

Article

Investigation into Spatial and Temporal Differences in Carbon Emissions and Driving Factors in the Pearl River Delta: The Perspective of Urbanization

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Abstract: Urbanization is a significant indicator of city progress, and as urbanization advances, carbon emissions exhibit an increasing trend that must not be disregarded. Therefore, it is imperative to thoroughly examine the spatial and temporal variations as well as the factors influencing carbon emissions during the urbanization process. In this paper, based on the 2009–2019 PRD region, carbon emissions are measured from energy consumption, industrial production process, solid waste, and wastewater according to the IPCC coefficients, and spatial and spatial differences in carbon emissions are combined with spatial analysis and the drivers analyzed using the gray correlation scale. The results show that: (1) The total carbon emissions in the PRD region have been increasing over the study period, and the distribution of total carbon emissions shows a pattern of “strong in the east and weak in the west”, with energy consumption accounting for the highest proportion of carbon emissions. (2) The global Moran Index of carbon emissions in the PRD has been decreasing, with low and low clustering concentrated in Shaoguan and Zhaoqing, high and high clustering concentrated in Dongguan and Shenzhen, and low and high clustering concentrated in Shenzhen and Guangzhou, with cold spots mainly concentrated in Zhaoqing and hot spots mainly distributed in Guangzhou, Shenzhen, and Dongguan. (3) The degree of economic growth has a substantial influence on carbon emissions in the PRD cities, and the influence of technical advancement has intensified. Guangzhou City is propelled by low-carbon regulations that have a more equitable influence on all elements. Zhuhai City has a more significant influence on energy intensity, while Foshan City has a more noticeable decrease in the effect of foreign investment. To address the issue of carbon emissions, the government should establish appropriate rules to regulate carbon emissions in areas with high emissions, foster collaborative efforts across cities, and encourage the growth of environmentally friendly enterprises.

Keywords: carbon emissions; spatiotemporal differences; driving factors; the Pearl River Delta



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1. Introduction

Cities are the primary sources of carbon emissions, and their coordinated role in driving socioeconomic transformation during urbanization is crucial for advancing energy efficiency and achieving China’s goals of carbon peaking and carbon neutrality [1]. Cities, which are the primary hubs of human socioeconomic activity, cover about 3% of the Earth’s surface area yet account for over 75% of the world’s energy consumption and contribute to nearly 80% of global carbon emissions [2]. Consequently, achieving carbon peaking in cities has become a significant agenda for mitigating climate change [3]. Urbanization has caused a cascade of ecological and environmental problems, including scarcity of resources,

damage to the environment, and pollution [4]. Urbanization and carbon emissions have a very complicated connection. It is now critical and necessary to coordinate the interaction between urbanization and carbon emissions. Conducting research on carbon emissions, finely characterizing the spatiotemporal distribution patterns, and identifying influencing factors are of crucial importance. This research not only contributes to promoting regional coordinated development but also holds significant reference value for enhancing the scientific, targeted, and practical aspects of energy-saving and emission-reduction policies [5].

In recent years, both domestic and international scholars have undertaken comprehensive research on carbon emissions, examining diverse perspectives. Their investigations encompass the estimation of total emissions [6], performance metrics [7], and emission intensity [8] from various angles. Concurrently, these studies have delved into specific industries, including the financial sector [9], agriculture [6], industry [10], and tourism [11], in order to conduct in-depth analyses of carbon emissions. Li et al. (2015) conducted a thorough examination of carbon emissions at the county, municipal, and provincial levels; the findings revealed distinct patterns of regional distribution [12].

Zhao et al. (2018) observed distinct patterns of carbon emissions at the province level, characterized by a high concentration of emissions and a low amount of clustering [13]. When examining carbon emissions at the municipal level, Wu et al. (2023) identified clustering patterns. They noticed that per capita carbon emissions tend to rise from south to north and decrease from the eastern coastal regions towards the interior areas [14]. Wang et al. (2021) observed that at the county level, there is a clear spatial intensification associated with carbon emissions. They found a consistent geographic pattern of “higher in the north, lower in the south”, in economically developed regions in China having more per capita carbon emissions compared to other areas [5]. Wang et al. (2015) discovered that the factors that affect carbon emissions are intricate and varied at the same time [15]. Li et al. (2015) investigated the geographical heterogeneity and spatial autocorrelation of carbon emissions using spatial panel econometric models and exploratory spatial data analysis (ESDA) techniques [12]. Liu et al. (2019) investigated the effects of production scale, the intensity of energy use, the structure of the industry, population size, and the structure of energy on carbon emissions consumption using the Logarithmic Mean Divisia Index (LMDI) model [16]. Geographic detectors were utilized to uncover the significant explanatory capability of economic urbanization in accounting for the variations in carbon emissions at the county level [17]. Using the STIRPAT model, Chen et al. (2018) found that a city’s carbon emissions are greatly increased by population growth and the proportion of its output value that comes from secondary industries [18]. Song et al. (2023) applied geographic weighted regression and panel data regression models to identify varying levels of carbon emissions and major influencing factors among different types of counties [19].

Numerous academics have examined carbon emissions within the context of urbanization from the angles of drivers, geographical organization, and economic expansion. In terms of economic growth research, studies are usually conducted in two directions: economic growth in general or in a single sector. Among them, Wang et al. (2023) discovered a connection between economic development and the increase in CO₂ emissions when they examined carbon emissions from the perspective of general economic growth [20]. In their research, Dong et al. (2020) focused on six key sectors, including agriculture, industry, and construction, to examine the effects of carbon emissions. Their findings indicate that the transportation industry has the greatest influence [21]. Within the study of spatial structure, as the city size continues to expand, there is a growing trend of continuity and concentration of built-up regions, leading to an increase in carbon emissions [22]. The majority of studies employ the Geographically and Temporally Weighted Regression (GTWR) model, enabling an examination of urban agglomeration. It has been observed that the multifaceted structure of certain urban agglomerations fails to effectively reduce carbon emissions to a significant extent [23]. However, the GTWR model can analyze the urban change pattern by considering the factors that influence it, incorporating both temporal

and spatial dimensions. It reveals that the direction and strength of influence vary among different cities at different stages of development [24]. Ding et al. (2022) discovered that when urban agglomerations reach a more advanced stage of development, the degree of land use and land cover change (LUCE) increases, along with a greater concentration of districts and counties with a high level of carbon emissions [25]. China's energy sector produces carbon emissions that are typically greater than those of the rest of the world, and the country's growing economy is the main cause pushing up carbon emissions [26]. Yang et al. (2023) linked carbon emissions to urban high-quality development, demonstrating that advancements in technology, environmental governance, and economic growth are critical factors that may favorably impact both the moderate decrease in carbon emissions and the enhancement of environmental quality [27].

Based on the current study, there is still an opportunity for growth in this area even though studies on carbon emissions have been trending upward recently. The dominant techniques for measuring carbon emissions in metropolitan areas are largely concerned with emissions connected to energy consumption in the accounting process of carbon dioxide emissions [28]. This concentration leads to significant discrepancies between the calculated urban carbon emissions and the actual values. Second, the current research has mostly targeted provincial scales, with limited studies focusing on cities, and there is a scarcity of regional studies based on cities [5]. Third, there are very few studies on the spatiotemporal variations and driving forces of regional carbon emissions. Instead, research on carbon emission efficiency and productivity disparities has dominated the field.

