the northern region of Guangxi has relatively low carbon emissions and a relatively slow growth trend, while the southern region has higher carbon emissions and a faster growth rate, with significant regional differences in carbon emissions.

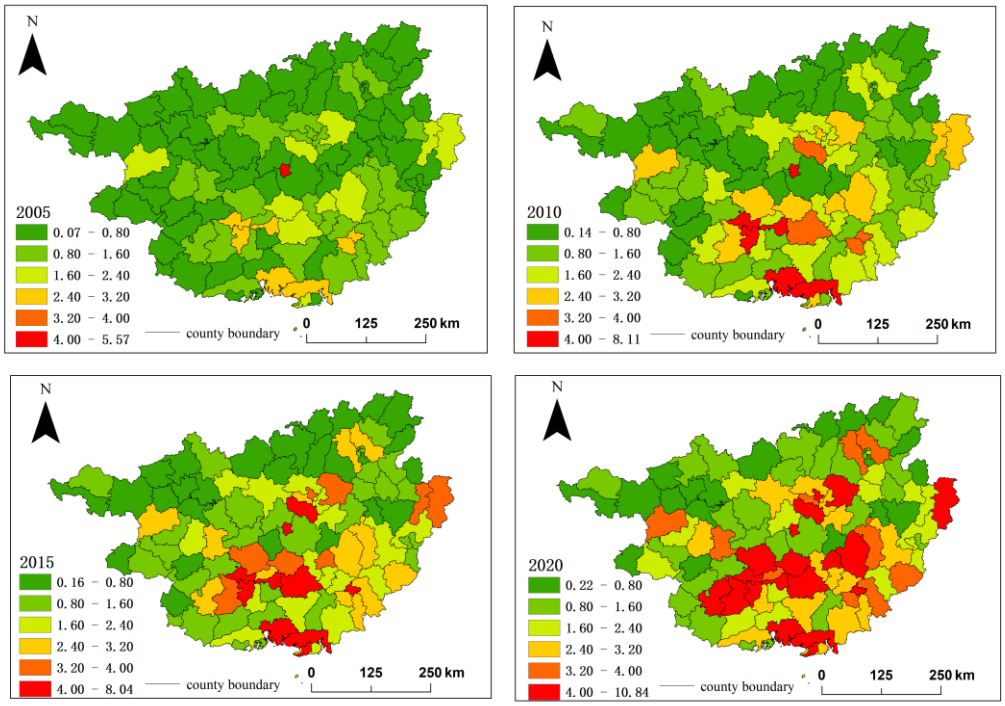


Figure 3. Spatial and temporal patterns of carbon emissions in Guangxi from 2005 to 2020.

3.2. Spatial Autocorrelation Analysis of Carbon Emissions in Guangxi

According to the local autocorrelation analysis results of carbon emission patterns in Guangxi (Figure 4), in 2005, the "high-high" clustering areas included Liujiang District, Heshan City, Binyang County, Qingxiu District, Xixiangtang District, Fusui County, Yuzhou District, Fumian District, Qinnan District, Hepu County, and Yinhai District, while the "low-low" clustering only included Fengshan County in northern Guangxi. In 2010, the "high-high" clustering added one district/county to Xingning District. In 2015 and 2020, Wuming District and Fusui County transformed into "high-high" clustering, ultimately forming a high-level carbon emission area centered around the city of Nanning, Liuzhou, and coastal cities (like Qinzhou, Beihai, and Fangchenggang).

The differences between the north and the south in carbon emissions levels and the core regional pattern also reflect the development of regional policies in Guangxi. In recent years, with the continuous implementation of the "the Belt and Road" strategy, the economic center and population center of Guangxi are moving southward. The population size and economic strength of southern cities has been increasing, which has strengthened the urbanization level of southern cities, thus leading to the increasing carbon emissions, while the cities of Liuzhou, the capital city of Nanning, and the three cities located in Beibu Gulf (the cities of Qinzhou, Beihai, and Fangchenggang) are important industrial development cities in Guangxi, undertaking the production tasks of large industrial enterprises. Carbon emissions also increase with the development of industrialization, making these regions the core cities for carbon emissions in Guangxi.

