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The Distribution and Impact Characteristics of Small-Scale Carbon Emissions in the Chengdu–Chongqing Region

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Abstract: In order to realize low-carbon and high-quality development, this study took the carbon emissions of each district and county in the Chengdu–Chongqing region from 2005 to 2017 as the research object and used the spatial autocorrelation model to analyze the spatial and temporal evolution characteristics of carbon emissions in the counties of the Chengdu–Chongqing region, so as to fill in the research blank of carbon emissions in the counties of the Chengdu–Chongqing region. Then, the geographical detector model is used to explore the interaction among influencing factors of carbon emissions and reveal the time changes and regional differences of influencing factors, so as to improve the lack of spatial and temporal heterogeneity of influencing factors of carbon emissions by geographical detector. The results show the following: (i) The overall carbon emissions of counties show a year-on-year growth trend with the main urban areas of Chengdu and Chongqing as the core, but the growth rate slows down after 2010. (ii) The carbon emissions showed a significant positive spatial autocorrelation, and the neighboring counties showed a spatial clustering characteristic of "high-high" or "low-low", and the clustering status tended to be enhanced. (iii) The carbon emissions are strongly influenced by industrial structure, economic development, investment level, financial situation, urbanization rate and social consumption, and their interactions are all enhanced, but the influence mostly tends to rise first and then fall. (iv) County carbon emissions can be divided into four types of geographical types, such as population size influencing type, urbanization rate influencing type, economic development influencing type and industrial structure influencing type. Therefore, a variety of factors need to be considered comprehensively, a multi-pronged approach, and a comprehensive policy to realize low-carbon transformation in the Chengdu–Chongqing region.

Keywords: Chengdu–Chongqing region; carbon emission; county scale; influencing factors

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1. Introduction

Located at the intersection of China's strategic urbanization pattern of "two horizontal and three vertical", the Chengdu–Chongqing region is a region with the highest level of development and great development potential in western China. It is the "fourth pole" of China's economic growth, following the Beijing–Tianjin–Hebei region, the Yangtze River Delta, and Guangdong, Hong Kong and Macao. By 2035, it will be an active growth pole with international influence and a powerful driving force for economic development. Under the guidance of the goal of "carbon peak by 2030 and carbon neutral by 2060", the Chengdu–Chongqing region is undoubtedly facing great challenges to promote a rapid economic rise and realize low-carbon and circular development. Counties are the basic spatial units and carriers of economic development and industrial transfer [1], as well as the main body to implement carbon emission reduction in China, accounting for 73% of the population, 60% of the GDP and 50% of carbon emissions [2]. Therefore, a detailed study of the spatio-temporal evolution of carbon emissions in Chengdu–Chongqing and its impact factors, starting from the county scale, will be an excellent reference for implementing low-carbon, high-quality development in Chengdu–Chongqing and improving the scientific, targeted and operational nature of energy conservation and emission policies.

As for the analysis of the spatial-temporal evolution characteristics of carbon emissions, scholars mainly used the coefficient of variation, Gini coefficient, Taylor index, standard deviation ellipse, kernel density estimation and other methods to investigate the spatial differences of carbon emissions [3–8]. For example, Sun et al. [3] analyzed the existence of carbon inequality at the urban level in China by using the kernel density estimation method and concluded that the carbon inequality at the urban level showed a declining trend during the study period through the coefficient of variation method. Liu Huajun et al. [8] discovered, by using the method of standard deviation ellipse and barycenter shift, that the barycenter of carbon emission distribution in China gradually moved westward, showing a trend of centripetal agglomeration in the direction of northeast–southwest and spatial divergence in the direction of northwest–southeast. A three-stage nested decomposition of the Theil index finds significant spatial differences, with an overall downward trend in the differences. However, the above research methods treat the research units as independent individuals and ignore the spatial correlation of geographic data, which may lead to a bias in the distribution of research objects [9]. Some scholars further studied the spatial correlation analysis of China's carbon emissions using the Moran's I index and generalized spatial model [10,11]. For example, Ying Wang et al. [12] found that there was a significant spatial positive autocorrelation of carbon emissions in 30 provinces in China during 2000–2015. Liu et al. [13] also found that the spatial and temporal distribution of carbon emissions in China has obvious spatial agglomeration characteristics at the scale of prefecture-level cities. Beijing, Shanghai, Tianjin, Suzhou, Chongqing, Chengdu and other large cities have much higher carbon emissions than other cities.