Through experience summarization, this study seeks to provide a scientific reference for accomplishing the "dual carbon" objectives. Firstly, using economic and social data from the "Guangdong Statistical Yearbook", carbon emissions in four sectors—energy consumption, industrial production processes, solid waste, and wastewater—are calculated for the nine cities. Secondly, the total carbon emissions are determined by adding the emissions from these four sectors, and the spatiotemporal variations in carbon emissions are examined using spatial autocorrelation analysis. Lastly, the research assesses the influence of driving characteristics on the overall carbon emissions based on these computations.

Thus, this research specifically examines the Pearl River Delta area, investigating the spatial and temporal changes in carbon emissions that occur throughout the process of urbanization. The study identifies influential elements and examines their effect on carbon emissions in the Pearl River Delta. Ultimately, policy suggestions are provided based on the study findings. These results may be used as a benchmark for conserving energy and reducing carbon emissions throughout the process of urbanization.

2. Study Area and Data Source

2.1. Study Area

The Pearl River Delta (PRD) is situated in the central–southern region of Guangdong Province, including the middle and lower sections of the Pearl River, inside the subtropical zone. Adjacent to Hong Kong and Macau, it comprises nine prefecture-level cities: Guangzhou, Foshan, Zhaoqing, Shenzhen, Dongguan, Huizhou, Zhuhai, Zhongshan, and Jiangmen [29,30]. It makes up over one-third of Guangdong Province's entire land area, with a total size of around 54,767 square kilometers. With a high urbanization rate of 87%, the Pearl River Delta, despite its size, concentrates 81% of the province's entire economic output. The geographical location of the PRD is shown in Figure 1.

Analyzing the spatial distribution characteristics, temporal evolution, and driving forces of carbon emissions in highly urbanized regions can be facilitated by examining the spatiotemporal differentiation and driving factors of carbon emissions in the PRD urban cluster, one of China's three major urban agglomerations.

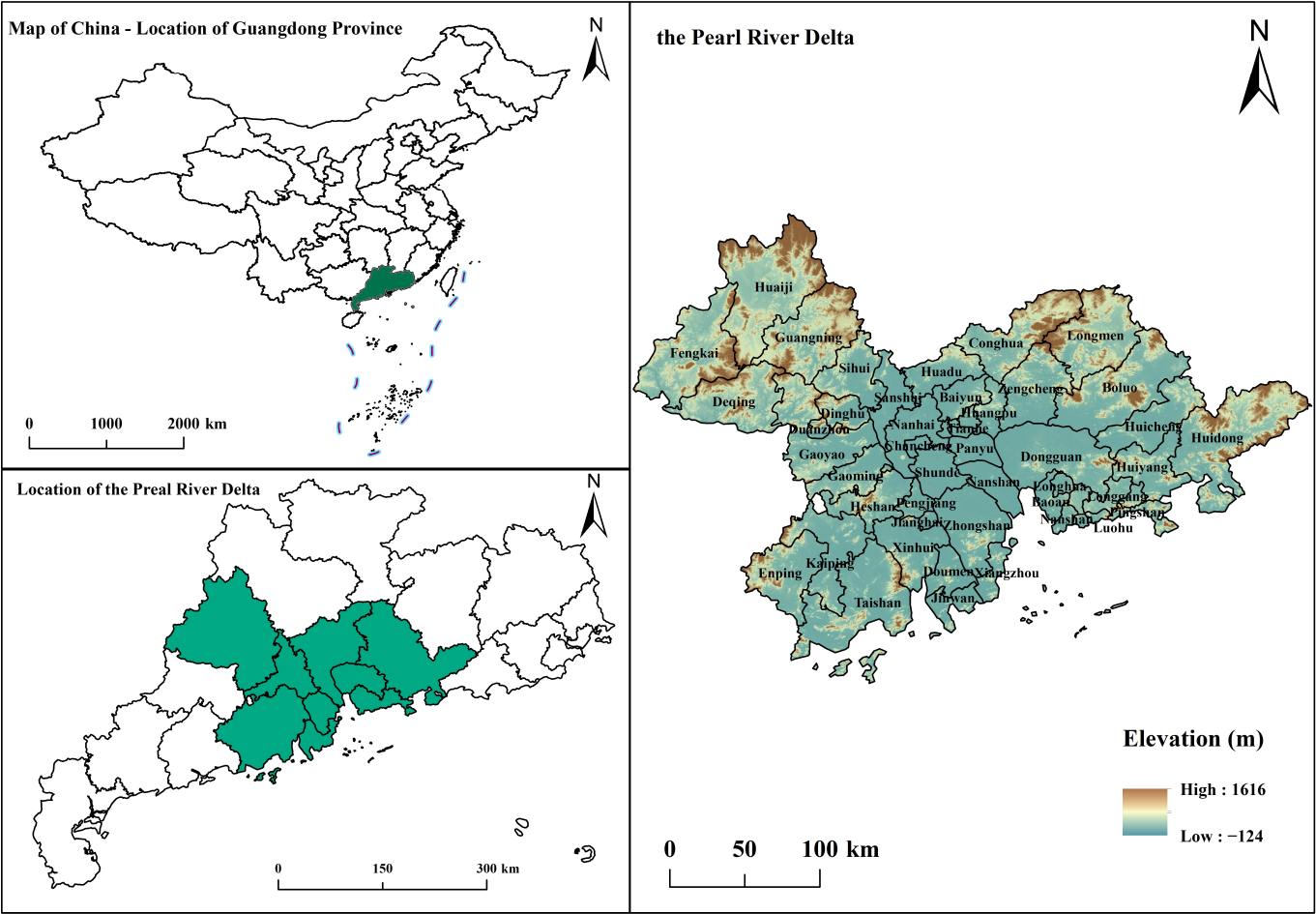


Figure 1. Study area.

2.2. Data Source

This research specifically examines the Pearl River Delta area and analyzes data on several carbon emission indicators, including raw coal, coke, domestic glass goods, pig iron, home waste emissions, household wastewater emissions, and industrial wastewater emissions. Indicators of economic development level, population size, urbanization level, energy intensity, and road network density are used as factors influencing urbanization-related carbon emissions. The Guangdong Statistics Yearbooks from 2009 to 2019 are the main source of the aforementioned statistics information. Linear interpolation and other sources like national economic and social development announcements and local statistics yearbooks are used to augment missing data [31]. Table 1 displays the specific information needed for this investigation.

Table 1. Details of each data.

Data Name	Data Description	Source
Fossil Fuel Consumption Data	Total annual energy consumption (raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, etc.)	Guangdong Provincial Statistical Yearbook, China Energy Statistical Yearbook, and Municipal Statistical Yearbook, 2009–2019
Industrial Production Data	Total production of industrial products (daily glass products, pig iron, crude steel, finished steel, cement, flat glass, etc.)	
Solid Waste Discharge Data	Domestic waste emission	
Wastewater Discharge Data	Domestic wastewater discharge, industrial wastewater discharge	

Table 1. Cont.