3.3. Analysis of Driving Factors for Carbon Emission Patterns in Guangxi

3.3.1. Factor Detector Analysis

In this study, we used factor detectors from geographical detectors to study the driving factors of the spatial pattern of carbon emissions in Guangxi. According to the results of geographical exploration (Table 2), the q values of NDVI, NLI, GDP, and POP in the four periods were all greater than 0.2, and all passed the 99% significance test, indicating that the NDVI, NLI, GDP, and POP have a high explanatory power for carbon emission changes; thus, these are important factors affecting the spatiotemporal distribution pattern of carbon emissions in Guangxi.

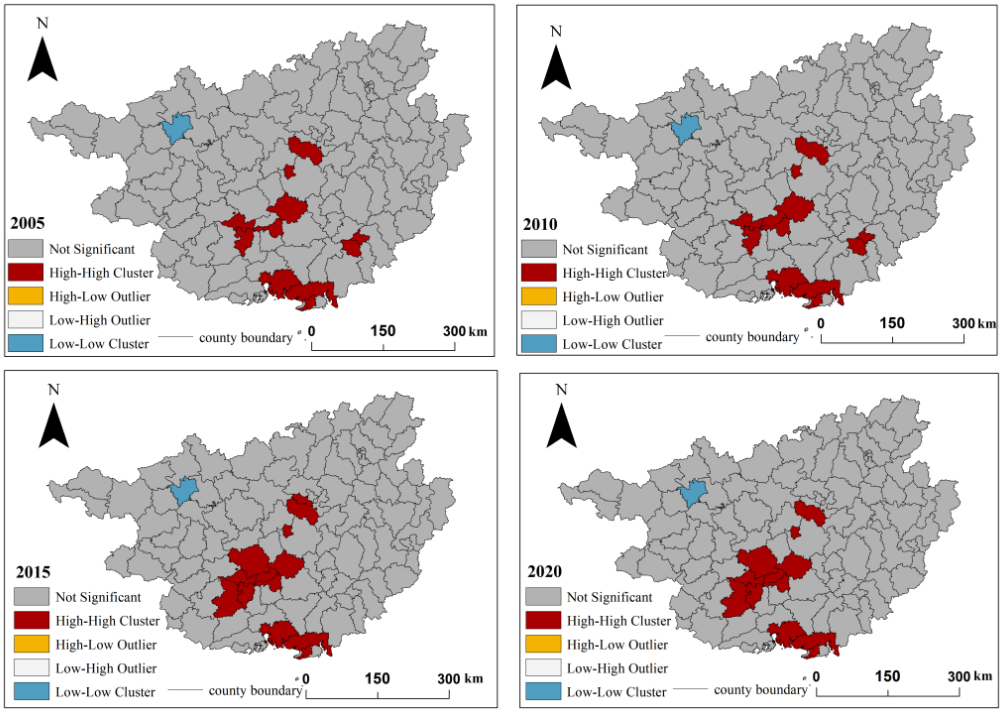


Figure 4. Local autocorrelation analysis of carbon emissions in Guangxi from 2005 to 2020.

Table 2. *q* value statistics of different influencing factors on carbon emissions changes in Guangxi from 2005 to 2020.