In the study of influencing factors of carbon emissions, the LMDI method [14,15], STIRPAT model [16,17], input–output method [18,19], spatial econometric regression model [20,21] and other methods are usually used to explore the relationship between population, economy, technology, energy, industrial structure and numerous other factors and carbon emissions. For example, Wang et al. [22] established the carbon emission STIRPAT model from 1990 to 2010 to study the impact of socioeconomic factors, urban form and the transportation network on carbon emissions, indicating that socioeconomic factors are significantly correlated with carbon emissions, and the pursuit of a compact urban development mode is conducive to reducing carbon emissions. At the same time, improving the coupling degree between urban spatial structure and transportation organization can reduce carbon emissions. Li et al. [23] pointed out that economic activities were the main reason for the substantial increase in carbon emissions in China's provinces, and technological changes and potential energy intensity changes had a considerable impact on carbon emissions. Wang [21] constructed a spatial panel model of China's city-scale carbon emissions from 1992 to 2013 and pointed out that urban carbon emissions have a spatial agglomeration effect. Per capita GDP, population, industrialization level, capital investment and population density all lead to increases in urban carbon emissions, while road density and traffic coupling factors all reduce urban carbon emissions. Li et al. [24] used the STIRPAT model to analyze the relationship between urbanization level and carbon emissions in the three major urban agglomerations: Beijing–Tianjin–Hebei, the Yangtze River Delta and the Pearl River Delta. The results showed that the relationship between urbanization level and carbon emissions in the three major urban agglomerations presented a "positive U-shaped" curve, which first decreased and then increased, while the relationship between economic development and carbon emissions was an "inverted U-shaped" curve. Total population and energy intensity have significant positive effects on carbon emissions. Liobikien et al. [25] conducted regression and simulation based on panel data of 147 countries and believed that the improvement of population urbanization would help to improve the utilization efficiency of urban infrastructure, thereby improving and enhancing energy utilization structure and efficiency and reducing carbon emissions. Some scholars believe that there is a significant positive correlation between the urbanization rate and CO_2 emission in China's provinces and urban agglomerations such as the Yangtze River Delta and Pearl River Delta [17,26,27]. Shen et al. [14] used the LMDI method to decompose emission factors into energy structure, energy intensity, industrial structure, economic output and population size, and the results pointed out that economic output and population size were the main driving factors for the increase in carbon emissions in Beijing. Based on the inversion of DMSP/OLS night light data in China from 1992 to 2013, Wang et al. [28] revealed that economic growth and the increase in the proportion of the secondary industry had a positive effect on the growth in carbon emissions, while population agglomeration, technology level, openness to the outside world and road transportation intensity showed a negative effect. However, carbon emission is a comprehensive and complex system of engineering where various variables of different factors interact and depend on each other [29]. Each factor does not act on carbon emission in isolation, and the effect of the same factor on carbon emission can be enhanced or weakened according to the situation of other factors. For example, Fan et al. [30] confirmed that the urbanization level can promote carbon emissions, but the interaction between population urbanization and real estate investment can inhibit carbon emissions, indicating that the "interaction effect" among factors should be paid attention to. However, most of the previous studies focused on the individual effects of a single factor on carbon emissions, and mostly ignored the interaction effects among factors.

The geographical detector is a spatial method based on spatial variance analysis, which can effectively explore the individual influence and interaction of geographical factors [31]. At present, it has been widely applied to various geographical variation problems, such as the influence factor of neural tube malformation [32], the influence of individual habitat factor and the interaction of two factors on locust occurrence in Inner Mongolia [33], the driving force of land expansion [34], the influence factor of spatial difference of county housing price [35] and the influence factor of PM2.5 pollution events [36]. A handful of scholars have applied the method to carbon-emitting regions. For example, Wu et al. [37] analyzed the influencing factors of industrial CO_2 emissions in Inner Mongolia, China by using the geographic detector model and found that the single influencing order was population > urbanization > per capita GDP > industrial level > energy intensity, and there are interactions among factors, the largest of which is that GDP and road density account for 71% of CO_2 emissions.

In general, the academic community has carried out a relatively systematic study on China's carbon emissions and achieved abundant results, which have an essential reference role for this study. However, there are the following deficiencies:

(1) From the perspective of research objects, previous studies mostly focused on carbon emissions in the Yangtze River Delta, Pearl River Delta, Beijing–Tianjin–Hebei and other economically developed areas [38–40]. With the implementation of Western development and the "the Belt and Road Initiatives" and additional strategies, the contribution of the western region to China's carbon emissions has gradually increased [41,42], but there are relatively few studies on carbon emissions in the western region, especially in the national emerging town clusters such as the Chengdu–Chongqing region. In addition to the lack of statistical data of energy utilization at the county level, there is no research on the detailed analysis of carbon emissions in the Chengdu–Chongqing region from the county perspective.

(2) From the perspective of research ideas, existing studies reveal the impact of a single factor on carbon emissions in a simple way, the use of the geographical detector model to analyze the interaction of carbon emissions impact factors is low, and most of the relevant studies ignore the development stage and regional differences, revealing that the spatio-temporal heterogeneity of the influencing factors is relatively lacking.

Based on these, the research objectives of this study are as follows:

(1) Analyze carbon emissions in the Chengdu–Chongqing region from the county scale to improve the detailed study of carbon emissions in western China.

(2) Reveal the spatio-temporal differences of the single and interactive factors affecting carbon emissions to fill the lack of studies on the spatio-temporal differences of influencing factors.

2. Study Area and Methodology

2.1. Study Area

Located in the upper reaches of the Yangtze River and in the Sichuan Basin, the Chengdu–Chongqing region consists of 16 cities centered on Chengdu and Chongqing, with a total area of about 185,000 square kilometers (Figure 1). It connects Shaanxi and Gansu in the north, Yunnan–Guizhou in the south, Qinghai–Tibet in the west and Xiang–Hubei in the east. The landform is mainly plain, hill, and middle and low mountains. To the west of Longquan Mountain is the Chengdu Plain, which is impacted by the sediment carried by the Minjiang River and Tuojiang River, and to the east is widely distributed with square hills. It is a subtropical monsoon humid climate with elevated temperatures and rain in summer, mild and less rain in winter, more rainy weather, more fog and less sunshine. With the Jialing River, Tuojiang River, Fujiang River, Minjiang River, Wujiang River and many more rivers, it is wealthy in water resources and hydropower resources. It has a variety of wild animals and plants, including the famous living fossil giant panda habitat. With natural gas, coal, phosphate ore, well salt and other mineral resources enrichment, its development potential is huge. The mountains and rivers of Sichuan are pleasant. Qingcheng Mountain, Emei Mountain, Dujiangyan and other famous tourist resources are influential national tourist destinations.