Data Name	Data Description	Source
Socio-economic Data	Annual gross domestic product, permanent resident population at the end of the year, urban population, gross domestic product of the secondary industry, gross domestic product of the tertiary industry, energy intensity, number of kilometers opened to traffic, etc.	Guangdong Provincial Statistical Yearbook and Municipal Statistical Yearbook, 2009–2019
Administrative Boundary	Pearl River Delta city, county vector boundary	National Geographic Information Directory Service
Urban Area	Data redefined in 2016	

3. Research Methods

3.1. Calculation of Carbon Emissions

Urban areas bear a substantial burden of carbon emissions. Energy consumption, industrial production processes, solid waste, and waste-water carbon emissions are all factors that contribute to the environmental impact of cities in terms of their production and everyday activities. Carbon emissions stem from energy use in various industries. Additionally, energy consumption in industrial processes, such as the production of cement, lime, and glass, constitutes industrial production energy consumption, leading to carbon emissions from industrial production processes. Cities also handle a considerable amount of municipal and industrial waste, and the incineration, landfilling, and treatment of these wastes contribute significantly to carbon emissions.

This research assesses carbon emissions from four aspects: energy consumption, industrial production processes, solid waste, and wastewater, by using pertinent studies and employing the calculating methodologies specified by the Intergovernmental Panel on Climate Change (IPCC) [28,32,33]. This estimate does not take into account carbon emissions from agricultural production activities such as straw burning. The precise calculating procedure is as follows:

$$C_n = Q_{n\sim i} \times e_{n\sim i} \quad (1)$$

$$C_g = Q_{g\sim i} \times e_{g\sim i} \times 12 \div 44 \quad (2)$$

$$C_{wb} = Q_{wb} \times V_w \times P_w \times EF_w \quad (3)$$

$$C_{wf} = Q_{wf} \times 0.167 \times (1 - 75\%) \quad (4)$$

$$C_{g1} = N_p \times BOD \times SBF \times C_{BOD} \times FTA \times 365 \quad (5)$$

$$C_{g2} = Q_{wf} \times COD \times C_{COD} \quad (6)$$

In the formula, C_n shows the carbon emissions resulting from energy consumption, $Q_{n\sim i}$ denotes the energy type i th's usage, and $e_{n\sim i}$ shows the energy type i th's carbon emission coefficient. Class i industrial product consumption is denoted by $Q_{g\sim i}$, the carbon emission coefficient of Class i industrial goods is $e_{g\sim i}$, and C_g is the carbon emission of the industrial production process. The carbon emissions from waste incineration are denoted by C_{wb} , Q_{wb} , V_w , and P_w . The percentages of carbon content and mineral carbon in waste are 40% and 40%, respectively, and the total combustion efficiency of the waste combustion furnace is represented by EF_w , which is 95%. The landfill's water content is 71.5%, its carbon emission is C_{wf} , its quantity is Q_{wf} , and its CH_4 emission coefficient is 0.167. N_p is the population and C_{g1} is the carbon emissions from home wastewater. BOD stands for the organic matter content per capita, SBF for readily precipitable BOD , C_{BOD} for BOD emission factor, and FTA for BOD that degrades in wastewater without oxygen. The carbon dioxide (C_{g2}) emission of industrial wastewater is determined using the average COD value of different industrial wastewater reported by the IPCC. The maximal ability

to produce CH_4 is represented by C_{COD} . Q_{wf} is the volume of wastewater. COD is the chemical oxygen demand.

3.2. Spatial Autocorrelation

The first law of geography is that there is a higher likelihood of correlation between occurrences that are near each other. Within a certain geographical extent, the entire spatial dependency is reflected by global spatial autocorrelation [34]. This work computes the global geographical autocorrelation using Moran's I [35,36]. The exact method for calculating it is as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (7)$$

In the formula, variables x_i and x_j define the carbon emissions comprising unit i and unit j , respectively. W_{ij} represents the geographic weighting matrix of each unit i and unit j inside the research region. Moran's I is a statistical measure that ranges from -1 to 1 . If the value is greater than zero, it shows a positive connection. When the value of I is less than 0 , it indicates a negative correlation, with a greater magnitude indicating a greater amount of autocorrelation between spaces. When the value of I is equal to 0 , it signifies an arbitrary distribution of space.

This article employs Getis-Ord G_i^* to examine the hot spots and cold spots in order to further investigate the accumulation regions of extreme and low values in space [37–39]. The precise computation procedure is as follows:

$$G_i^* = \frac{\sum_{i=1}^n W_{ij} x_i}{\sum_{i=1}^n x_i} \quad (8)$$

In the formula, the geographical weighting matrix, W_{ij} , represents the relationship across each unit i and unit j in the research region. When G_i^* exhibits strong regularity, it indicates that the region is a concentrated area of high value, sometimes referred to as a hot spot. If G_i^* is strongly negative, it suggests the region represents a low-value accumulation area, namely a cold spot area.

3.3. Grey Correlation Degree

The Grey Relational Analysis method utilizes the geometric similarity of sequence curves to determine whether different sequences are closely linked, which can make up for the deficiencies of combining statistical system analysis and has no special requirements on the required sample size [40]. Therefore, it can eliminate the errors caused by the limited sample size and has now become an effective tool for measuring the drivers of carbon emissions [41,42].

Based on the current research, the following nine elements that have an impact were chosen: The city's economic growth has a beneficial effect on carbon emissions inside its boundaries [43]. The yearly gross domestic product (GDP) serves as an index to gauge the economic status of each city. Urbanization results in growth in the urban population, but the focal point of urbanization is the concentrated makeup of people living in cities [44]. In this study, the year-end resident population and the proportion of the urban population to the total population are selected as indicators of population size and urbanization level. The secondary industry in China is responsible for 70% of the pollution generated by the production of goods [45]. Therefore, the scale of the secondary industry can be used as an indicator to examine the connection between urbanization and carbon emissions [46]. Additionally, the total economic output of the secondary industry is used as a measure of its size. The size of the tertiary industry scale is an indicator of the level of coordination during urban growth in the process of urbanization [47]. The gross domestic product of the tertiary industry is used to measure the size of the tertiary industry scale. The process of carbon emission is heavily influenced by energy intensity, making it the primary driving

factor [48]. Urbanization results in a larger land area being used [44] and the density of road networks is used as a measure of spatial urbanization. Foreign investment does not have a substantial impact on carbon emissions in China as a whole. However, it does have a major impact on carbon emissions in areas with varying energy intensities [49]. Therefore, this article considers foreign investment as a key factor. The role of science and technology in reducing carbon emissions has been generally acknowledged [50]. This article uses the number of patents as an indicator of the degree of technology in a certain region. Table 2 displays the elements that influence the variations in carbon emissions across different locations and time periods.

Table 2. Influences on the variations in carbon emissions in terms of distance and time.

Influence Factor	Unit	Indicator Specification	Symbol
Economic Development	10,000 yuan	Gross Annual Product	X_1
Population Size	10,000	Permanent Population at the end of the Year	X_2
Urbanization Level	%	Proportion of Permanent Urban Population in Total Population	X_3
Secondary Industry Scale	%	Proportion of the Gross Product of the Secondary Industry to the Gross Product	X_4
Tertiary Industry Scale	%	Proportion of the Gross Product of the Tertiary Industry to the Gross Product	X_5
Energy Intensity	Tons of standard coal/10,000 yuan	Ratio of Total Energy Consumption to Gross Domestic Product	X_6
Road Network Density	km/km ²	Traffic Mileage Per Square Kilometer	X_7
Foreign Investment	10,000 yuan	Cities Utilize Actual Foreign Investment	X_8
Technological Level	individual	Number of Patents Granted	X_9

Dimensionalization without meaning is used to standardize the data. To get the gray correlation coefficient, the following precise calculation method is used:

$$\xi_i(t) = \frac{\min_i[\Delta_i(\min)] + \rho \max_i[\Delta_i(\max)]}{|x_0(t) - x_i(t)| + \rho \max_i[\Delta_i(\max)]} \quad (9)$$

$$\Delta_i(\min) = \min_t |x_0(t) - x_i(t)| \quad (10)$$

$$\Delta_i(\max) = \max_t |x_0(t) - x_i(t)| \quad (11)$$

where t is year t and ρ is the resolution; this paper takes 0.5.