Factor	2005	2010	2015	2020
NDVI	0.265 ***	0.277 ***	0.342 ***	0.274 ***
NLI	0.393 ***	0.380 ***	0.544 ***	0.387 ***
GDP	0.396 ***	0.359 ***	0.342 ***	0.303 ***
POP	0.302 ***	0.315 ***	0.315 ***	0.245 ***

***: $p < 0.01$.

In 2005, the explanatory power of the four factors was ranked as follows: GDP > NLI > POP > NDVI, with the *q* values of GDP, NLI, and POP all exceeding 0.3. In 2010, the explanatory power of each factor was ranked as follows: NLI > GDP > POP > NDVI. The *q* values of GDP, NLI, and POP all exceeded 0.3, and the explanatory power of NDVI was also slightly increased. In 2015, the order of explanatory power was as follows: NLI > GDP = NDVI > POP, with a *q* value of over 0.5 for NLI. The impact of NDVI on carbon emissions also rose further. In 2020, the order of explanatory power was NLI > GDP > NDVI > POP, and the *q* values of all four factors degraded. From the perspective of the impact of the four driving factors on the carbon emission pattern during the four periods, the NLI, GDP, and POP all rank in the top three in terms of explanatory power, indicating that urbanization factors have a greater impact on the carbon emission pattern than NDVI in Guangxi, and the impact of human activities on carbon emissions is particularly crucial. Based on the spatiotemporal distribution pattern of carbon emissions from 2005 to 2020 in Guangxi, regions with developed economics, large population, and high urbanization often have relatively high carbon emissions.

From the changes in *q* values of different factors, it can be seen that, from 2005 to 2015, the explanatory power of the four driving factors on carbon emissions increased, but, by 2020, the *q* value declined again. Among them, the explanatory power level of NDVI gradually increased, with a *q* value of 0.174 in 2020, increasing compared to those in 2005. This indicates that, in the past 15 years, the government and relevant institutions have continuously strengthened their awareness of ecological environment protection, reducing

regional differences in carbon emissions levels by protecting vegetation and increasing vegetation coverage. From a numerical perspective, the q values of NLI, GDP, and POP in 2020 decreased compared to 2005, and their impact on carbon emissions also continuously decreased. The fluctuations in urbanization factors may be related to severe population loss, weak economic development, and slow progress in urban infrastructure construction in some cities of Guangxi.

3.3.2. Interaction Analysis

In order to further analyze the interaction between factors, for this article, we adopted the interaction detector in the geographic detector to analyze the interaction relationship between NDVI, NLI, GDP, and POP. The analysis results are shown in Table 3. The interaction q value between the four factors is greater than that of a single-factor q value, indicating that the impact of the interaction between the two factors on carbon emissions is much greater than that of a single factor. In 2005, the q value of NLI and POP was the highest, and the interaction between the two was non-linear enhancement. The relationships between POP ∩ GDP and POP ∩ NDVI were also bilinear enhancement, and their interaction had a significant impact on carbon emissions. The NDVI ∩ GDP, NLI ∩ GDP, and NLI ∩ NDVI were all enhanced by two factors. In 2010, the NDVI ∩ GDP had the highest q value, indicating a bilinear enhancement relationship. The interaction between other factors was double-factor enhancement. In 2015 and 2020, the interaction between the four factors was a dual-factor-enhanced relationship, and NLI ⋂ POP had the strongest impact on carbon emissions in these two years.

Table 3. Results of carbon emission interaction factor detectors in Guangxi from 2005 to 2020.

	2005	**2010**	**2015**	**2020**
Interaction	GDP ∩ NDVI	GDP ∩ NDVI	GDP ∩ NDVI	GDP ∩ NDVI
q value	0.60	0.72	0.54	0.37
Interaction	GDP ∩ POP	GDP ∩ POP	GDP ∩ POP	GDP ∩ POP
q value	0.74	0.56	0.44	0.45
Interaction	GDP ∩ NLI	GDP ∩ NLI	GDP ∩ NLI	GDP ∩ NLI
q value	0.67	0.62	0.65	0.51
Interaction	NDVI ∩ POP	NDVI ∩ POP	NDVI ∩ POP	NDVI ∩ POP
q value	0.68	0.54	0.55	0.49
Interaction	NDVI ∩ NLI	NDVI ∩ NLI	NDVI ∩ NLI	NDVI ∩ NLI
q value	0.52	0.65	0.65	0.53
Interaction	POP ∩ NLI	POP ∩ NLI	POP ∩ NLI	POP ∩ NLI
q value	0.82	0.55	0.68	0.60