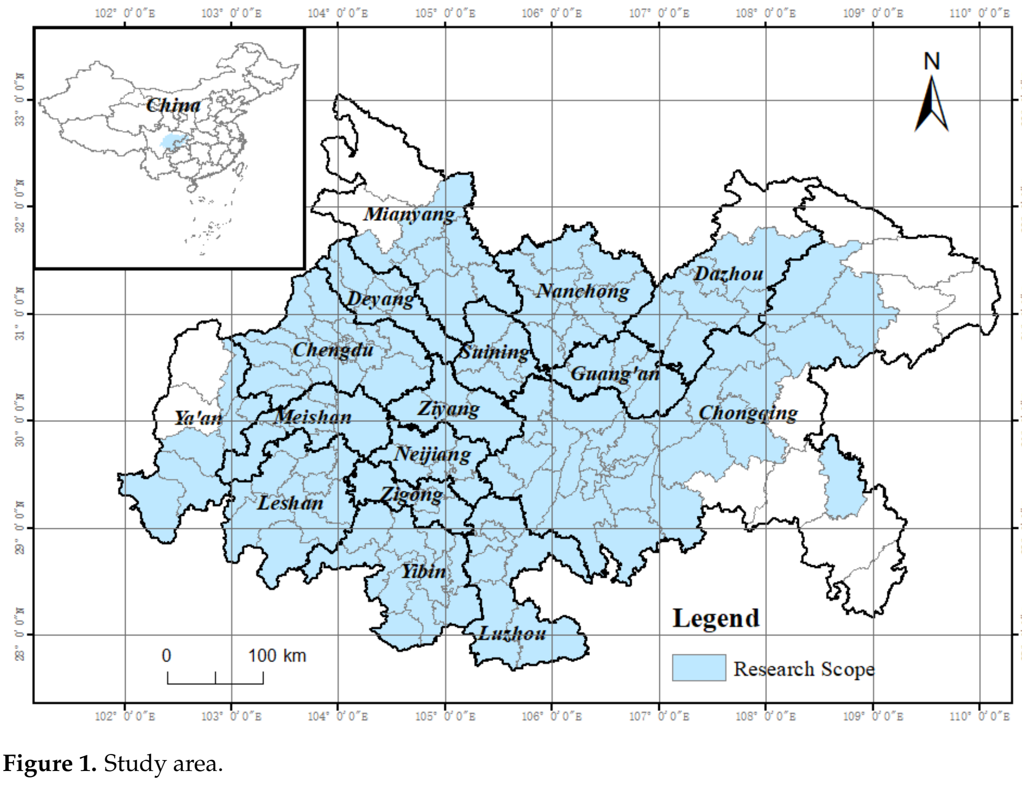


Figure 1. Study area.

The area proportion of the regional land use type is cultivated land, forest land, grassland, construction land, water area and unused land in descending order [43]. The cultivated land is relatively concentrated and the hilly terraces are widely distributed, making it one of the main grain producing areas in China. Sugarcane is mainly produced in the Tuojiang River Basin; mulberry is abundant in the Nanchong and Leshan areas; tea, bamboo and fruit trees are widely planted on the edge of the basin and the hilly areas in the middle of Sichuan; and pigs, cattle and poultry are commonly raised. With a sound industrial foundation, it is an influential industrial base in southwest China, among which Chongqing is famous for its machinery, chemical, metallurgy, food and textile industries. Chengdu is famous for its electronics, aviation and light textile industries, as well as the Neijiang sugar industry, Zigong salt chemical industry and Nanchong silk industry. In addition, Chongqing and Chengdu are the famous industrial bases of heavy vehicles, large automatic instruments and electronics in China, respectively. They are also the transportation hubs in southwest China. Chongqing Port is the first land and water transport terminal of the Sichuan River.

By 2019, the Chengdu–Chongqing region had 96 million permanent residents, with an urbanization rate of more than 60 percent. Its GDP reached 6.3 trillion yuan, with an average annual growth rate of more than 8 percent. However, at the same time, carbon emissions from energy consumption in the Chengdu–Chongqing region increased from 7,374,300 tons in 2006 to 15,552,320,200 tons in 2019, a two-fold increase [44]. Therefore, it is urgent to promote the total carbon emission control in the Chengdu–Chongqing region.

2.2. Research Methodology

2.2.1. Spatial and Temporal Evolution Analysis Model of Carbon Emissions

Spatial autocorrelation is a spatial data analysis method, which is used to estimate and analyze the degree of dependence between spatial study regions, and can reveal the spatial dependence and spatial heterogeneity of geographic data [9], including global autocorrelation and local autocorrelation.

Global autocorrelation can analyze the overall carbon emission concentration in a region, which is generally expressed by the global Moran's I index [45]. For specific expressions, see Formula (1). The value range of the global Moran's I is [–1, 1]. If Moran's I > 0, carbon emissions are positively correlated; that is, counties with higher (lower) carbon emissions are spatially clustered. If Moran's I < 0, carbon emissions are negatively correlated; that is, carbon emissions of adjacent districts and counties have significant spatial differences.

Local autocorrelation is used to further identify the degree of the local correlation of carbon emissions in neighboring districts and counties, which is often expressed by the local Moran's I index. For specific expressions, see Formula (2). If the local Moran's I > 0, it indicates that districts with high carbon emissions and counties with low carbon emissions cluster in space, respectively. If the local Moran's I < 0, it indicates that the counties with high carbon emission and those with low carbon emission are dislocated in space. According to local indicators of spatial association (LISA) [46], it can be divided into five types: high-high clustering, high-low clustering, low-high clustering, low-low clustering and non-significant clustering, as shown in Table 1.

$$\text{Gobal Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{1}$$

$$\text{Local Moran's I} = \frac{n\left(Y_i - \overline{Y}\right)\sum_{j=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right)}{\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2} = \frac{\left(Y_i - \overline{Y}\right)}{S^2}\sum_{j=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right) \tag{2}$$

where $S^2 = \frac{1}{n}\sum\limits_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2$, $\overline{Y} = \frac{1}{n}\sum\limits_{i=1}^{n} Y_i$, n is the number of samples; Y_i and Y_j are the carbon emissions of districts and counties i and j, respectively; and W_{ij} is the spatial weight matrix, using Queen adjacency (W_{ij} = 1 when adjacent, W_{ij} = 0 when not adjacent).