Grey relational degree r_i is obtained as:

$$r_i = \frac{1}{n} \sum_{t=1}^n \xi_i(t) \quad (12)$$

In the formula, the closer the correlation degree is to 1, the higher the correlation degree.

4. Results

4.1. Urban Carbon Emissions

It is evident from Figure 2 that the Pearl River Delta's carbon emissions measurement data indicate an overall rise in carbon emissions from energy use in the PRD between 2009 and 2019. Foshan witnessed the highest surge, adding 16.338 million tons, while Guangzhou experienced a reduction of 8.616 million tons in energy-related carbon emissions. The proportion of Foshan's energy-related carbon emissions in the PRD as a whole increased by 9.56% over time. In contrast, Guangzhou's share decreased from 28.74% to 15.42%.

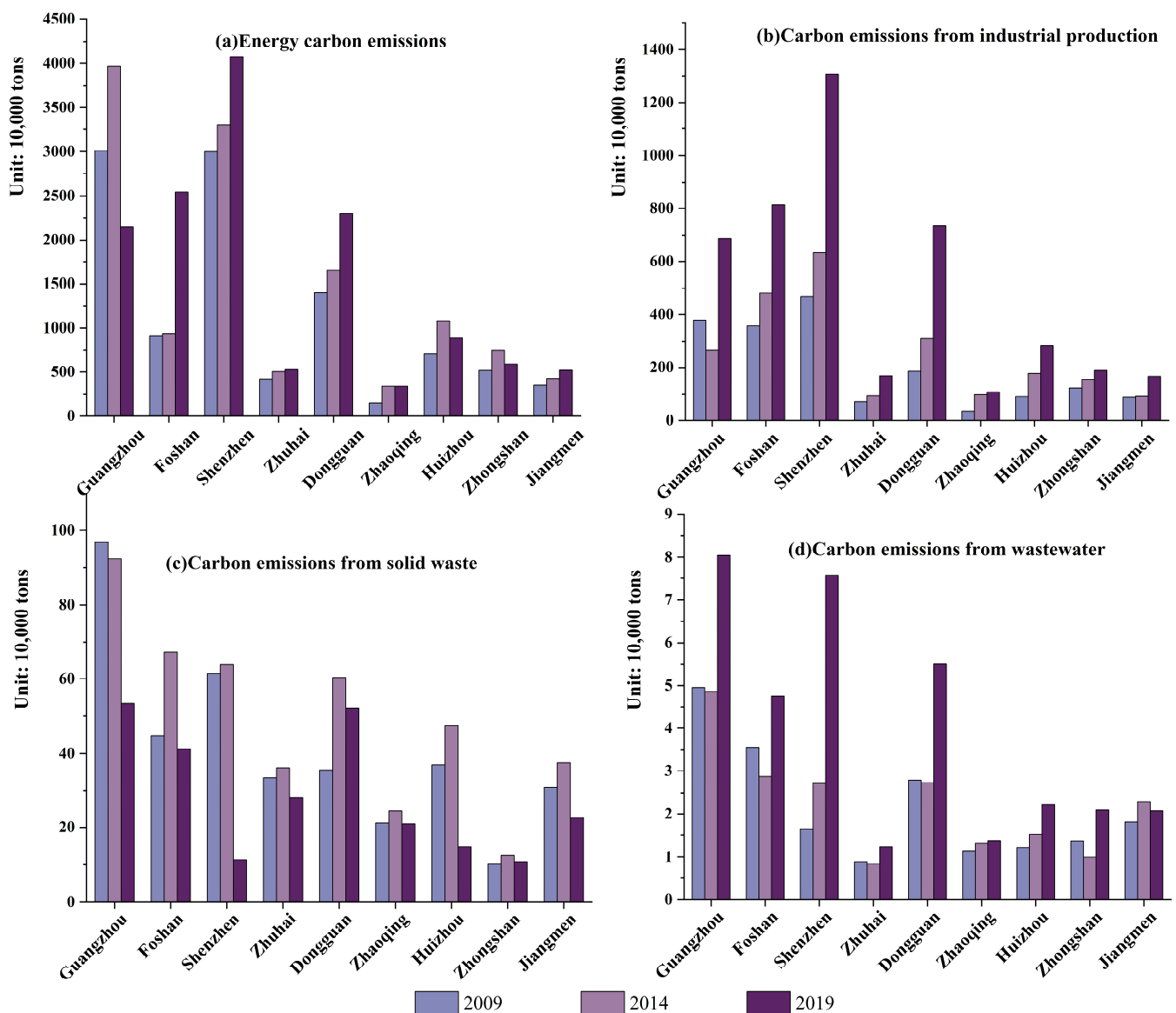


Figure 2. Carbon emissions from various sectors in the Pearl River Delta, 2009–2019.

For carbon emissions from industrial production, all the PRD cities recorded an overall increase, with Shenzhen leading the surge by 8.363 million tons and Zhaoqing having the smallest increase of 0.731 million tons. The proportion of industrial production carbon emissions for most cities showed a declining trend, with Guangzhou decreasing by 5.56%. However, Dongguan's proportion increased, rising from 10.25% to 16.49%.

Regarding carbon emissions from solid waste, an increase was observed from 2009 to 2014, followed by a decrease from 2014 to 2019. Carbon emissions from solid waste were significantly reduced in Shenzhen, Guangzhou, and Huizhou; they were down about 0.501 million tons, 0.436 million tons, and 0.221 million tons, respectively. Carbon emissions from solid waste in Dongguan increased to 0.204 million tons from 0.096 million tons. Dongguan also saw a 10.85% increase in the proportion of solid waste carbon emissions, while Shenzhen, Guangzhou, and Huizhou experienced decreases of 12.11%, 5.24%, and 4.15%, respectively.

Compared to carbon emissions from industrial production, wastewater carbon emissions generally showed an upward trend. Dongguan had the smallest increase, with carbon emissions rising about 0.021 million tons to 0.027 million tons, while Shenzhen and Guangzhou experienced the largest increases, adding 0.059 million tons and 0.031 mil-

lion tons, respectively. Wastewater carbon emissions represent the smallest portion of overall carbon emissions. Shenzhen's proportion increased from 8.45% to 21.72%. Although Guangzhou and Foshan saw significant increases in carbon emissions, their proportions decreased by 2.57% and 4.76%, respectively.

4.2. County Carbon Emissions

A geographical study of carbon emissions throughout the process of urbanization within the Pearl River Delta for major periods 2009, 2014, and 2019 was undertaken using ArcGIS 10.8 software. The purpose was to visually represent the variations in carbon emissions across different locations (Figure 3).