From the perspective of the impact of a single factor on other factors, the interaction between the NLI and other factors can greatly enhance the impact of a single factor on carbon emissions, while the impact of a single factor on the spatial pattern evolution of carbon emissions is relatively small. However, under the joint action of other factors, its q value significantly increases, and its impact on carbon emissions also greatly increases. In 2015, NDVI ∩ GDP became the dominant factor affecting carbon emissions, which also indicates that human activities have an impact on vegetation coverage and, thus, on the spatial pattern of carbon emissions.

4. Discussion

According to the previous analysis, the spatiotemporal pattern of carbon emissions and the pattern of carbon emission change rate in Guangxi show significant differences between the north and the south. Combined with the analysis results of factor detectors, it can be seen that urbanization has become the main reason for the differences in carbon emissions in Guangxi. Among several regions with relatively high carbon emissions and carbon emission change rates, the city of Nanning, as the capital of Guangxi, ranks first in terms of economic volume and population and has a high urbanization rate within Guangxi.

At the same time, as a core city in the Beibu Gulf, the city of Nanning has a relatively large number of industrial enterprises and significant urban expansion, resulting in higher carbon emissions in the jurisdiction of Nanning and surrounding counties. The city of Liuzhou is an important industrial city in Guangxi, with secondary industry as the pillar industry and high carbon emissions in industrial production, which also leads to high carbon emissions in the jurisdiction and surrounding counties of Liuzhou City. In the coastal Beibu Gulf region, some districts and counties, such as Qinnan District, Hepu County, and Yinhai District, benefit from the advantages of the Beibu Gulf policy and host the processing and manufacturing industries of Guangdong. Industry has developed soundly, leading to a continuous increase in POP. In recent years, the economy has developed rapidly and human activities have further strengthened, exacerbating carbon emissions. The carbon emissions and change rates of carbon emissions in the western and northern regions of Guangxi are relatively low, which may be due to the rugged terrain, limited development of urbanization, slow economic development, and low population density, resulting in lower anthropogenic carbon emissions. However, the high vegetation coverage in these regions can also suppress some carbon emissions.

In the analysis of factor detectors, NLI, GDP, and POP are important factors that affect carbon emissions in Guangxi. However, between 2005 and 2020, the q values of these three factors showed a fluctuating downward trend, and their impact on the spatiotemporal pattern of carbon emissions was also continuously weakening. On the one hand, this indicates that, in recent years, the urbanization process of most cities and counties in Guangxi has been in a weak stage, except for the capital city of Nanning and the city of Liuzhou. The economic and population growth in other regions has been relatively slow. On the other hand, this also indicates that the government and relevant institutions weaken the impact of urbanization factors on carbon emissions by suppressing human activities, including returning farmland to forests to prevent land desertification by increasing vegetation coverage, rectifying industrial enterprises with high carbon emissions, and promoting the use of clean energy. Among the four factors, the weakening of GDP's impact on carbon emissions is the most significant. However, based on the proportion of industries in the past 15 years, Guangxi has actively adjusted its industrial structure, and the proportion of tertiary industry has gradually increased, especially in the capital city of Nanning and the city of Guilin. This has enabled economic development to not overly rely on secondary industries with higher carbon emissions.