Table 1. Local autocorrelation cluster type.

Name	High-High Clustering	High-Low Clustering	Low-High Clustering	Low-Low Clustering
Correlation judgment	Space-positive correlation	Space-negative correlation	Space-positive correlation	Space-negative correlation
Aggregation mode	High values surrounded by high values	High values surrounded by low values	Low values surrounded by high values	Low values surrounded by low values

2.2.2. Analysis Model of Carbon Emission Influencing Factors

The geographical detector is a spatial statistical model to detect spatial heterogeneity and reveal the driving force behind it [31]. Its core idea is based on the assumption that, if an independent variable has an important influence on a dependent variable, then the spatial distribution of the independent variable and the dependent variable should be similar [47,48]. It includes the factor detector, the interaction detector, the ecological detector and the risk detector. In this study, the factor detector and the interaction detector are mainly used to identify which factor has a greater impact on carbon emissions and how different factors interact with each other.

(i). The factor detector

The factor detector can detect the extent to which a factor X explains the spatial variation of the property Y. In this study, the q value is used to measure the influence of a single factor on carbon emissions, and the value range is [0, 1]; the larger the q value is, the greater the degree of explanation of the factor on carbon emissions. When q = 0, it means that the factor cannot explain the change in carbon emission. When q = 1, it means that the factor completely explains the change in carbon emission. It is generally considered that when $q \geq 0.3$ it indicates that the factor has a strong influence on carbon emissions [49]. The formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h {\sigma_h}^2}{N\sigma^2} \tag{3}$$

where h (h = 1,..., L) is the number of layers explaining the factor *X*; N_h and N are the number of samples in layer h and the total number of samples, respectively; and ${\sigma_h}^2$ and σ^2 are the variance of layer h and the overall variance, respectively.

(ii). The interaction detector

The interaction detector can identify the interaction between different factors, that is, evaluate the influence $q(x_1 \cap x_2)$ on carbon emissions after the interaction of x_1 and x_2 factors. Compared with the influence $q(x_1)$ and $q(x_2)$ of a single factor, it is weakened, strengthened or independent, which can be divided into 5 types, as shown in Table 2.

Table 2. Defined interaction relationships [50].

Description	Interaction
$q(x_1 \cap x_2) < Min(q(x_1), q(x_2))$	Weakening, nonlinear
$Min(q(x_1), q(x_2)) < q(x_1 \cap x_2) < Max(q(x_1), q(x_2))$	Weakened, unique
$q(x_1 \cap x_2) > Max(q(x_1), q(x_2))$	Enhanced, bilinear
$q(x_1 \cap x_2) = q(x_1) + q(x_2)$	Independent
$q(x_1 \cap x_2) > q(x_1) + q(x_2)$	Enhanced, nonlinear

It should be noted that these three types of enhancements are different. For example, if $q(x_1) < q(x_1 \cap x_2) < q(x_2) < (q(x_1) + q(x_2))$, this shows that x_2 enhances x_1 and x_1 weakens x_2; if $q(x_1)$ and $q(x_2) < q(x_1 \cap x_2) < (q(x_1) + q(x_2))$, this suggests that x_1 and x_2 are mutually reinforcing; if $q(x_1 \cap x_2) > (q(x_1) + q(x_2))$, this means the nonlinear enhancement of x_1 and x_2. Thus, "nonlinear enhancement" has the strongest interaction and "unique enhancement" has the weakest interaction.

2.3. Data Sources

With reference to the previous research results and considering the actual situation in the Chengdu–Chongqing region, based on the availability of data from each district and county, the period of 2005–2017 was selected as the research period, and the carbon emissions of 140 districts and counties in the Chengdu–Chongqing region were taken as the research object, with population, economic development level, industrial structure and financial situation as explanatory factors, and the descriptive statistics of each variable are shown in Table 3. The natural breakpoint method in Arcgis was used to discrete each explanatory factor into type quantities.

Table 3. Descriptive statistics of variables.

<table>
<tr><th>Variables</th><th>Indicator Description</th><th>Unit</th><th>AVG</th><th>SD</th><th>Min</th><th>Max</th></tr>
<tr><td>Carbon emissions</td><td>Total carbon emissions (Y)</td><td>Million tons</td><td>2.47</td><td>2.22</td><td>0.08</td><td>14.75</td></tr>
<tr><td>Population size</td><td>Year-end population (X_1)</td><td>10000 persons</td><td>72.48</td><td>37.80</td><td>4.99</td><td>181.30</td></tr>
<tr><td>Urban rate</td><td>Proportion of urban population to total population (X_2)</td><td>%</td><td>33.59</td><td>22.96</td><td>5.52</td><td>100.00</td></tr>
<tr><td>Economic development</td><td>Gross domestic product (X_3)</td><td rowspan="7">100 million CNY</td><td>194.40</td><td>197.63</td><td>6.94</td><td>1447.20</td></tr>
<tr><td rowspan="2">Industrial structure</td><td>Scale of output value of secondary industry (X_4)</td><td>95.49</td><td>101.70</td><td>1.91</td><td>926.84</td></tr>
<tr><td>Scale of output value of tertiary industry (X_5)</td><td>77.06</td><td>119.97</td><td>1.06</td><td>1089.88</td></tr>
<tr><td rowspan="2">Financial situation</td><td>General public budget revenue (X_6)</td><td>10.89</td><td>14.83</td><td>0.15</td><td>113.49</td></tr>
<tr><td>General public budget expenditure (X_7)</td><td>25.87</td><td>22.51</td><td>0.97</td><td>14.99</td></tr>
<tr><td>Investment level</td><td>Total social fixed asset investment (X_8)</td><td>150.50</td><td>159.92</td><td>1.49</td><td>1248.22</td></tr>
<tr><td>Social consumption</td><td>Total retail sales of consumer goods (X_9)</td><td>80.81</td><td>112.73</td><td>1.10</td><td>956.29</td></tr>
<tr><td>Technological progress</td><td>Carbon emission intensity (X_{10})</td><td>Tons/10000 CNY</td><td>1.55</td><td>0.98</td><td>0.03</td><td>6.72</td></tr>
</table>

Note: The "AVG" stands for average value; the "SD" stands for standard deviation; the "Min" stands for minimum value; the "Max" stands for maximum value.