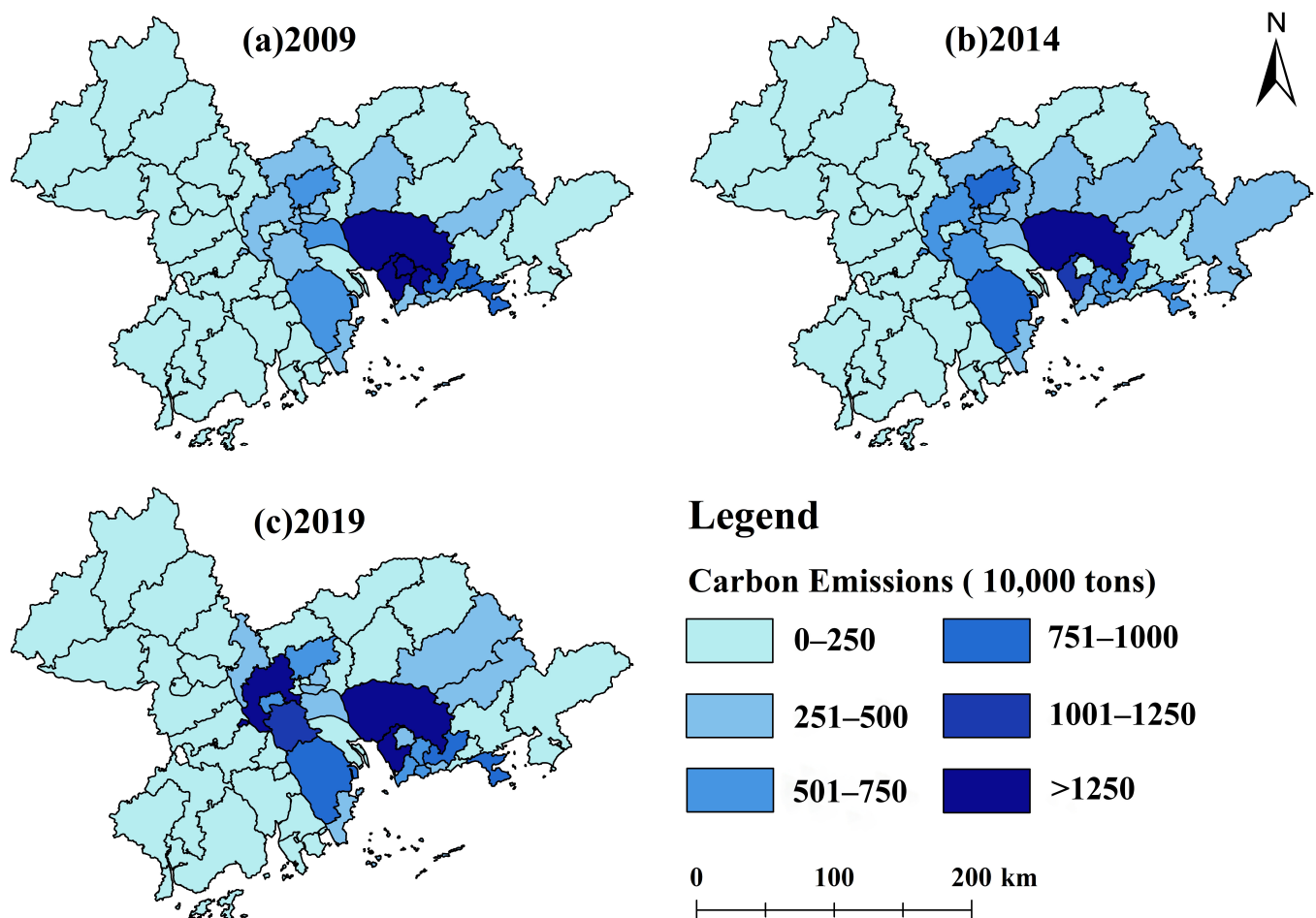


Figure 3. 2009–2019 carbon emissions in the Pearl River Delta counties.

The timeframe from 2009 to 2019 demonstrates an aggregate growing trajectory in carbon emissions throughout the PRD. In 2009, at the county level within the PRD, the majority of carbon emissions were below 5 million tons, with one-third even falling below 1 million tons. By 2019, most county-level carbon emissions exceeded 2 million tons, with an increasing number of counties surpassing 6 million tons.

From a geographical standpoint, the carbon emissions in the PRD region exhibit a pattern of being “high in the east and low in the west”. The southern portion of the PRD Central Axis exhibits the highest levels of carbon emissions, primarily attributed to economic advancement, high population density, and frequent consumption. In 2009, carbon emissions were predominantly concentrated in Bao’an, Longgang, Zhongshan, Baiyun, and other regions. However, by 2019, the concentration shifted to Dongguan, Bao’an, Nanhai, Shunde, and Longgang. Notably, Nanhai and Shunde experienced significant growth in

carbon emissions between 2009 and 2019, while Shenzhen, Foshan, Dongguan, and Zhuhai exhibited the most substantial increase in emissions.

4.3. Spatial Aggregation Characteristics

The research investigated the geographical distribution of carbon emissions in Guangdong Province from 2009 to 2019, using global spatial autocorrelation analysis (Table 3). The findings showed a strong positive connection in carbon emissions, suggesting that emissions had a tendency to cluster. Areas with higher emissions were found to be next to other areas with higher emissions, while areas with lower emissions were next to each other. Regarding specific numerical values, Moran's I index exhibited a decreasing trend, declining from 0.329 to 0.168, indicating a reduction of 48.9%. This points towards a diminishing spatial interdependence and clustering of carbon emissions, primarily attributed to the gradual reduction in cold spots.

Table 3. Global carbon emissions index, Moran's I index, 2009–2019.

Year	2009	2014	2019
Moran's I	0.329	0.275	0.168
Z-score	3.911	3.836	2.443
p	0.000009	0.000125	0.00145

The Pearl River Delta region's carbon emissions are intricately clustered, with concentrated zones with high and low emissions mostly located in the northwest and western regions (Figure 4). In 2009, Kaifeng, Deqing, Guangning, Sihui, Dinghu, Duanzhou, and Gaoyao had a low–low clustering pattern, but western Dongguan and Shenzhen showed a high–high clustering pattern. In 2014, Gaoming, Kaiping, and Enping were added to the low domain. In 2019, low–low clusters were detected in Fengkai, Deqing, Sihui, Gaoyao, and Duanzhou, whereas low–high clusters were found in Guangming and Nansha. While the high–high cluster is mostly concentrated in Shenzhen and Dongguan, the low–low cluster resides primarily in the western and northwest parts of the PRD. However, there exist substantial geographical disparities within Guangzhou and Shenzhen, resulting in low and high clusters also being concentrated in these places. The time scale development reveals minor fluctuations in the clusters of high and low values, with the low clusters moving from the Northwest to the West and then returning to the Northwest. This suggests that carbon emissions in the Northwest are rising.

A study using the Getis-Ord G_i^* method was performed to detect the specific local correlation patterns of carbon emissions throughout the process of urbanization in Guangdong Province (Figure 5). The findings indicated that the areas with the highest concentrations of carbon emissions in the Pearl River Delta (PRD) region between 2009 and 2019 were mostly located in Shenzhen, Dongguan, and Guangzhou. In 2009, Zengcheng, Huangpu, Panyu, and Longgang had a hotspot confidence level of 95%, while Bao'an, Nanshan, Futian, Luohu, Nansha, and Dongguan had a higher confidence level of 99%. In 2014, the cities of Guangzhou, Shenzhen, and Dongguan exhibited the highest levels of confidence in terms of becoming hotspots. In 2019, the number of locations with a hotspot confidence level of 99% decreased, while Bao'an, Guangming, Longhua, Nanshan, Futian, and Luohu had confidence levels of 95%. This is due to both the increasing emissions from places with relatively lower carbon emissions and the elevated carbon emissions inside the PRD.