In the interaction factor analysis, the interaction between the nighttime light index, GDP, and POP in 2005 had a significant impact on carbon emissions. However, from the perspective of Guangxi's GDP and growth trend, from 2000 to 2007, the growth rate of Guangxi's GDP was on the rise, indicating that, during this stage, Guangxi's economy developed rapidly, and the economic development also promoted population growth and migration. Further human activity and urban expansion led to an increase in construction land, an increase in the number of industrial enterprises, and a corresponding increase in carbon emissions. At the same time, the urbanization process affects economic development, industrial structure, and residential consumption, thereby affecting energy consumption and carbon emission patterns [42–44]. This makes urbanization become the dominant factor affecting carbon emissions at this stage. In 2010, 2015, and 2020, the interaction between urbanization factors gradually weakened the impact on carbon emissions. However, since 2010, the growth rate of Guangxi's gross domestic product (GDP) has continued to decrease, the speed of economic development has slowed down, and the processes of urbanization and human activity have also been further restricted, resulting in a weakened impact on carbon emissions. The interaction between NDVI and other factors greatly enhances its own impact on carbon emissions, indicating that human activity, economic development, and population development have an impact on vegetation and are also some of the main factors affecting carbon emissions. In the process of urbanization, changes in land use types, decreased vegetation, and reduced vegetation coverage caused by human activities can all affect the spatial pattern of carbon emissions to a certain extent, and excessive emissions of

harmful substances by industrial enterprises can also lead to vegetation degradation. At the same time, human intervention, such as establishing nature reserves, keeping factories away from nature reserves, and artificial vegetation restoration, can effectively reduce the impact of urbanization factors on vegetation coverage, thereby affecting carbon emissions.

5. Conclusions

In this study, we analyzed the spatiotemporal patterns of carbon emissions in the counties of Guangxi in 2005, 2010, 2015, and 2020, selecting NDVI, NLI, GDP, and POP as driving factors. Geographical detectors were used to analyze the impact of these four factors on the spatiotemporal patterns of carbon emissions in Guangxi. The following conclusions were drawn:

(1) From 2005 to 2020, the total carbon emissions in Guangxi continued to increase. The changes in carbon emissions in the northern regions and counties of Guangxi are relatively low, while the changes in carbon emissions in the southern regions and counties are more severe. In 2005, the carbon emission levels in most regions of Guangxi were relatively low. However, in the following 15 years, the carbon emission pattern in Guangxi gradually formed a "high in the south and low in the north" spatiotemporal pattern. The southern region formed a high-value contiguous area around the cities in the Beibu Gulf of Guangxi, while the northern edge region still remained at a relatively low level of carbon emissions;

(2) According to the results of local spatial autocorrelation, Guangxi has gradually formed a region with high carbon emissions centered around the capital city of Nanning, the city of Liuzhou, and coastal cities (such as the cities of Qinzhou, Beihai, and Fangchenggang). At the same time, the spatial pattern of carbon emissions also reflects the development of regional policies in Guangxi;

(3) Using factor detector analysis, the q values of NDVI, NLI, GDP, and POP are all greater than 0.2, which means they strongly explain the spatial pattern of carbon emissions. This indicates that the above four factors are important factors affecting the pattern of carbon emissions in Guangxi. The impact of urbanization factors (NLI, GDP, and POP) on carbon emissions is greater than that of NDVI. However, between 2005 and 2020, the impact of urbanization on the carbon emission pattern in Guangxi decreased, while the impact of NDVI increased;

(4) Interaction detector analysis was conducted on four factors, and the results show that the interaction between NDVI, NLI, GDP, and POP all strengthened their own impact on carbon emissions. The interaction between NLI and other factors had a significant impact on the spatial pattern of carbon emissions. At the same time, the impact of NDVI on carbon emissions was not very significant, but, after interacting with other factors, its impact increased significantly.

The above research results can provide a theoretical basis for the formulation of regional carbon sequestration policies for the economic development of Guangxi to a certain extent. However, this study also has certain shortcomings. It unifies the carbon emissions caused by human activities and land use change, neglecting the principles and driving mechanisms of these two types of carbon emissions. In subsequent carbon emission studies, these two types of carbon emissions can be studied separately, which can better explore the mechanism and driving factors of carbon sinks. Meanwhile, in terms of selecting factors that affect carbon emissions, in this study, we only selected four representative factors, and the research results still have certain limitations. In future research, the impact of energy consumption, consumption structure, and household consumption on carbon emissions can be considered on the basis of these four factors.

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