The basic geographic information data are from the National Geographic Information Database of the National Basic Information Website "https://www.webmap.cn/commres.do?method=result100W" (accessed on 23 March 2022), the carbon emission data are from the China Carbon Accounting Database CEADs "https://www.ceads.net.cn/data/" (accessed on 23 March 2022), and the socio-economic data are from the Sichuan Statistical Yearbook, Chongqing Statistical Yearbook, local statistical yearbooks and the National Economic and Social Development Statistical Bulletin of each district and county "http://www.stats.gov.cn/tjsj/" (accessed on 18 April 2022).

3. Results

3.1. Spatial and Temporal Distribution of Carbon Emissions in the Chengdu–Chongqing Region

3.1.1. Spatial and Temporal Distribution Patterns of Carbon Emissions

Based on the ArcGIS10.8 software, the spatial and temporal distributions of the carbon emissions of the Chengdu–Chongqing region in 2005, 2010, 2015 and 2017 are depicted in Figure 2.

In terms of time, from 2005 to 2017, the average carbon emissions of the counties in the Chengdu–Chongqing region increased from 172 million tons to 283 million tons, with an overall growth rate of 64.53 percent and an average annual growth rate of 4.24 percent. From 2005 to 2010, the counties' average carbon emissions increased from 172 million tons to 253 million tons, with an average annual growth rate of 8.02 percent, a wide range of growth that belongs to the rapid growth phase. From 2010 to 2017, the counties' average carbon emissions increased from 253 million tons to 283 million tons, with an average annual growth rate of 1.61 percent, which is a moderate growth phase.

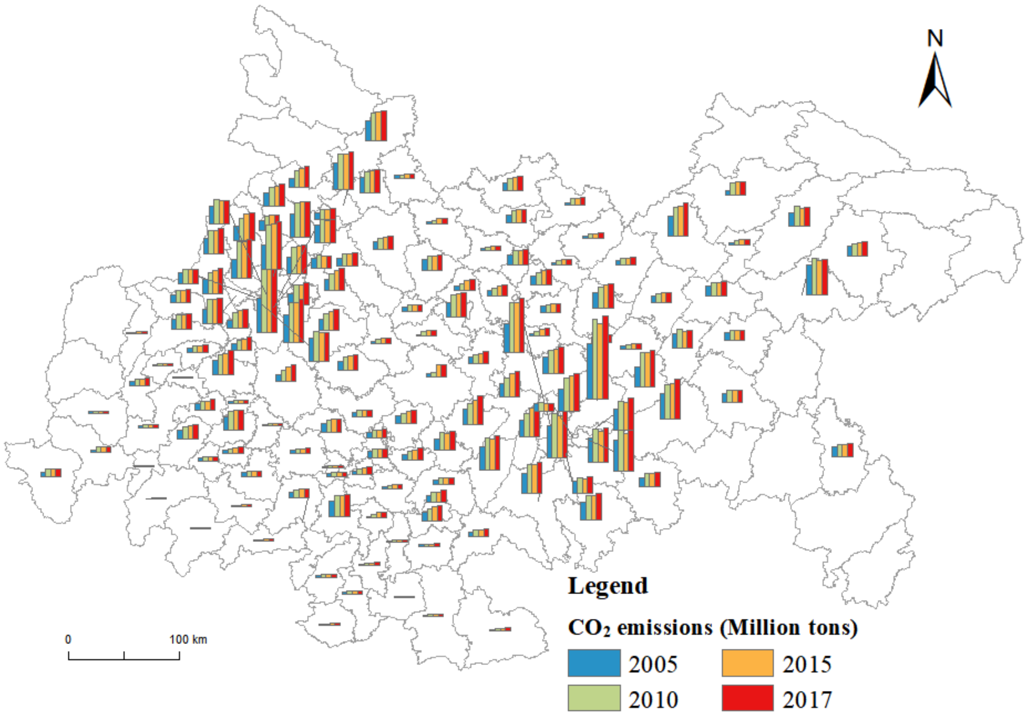


Figure 2. The spatial and temporal distributions of carbon emissions in 2005, 2010, 2015 and 2017.

From the perspective of space, county carbon emissions in the Chengdu–Chongqing region from 2005 to 2017 showed a circular pattern with the main urban areas of Chengdu and Chongqing as the core. Among them, Chengdu and Chongqing are high carbon emission areas with elevated carbon emission levels. Ya'an, Leshan, Luzhou and other southern counties have low levels of carbon emissions and are considered low-carbon areas. The central and northern regions are both high- and low-carbon emitting regions, which are a transition zone between high- and low-carbon emitting regions.

3.1.2. Spatial Autocorrelation Analysis

The carbon emissions in 2005, 2010, 2015 and 2017 were selected as the observed values for the spatial autocorrelation analysis in ArcMap10.8 software, and the spatial weight matrix was set using the Queen neighborhood.