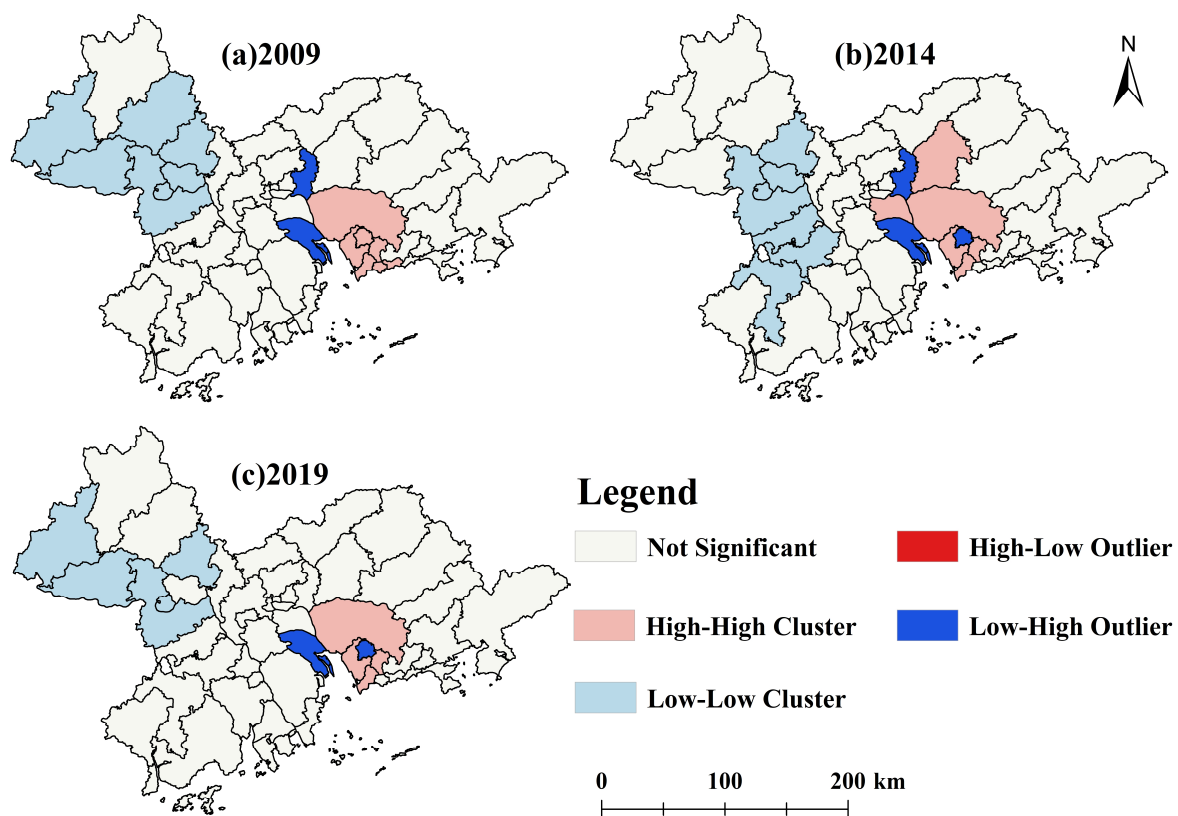


Figure 4. High and low carbon emissions in the Pearl River Delta are clustered, 2009–2019.

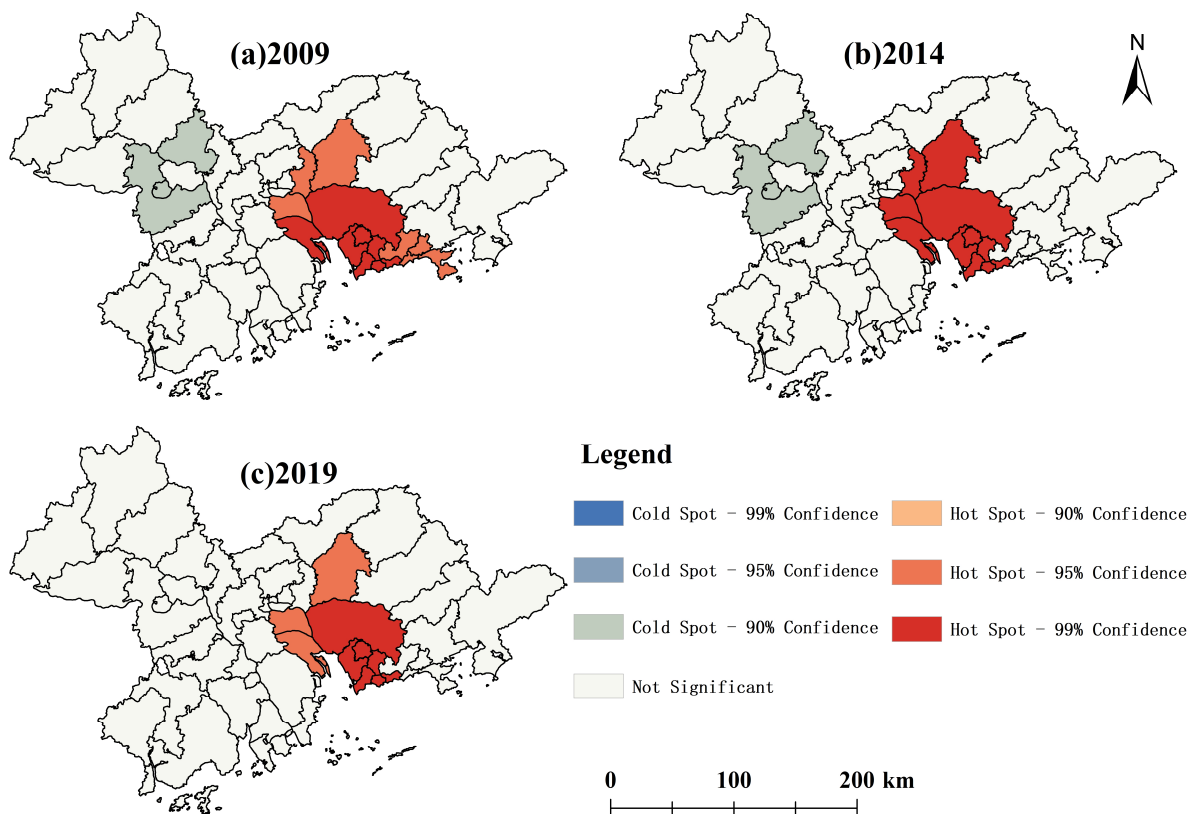


Figure 5. Pearl River Delta cold and hot spots in 2009–2019.

4.4. Analysis of Urban Carbon Emission Drivers

4.4.1. Gray Correlation Cross-Section Analysis Results

All relevant factors were accurately represented and analyzed using the results of the gray relational analysis (Figure 6). The research examined the relationship between the amount of urbanization, the structure of the secondary industry, and the density of the road network in Guangzhou and Shenzhen. It also investigated the variables that affect carbon emissions in Zhuhai and Shenzhen. The variables with stronger connections were urbanization level, secondary industry structure, and road network density, while the variables with weaker correlations were foreign investment and technology level.