(i). Global Autocorrelation Analysis

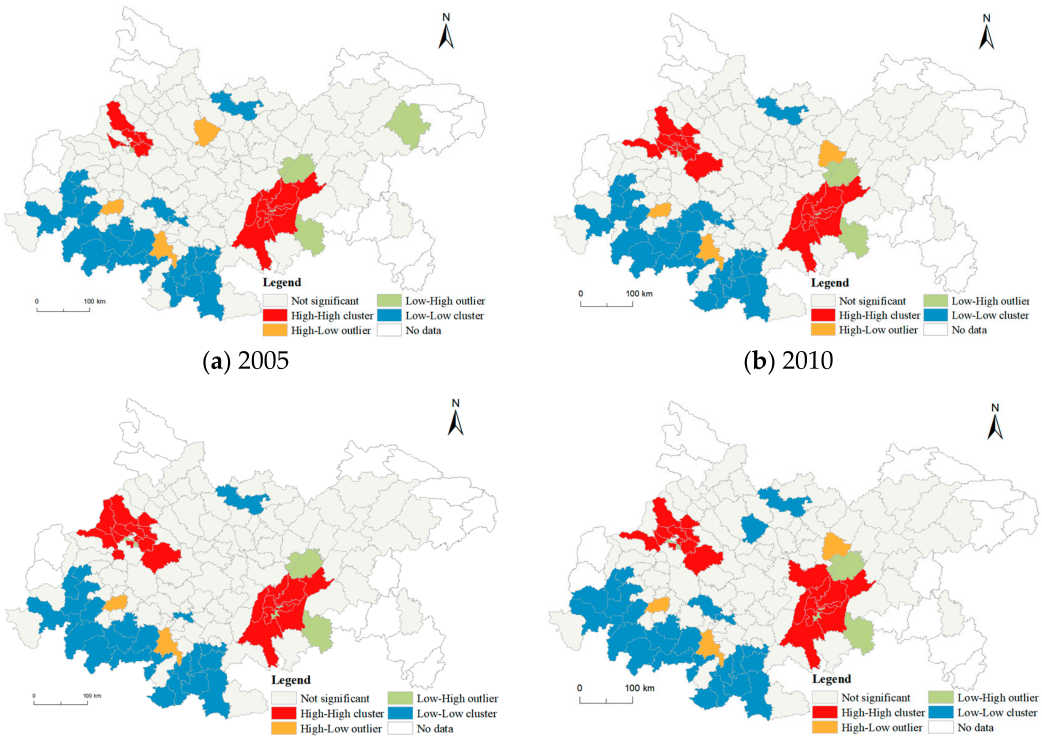
The global Moran's I index obtained from the global autocorrelation analysis is shown in Table 4. It can be seen that the global Moran's I index values of county carbon emissions in the Chengdu–Chongqing region from 2005 to 2017 are all positive, and all Z-values are greater than 2.58 after passing the significance level test of 0.01, indicating that county carbon emissions in the Chengdu–Chongqing region present a significant agglomeration phenomenon in spatial distribution. At the same time, the global Moran's I value of county carbon emissions in the Chengdu–Chongqing region showed an increasing trend from 2005 to 2017, but the growth rate of the global Moran's I index decreased from 2010, indicating that the spatial aggregation of county carbon emissions in the Chengdu–Chongqing region continued to improve during 2005 to 2017. Moreover, the spatial clustering properties have been stable since 2010.

Table 4. The Global Moran's I index from 2005 to 2017.

Year	2005	2010	2015	2017
Moran's I	0.446	0.459	0.460	0.463
Z	8.686	8.939	8.939	8.999
P	0.000	0.000	0.000	0.000

(ii). Local Autocorrelation Analysis

The 2005, 2010, 2015 and 2017 LISA agglomeration maps from the local autocorrelation analysis are shown in Figure 3. It can be seen that the local aggregation characteristics of county carbon emissions in the Chengdu–Chongqing region were relatively stable from 2005 to 2017, mainly manifested as low-low clustering and high-high clustering. Among them, the number of low-low cluster counties increased from 21 in 2005 to 25 in 2017, mainly distributed in the southern and northern regions, and gradually spread to the periphery, which is basically consistent with the spatial distribution pattern of counties with low carbon emission. The number of high-high cluster districts and counties increased from 18 in 2005 to 22 in 2017, mainly distributed in the main urban areas of Chengdu and Chongqing, and gradually spread to the surrounding districts and counties, which was basically consistent with the spatial distribution pattern of high-carbon-emission districts and counties. This indicates that economically developed areas and counties may be more likely to produce high carbon emissions, and will drive the increase of carbon emissions in neighboring areas and counties.



(**a**) 2005 (**b**) 2010

(**c**) 2015 (**d**) 2017

Figure 3. The LISA agglomeration map of 2005, 2010, 2015, and 2017.

3.2. Factors Influencing County-Level Carbon Emissions in the Chengdu–Chongqing Region

3.2.1. Temporal Variation of the Influencing Factors

Using GeoDetector software, the single-factor and interactive-factor influences of each impact factor on county carbon emissions in 2005, 2010, 2015 and 2017 are shown in Figure 4. At the same time, in order to make up for the failure of the geographical detector model to detect the positive and negative effects of influencing factors, carbon emission and influencing factors were taken as dependent variables and independent variables, respectively, to make scatter plots (Figure 5), and the positive and negative effects of the detecting factors on carbon emission were identified through the trend line.

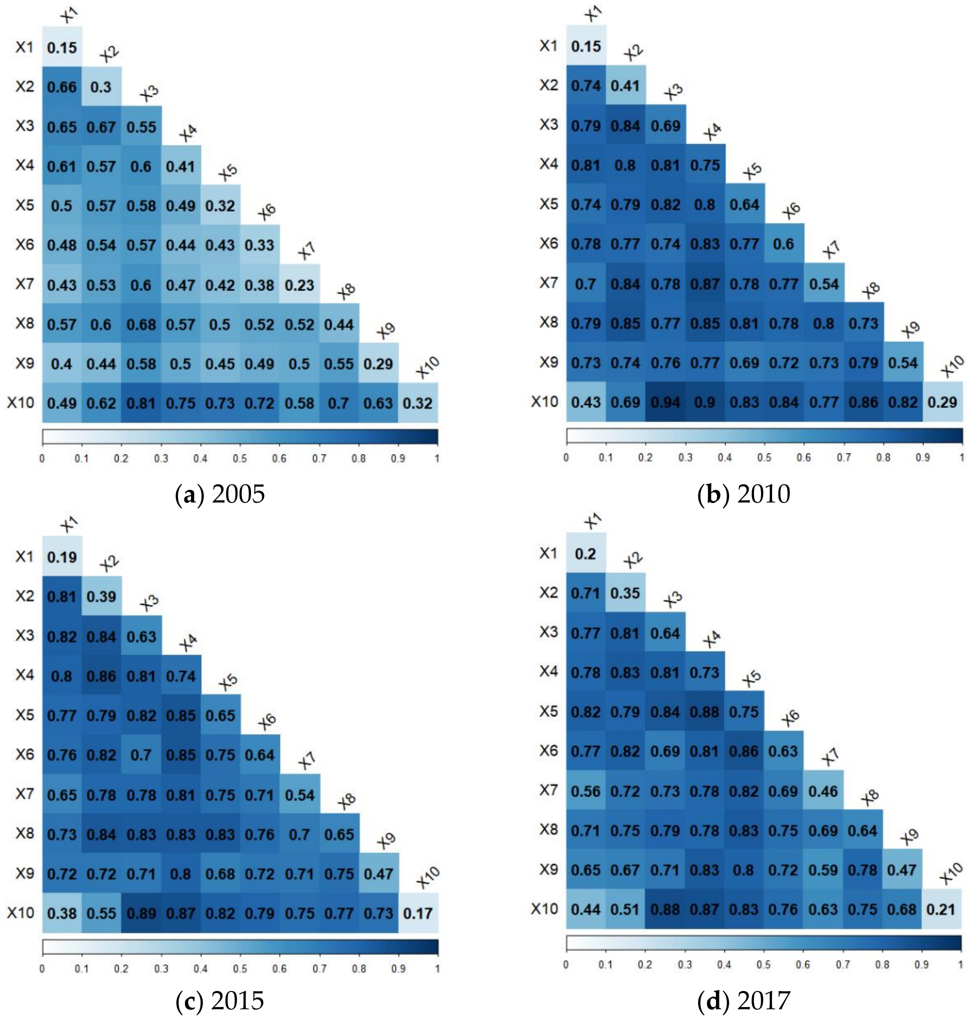


Figure 4. Detected results of impact factors contributing to carbon emissions. The diagonal line shows the factor detection results ($p < 0.05$), and the lower triangle shows the interaction detection results.

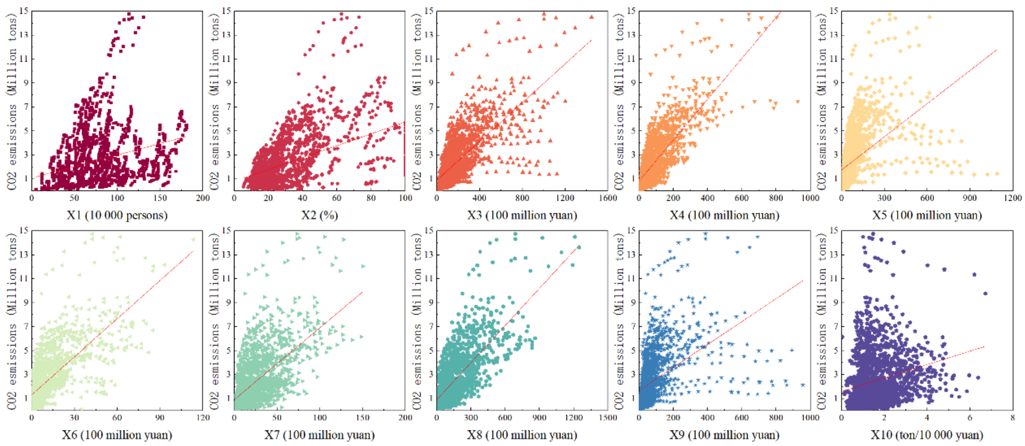


Figure 5. Scatter diagrams of the influence of detection factor on carbon emissions.

According to the results of the factor detector, the single factor influence size is sorted in Table 5. It can be seen that, from 2005 to 2017, eight influencing factors, including industrial structure, economic development, investment level, financial situation, social consumption and urbanization rate, all had strong positive driving effects on carbon emissions, while technological progress and population size had relatively small effects.

The average influence was as follows in descending order: industrial structure > economic development > investment level > financial situation > social consumption > urbanization rate > technological progress > population size. Among them, the factor influence of the scale of output value of the tertiary industry increased from the fifth (0.32) to the first (0.75), indicating that the role of the tertiary industry on carbon emissions is increasingly important. The scale of output value of the secondary industry increased from the third place (0.41) to the first place (0.75) and then dropped to the second place (0.73), indicating that the importance of the industrial development level of districts and counties had a trend of decline after a sharp rise. Although the influence of the total social fixed asset investment varied greatly, rising from 0.44 to 0.73 and then falling to 0.64, the importance of social fixed asset investment remained in the top three, indicating that investment level still played an important role in carbon emissions. The economic scale fluctuated from the first to the fourth, indicating that the economic development level of the districts and counties was becoming less important to carbon emissions. The influence of fiscal expenditure rose from 9th to 7th, while fiscal revenue dropped from 4th (0.32) to 5th, indicating that the influence of fiscal situation on carbon emissions is manifested as follows: the importance of fiscal expenditure is increasing, while fiscal revenue is weakening. However, compared with fiscal expenditure, increases in fiscal revenue have a greater impact on carbon emissions. The social consumption and urbanization rates have fluctuated, but not changed much.