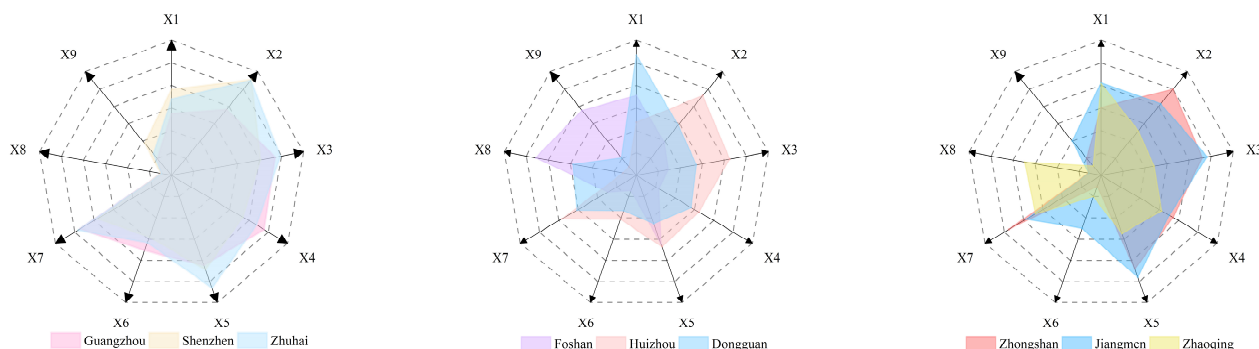


Figure 6. Grey correlation degree of carbon emission driver cross-section in the Pearl River Delta.

Zhuhai and Shenzhen have comparable sources of carbon emissions; however, Shenzhen's sources are more significant in terms of quantity. The determining variables in Zhuhai's impact are primarily its economic growth and the scale of its secondary sector, which is benchmarked against Shenzhen. The hierarchy of influencing variables in Zhuhai may be summarized as follows: population size, size of the tertiary industry, degree of urbanization, density of the road network, Shenzhen (replacing economic development and size of the secondary industry), energy intensity, level of research and technology, and foreign investment.

The correlation between Dongguan and Zhaoqing in terms of economic growth is 0.936 and 0.808, respectively. With correlations of 0.707 and 0.692, respectively, the relationship between the influencing factors of carbon emissions in Dongguan and the density of the road network and population size is also greater. The correlation between Zhaoqing's carbon-emission-influencing factors and energy intensity is 0.500, while the correlation between carbon-emission-influencing factors and technology level is 0.456.

In Foshan, foreign investment is the primary contributor to carbon emissions, with a value of 0.857, while energy intensity has the lowest impact, with a value of 0.471. The growth in carbon emissions in Jiangmen may be attributed to the high degree of urbanization and the significant amount of the tertiary sector, with coefficients of 0.882 and 0.880, respectively. The association between Jiangmen and carbon emissions is weakest in the case of foreign investment, with a coefficient of 0.456.

The rising population of Shenzhen, Zhuhai, Huizhou, and Zhongshan has a substantial impact on carbon emissions due to the process of urbanization. These cities have lower levels of impact from characteristics such as energy intensity and transportation network density.

4.4.2. Gray Correlation Time Series Analysis Results

The gray relational analysis indicates that the influence of economic growth, population size, and transportation network density on cities has changed over time (Table 4). In 2009, Guangzhou was mostly influenced by economic growth, whilst Zhongshan was primarily impacted by population size. Foshan was most significantly affected by foreign

investment, but both road network density and foreign investment had the greatest effect on Huizhou.

Table 4. The Pearl River Delta’s carbon emissions driving elements have a grey correlation degree, 2009–2019.

Area		Guangzhou	Shenzhen	Zhuhai	Foshan	Huizhou	Dongguan	Zhongshan	Jiangmen	Zhaoqing
Year	Influence Factor									
2009	X ₁	1.000	0.867	0.932	0.712	0.821	0.956	0.982	0.963	0.932
	X ₂	0.624	0.520	0.914	0.836	0.871	0.861	0.997	0.677	0.622
	X ₃	0.397	0.435	0.556	0.779	0.823	0.983	0.582	0.751	0.682
	X ₄	0.346	0.368	0.583	0.753	0.642	0.863	0.576	0.550	0.631
	X ₅	0.463	0.417	0.592	0.853	0.814	0.971	0.696	0.658	0.531
	X ₆	0.340	0.336	0.704	0.654	0.600	0.741	0.341	0.587	0.486
	X ₇	0.403	0.373	0.697	0.749	0.765	0.735	0.694	0.589	0.651
	X ₈	0.627	0.719	0.802	0.981	0.889	0.869	0.940	0.864	0.755
	X ₉	0.436	0.658	0.920	0.548	0.682	0.880	0.806	0.816	0.901
2014	X ₁	0.882	0.822	0.922	0.736	0.757	0.798	0.924	0.984	0.988
	X ₂	0.673	0.595	0.891	0.756	0.996	0.859	0.977	0.699	0.712
	X ₃	0.390	0.465	0.551	0.732	0.922	0.952	0.610	0.652	0.763
	X ₄	0.334	0.389	0.577	0.700	0.685	0.793	0.605	0.564	0.566
	X ₅	0.457	0.460	0.585	0.930	0.943	0.993	0.700	0.609	0.632
	X ₆	0.338	0.409	0.629	0.726	0.579	0.845	0.622	0.525	0.470
	X ₇	0.386	0.363	0.727	0.755	0.917	0.623	0.566	0.615	0.650
	X ₈	0.600	0.854	0.755	0.878	0.970	0.706	0.770	0.959	0.807
	X ₉	0.500	0.564	0.927	0.737	0.701	0.822	0.733	1.000	0.829
2019	X ₁	0.458	0.925	0.985	0.645	0.898	0.631	0.987	0.990	0.993
	X ₂	0.570	0.567	0.934	0.657	0.901	0.774	0.921	0.759	0.729
	X ₃	0.744	0.411	0.563	0.672	0.773	0.724	0.581	0.675	0.734
	X ₄	0.550	0.362	0.567	0.713	0.624	0.701	0.582	0.572	0.640
	X ₅	0.958	0.391	0.630	0.627	0.704	0.628	0.642	0.665	0.585
	X ₆	0.577	0.360	0.626	0.450	0.462	0.623	0.581	0.559	0.486
	X ₇	0.736	0.337	0.735	0.666	0.795	0.822	0.536	0.643	0.649
	X ₈	0.439	0.540	0.584	0.420	0.871	0.509	0.876	0.984	0.861
	X ₉	0.667	0.745	1.000	0.631	0.789	0.910	0.747	0.928	0.876

In 2014, Zhaoqing was mostly influenced by economic development, while Zhongshan was primarily impacted by population size. The effect on Dongguan was primarily influenced by the amount of urbanization, the structure of the secondary sector, the structure of the tertiary industry, and the intensity of energy use. Huizhou was most significantly influenced by road network density and foreign investment, whereas Jiangmen was most significantly influenced by the degree of research and technology.

In 2019, the economic factor had the most significant influence on Zhaoqing, while population size, energy intensity, and science and technology level had the most effect on Zhuhai. Shenzhen had the greatest fluctuation in its impact factor, with foreign investment playing the most prominent role. The most significant transformation in Zhuhai between 2009 and 2014 occurred in terms of energy intensity, but the most substantial shift between 2014 and 2019 was seen in foreign investment.

During the research period, Huizhou exhibited the highest population size, urbanization level, secondary industry structure, tertiary industry structure, road network density, and foreign investment. In Dongguan, the population size and foreign investment effect indices are consistently decreasing, while the impact indices of tertiary industrial size and energy intensity show an initial increase followed by a decrease. The foreign investment effect index in Jiangmen is on the rise, whereas the impact index of the scientific and technology level first climbs and then declines. Zhaoqing has very minor fluctuations in each of the impact variables but displays more pronounced variations in economic level, population size, and foreign investment.

5. Discussion

5.1. Discussion of the Research

This research presents three primary advancements. Firstly, it quantifies the amount of carbon dioxide released into the atmosphere as a result of urbanization. This is done by considering four specific sectors: energy consumption, industrial production processes, solid waste, and wastewater emissions. This broadens the range of carbon emissions that occur during urbanization, instead of just considering carbon emissions connected to energy. Furthermore, it examines the changing patterns of carbon emissions at the county level, providing a more in-depth comprehension of the characteristics of emission evolution at a very small scale. Finally, it scrutinizes the variables that have an impact on carbon emissions, assessing the specific roles played by each element. This analysis may serve as a realistic foundation for the government to develop policies aimed at reducing carbon emissions.

An attempt is put forward to confirm the dependability of the findings through contrasts of what is learned from this investigation with previous research results. Zhao et al. discovered that carbon emissions from land use within the study area follow a distribution pattern characterized by high values in the central region and lower values in the surrounding areas [51]. The geographic distribution pattern for urban carbon emissions has a resemblance with the observed pattern of “high in the east and low in the west” in this research.

Regarding the elements that influence carbon emissions, several researchers have extensively examined these aspects using the MEIC model. Their study reveals that economic urbanization has the greatest influence on carbon emissions [52]. Researchers have used the LMDI model to break down carbon emissions by industry and city in the Pearl River Delta area. Their analysis has shown that the rise in carbon emissions is mostly driven by economic expansion and population impact [53]. Researchers have analyzed carbon emissions in the context of urban agglomeration geography and discovered a notable polarization occurrence in the Pearl River Delta. This indicates an imbalance in regional development [23]. The results described above align closely with the outcomes of this investigation. Hence, it is essential to implement customized management and governance measures for carbon emissions, in addition to developing appropriate plans.

5.2. Carbon Emissions Optimization Policy

(1) Tailor-Made, Differentiated Carbon Emission Control Strategies.

In response to the spatial clustering and spatiotemporal differences of carbon emissions, regions with high carbon emissions should promote inter-city cooperation to foster the development of high-tech and innovative industries, forming collaborative emission reduction mechanisms across regions. For high-emission areas such as Guangzhou, Shenzhen, Foshan, and Dongguan, which are economically developed cities, emphasis should be placed on developing green industries, promoting clean and low-carbon energy, and optimizing industrial and energy structures [54–56]. Particularly in reducing carbon emission intensity, these cities should intensify efforts in research and application of new energy vehicles, renewable energy, and high-efficiency technologies. Meanwhile, economically weaker cities such as Zhaoqing, still in the industrialization phase, are expected to see an increase in carbon emissions [57,58]. Therefore, these cities need to prioritize reducing carbon emission intensity and promoting clean energy use as the core of clean production, driving the transformation of traditional industries towards green and low-carbon industries.

(2) Advancement of environmentally friendly technology, enhancement of energy infrastructure efficiency, and provision of policy direction.

To address the ongoing rise in carbon emissions in the Pearl River Delta region, policymakers ought to decrease the utilization of high-carbon energy sources like coal and coke. They should also limit the growth of energy-intensive industries and develop more logical regulations at the local government level to ensure the improvement of energy composition. It is important to actively promote the use of natural gas and renewable

energy and to stimulate the replacement of fossil fuels with low-carbon energy sources in order to decrease carbon emissions [59,60]. In addition, it is crucial to develop and enforce stringent carbon emission regulations and evaluation systems to encourage the adoption of environmentally friendly technology and renewable energy sources, enhance energy efficiency, and facilitate the widespread use and commercialization of eco-friendly and low-carbon technologies.

(3) People-Oriented Approach, Advancing Green Technology Innovation, and Low-Carbon Community Construction.

The Pearl River Delta, being a highly developed region economically, ought to concentrate on managing population size, enhancing population structure and quality, investigating the development of low-carbon homes and communities, and encouraging the adoption and popularization of low-carbon lifestyles [61,62]. The government must increase its support for green technology and alternative energy innovation, as well as set up suitable incentive systems and policy support in order to promote the development of new low-carbon industry types, optimize the industrial structure, and encourage the growth of green industries and technological innovation [63]. Through initiatives like the creation of green innovation funds, tax breaks, and fiscal subsidies, companies and academic institutions should be encouraged to carry out scientific investigations as well as the application of green technologies. They should also be encouraged to support the creation and growth of low-carbon cities, establish a supportive environment and policy framework, and advance the Pearl River Delta region's transition to a low-carbon economy.

5.3. Research Limitations and Perspectives

There are several further restrictions on this research. Firstly, regarding the method for calculating carbon emissions, although IPCC has become one of the most commonly used methods for carbon emission calculation, issues still exist due to its inherent limitations, leading to inaccuracies in carbon emission calculations. Secondly, climate and terrain factors were not considered in the carbon emission calculations. Lastly, the study used economic development and population size as driving factors, but the analysis may not be sufficiently in-depth. Therefore, future research could address these limitations by first considering factors such as climate and terrain in carbon emission calculations and validating the accuracy of the estimated data by fitting it with widely used techniques for estimating carbon emissions, such as data from evening lights. Second, using more specific social and economic variables to investigate the influence of variables like public attitudes, education level, and income distribution on environmental concerns in the study of population growth and economic development.

6. Conclusions

This research used the gray relational model and spatial analysis to examine the spatiotemporal distribution patterns of carbon dioxide throughout the urbanization process using data from nine cities in the PRD between 2009 and 2019. The present investigation also examined the impact of relevant influencing factors on carbon emissions. The following are the outcomes:

Firstly, there was an increase in the region's total carbon emissions from 2009 to 2019 in the Pearl River Delta. The biggest amount of carbon emissions came from energy-related sources, then the industrial output; the lowest percentage came from wastewater-related sources. Guangzhou showed a decrease in carbon emissions due to energy use, whereas Foshan and Shenzhen saw the largest increases in carbon emissions.

Secondly, there is an "east-high, west-low" trend in the geographical distribution of carbon emissions in the Pearl River Delta region. The majority of regions with comparatively large carbon emissions are found in places like Baiyun District, Zhongshan City, Longgang District, and Bao'an District. The carbon emissions in these regions rose even more in 2019, exhibiting a pronounced geographical clustering impact. The Pearl River Delta region's spatial autocorrelation of carbon emissions dropped from 0.329 to

0.168 between 2009 and 2019, according to global Moran's *I* analysis. This implies that the reduction in cold spot regions is the primary cause of the progressive weakening of the spatial linkages and clustering degree of carbon emissions.

Thirdly, gray relational analysis shows that while economic growth has a significant influence on carbon emissions, its impact is declining while the impact of technological level is increasing. When comparing the gray-related degrees of two cities, Zhaoqing and Jiangmen, the disparities in each carbon-emission-influencing factor were not more than 0.150. However, with variances of around 0.500 in each carbon-emission-influencing component, Guangzhou and Foshan showed greater fluctuations.

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