Table 5. Rank change in importance of influencing factors of carbon emissions.

Factors	2005	2010	2015	2017	Average
Scale of output value of secondary industry (X_4)	3 (0.41)	1 (0.75)	1 (0.74)	2 (0.73)	1 (0.66)
Gross domestic product (X_3)	1 (0.55)	3 (0.69)	5 (0.63)	4 (0.64)	2 (0.63)
Total social fixed asset investment (X_8)	2 (0.44)	2 (0.73)	3 (0.65)	3 (0.64)	3 (0.61)
Scale of output value of tertiary industry (X_5)	5 (0.32)	4 (0.64)	2 (0.65)	1 (0.75)	4 (0.59)
General public budget revenue (X_6)	4 (0.32)	5 (0.60)	4 (0.64)	5 (0.63)	5 (0.55)
General public budget expenditure (X_7)	9 (0.23)	7 (0.54)	6 (0.54)	7 (0.46)	6 (0.44)
Total retail sales of consumer goods (X_9)	8 (0.29)	6 (0.54)	7 (0.47)	6 (0.47)	7 (0.44)
Proportion of urban population to total population (X_2)	7 (0.30)	8 (0.41)	8 (0.39)	8 (0.35)	8 (0.36)
Carbon emission intensity (X_{10})	6 (0.32)	9 (0.29)	9 (0.16)	9 (0.21)	9 (0.25)
Year-end population (X_1)	10 (0.15)	10 (0.15)	10 (0.19)	10 (0.20)	10 (0.17)

According to the interaction detection results, the effect of all interaction factors on carbon emissions during 2005–2017 was significantly higher than the effect of a single factor, with two-factor enhancement or nonlinear enhancement effects. In 2005, the interaction factors of nonlinear enhancement are $X_1 \cap X_2$ (0.66 > 0.15 + 0.30), $X_1 \cap X_4$ (0.61 > 0.15 + 0.41), $X_1 \cap X_5$ (0.50 > 0.15 + 0.32), $X_1 \cap X_7$ (0.43 > 0.15 + 0.23) $X_1 \cap X_{10}$ (0.49 > 0.15 + 0.32), $X_4 \cap X_{10}$ (0.75 > 0.41 + 0.32), $X_5 \cap X_{10}$ (0.73 > 0.32 + 0.32), $X_6 \cap X_{10}$ (0.72 > 0.32 + 0.32), $X_7 \cap X_{10}$ (0.58 > 0.23 + 0.32) and $X_9 \cap X_{10}$ (0.62 > 0.29 + 0.32). However, in 2017, only $X_1 \cap X_2$ (0.71 > 0.20 + 0.35), $X_1 \cap X_{10}$ (0.44 > 0.20 + 0.21) and $X_3 \cap X_{10}$ (0.88 > 0.64 + 0.21) had the nonlinear enhancement effect on the interaction factor. This indicates that the 10-factor pairwise interaction effect on county-level carbon emissions in the Chengdu–Chongqing region is changing from a nonlinear enhancement to a two-factor enhancement, and the strength of the interaction is weakening, similar to the shift trend of the single-factor effect. The interaction factors with a high average influence are $X_3 \cap X_{10}$(0.88), $X_4 \cap X_{10}$(0.85), $X_5 \cap X_{10}$(0.80), $X_2 \cap X_3$(0.79), $X_6 \cap X_{10}$(0.78), $X_8 \cap X_{10}$(0.77), $X_3 \cap X_8$(0.77), $X_3 \cap X_5$(0.77), $X_2 \cap X_4$(0.77), $X_2 \cap X_8$(0.76), $X_3 \cap X_4$(0.76), $X_4 \cap X_8$(0.76), $X_1 \cap X_3$(0.76), $X_4 \cap X_5$(0.75), $X_1 \cap X_4$(0.75), $X_5 \cap X_8$(0.74), $X_2 \cap X_5$(0.74), $X_2 \cap X_6$(0.74), $X_4 \cap X_6$(0.73), $X_4 \cap X_7$(0.73), $X_1 \cap X_2$(0.73), $X_4 \cap X_9$(0.72), $X_3 \cap X_7$(0.72) and $X_8 \cap X_9$(0.72), which mostly contain X_3, X_4, X_5 and X_8, It shows that the key interaction factors including industrial structure, economic development and asset investment level have a more significant spatial superposition effect on carbon emissions. It is worth noting that X1 and X10 have average single-factor effects of only 0.17 and 0.25, respectively, but have enhanced effects after interactions with other factors. $X_{10} \cap X_3$ even becomes the largest interaction factor during the study, with an average interaction value of 0.88, indicating that the influence of each factor on carbon emission cannot be ignored. In particular, the nonlinear enhancement is due to the superposition of certain weak and other factors.

3.2.2. Regional Differences in the Influencing Factors

The influences of the impact factors on carbon emissions in different cities are shown in Figure 6, respectively, based on the GeoDetector software. The factor with the largest influence is chosen as the dominant factor. The leading factor of carbon emission in four cities, Deyang, Meishan, Ya'an and Zigong, was X_1; the leading factor of four cities, Mianyang, Leshan, Suining and Luzhou, was X_2; the leading factor of Dazhou was X_3. The leading influence factor of Chengdu, Ziyang, Neijiang, Yibin, Guang'an, Nanchong and Chongqing was X_4. Based on the influence of the four dominant factors, the Chengdu–Chongqing region can be divided into four types of regions that affect carbon emissions: population size, urbanization rate, economic development and industrial structure.

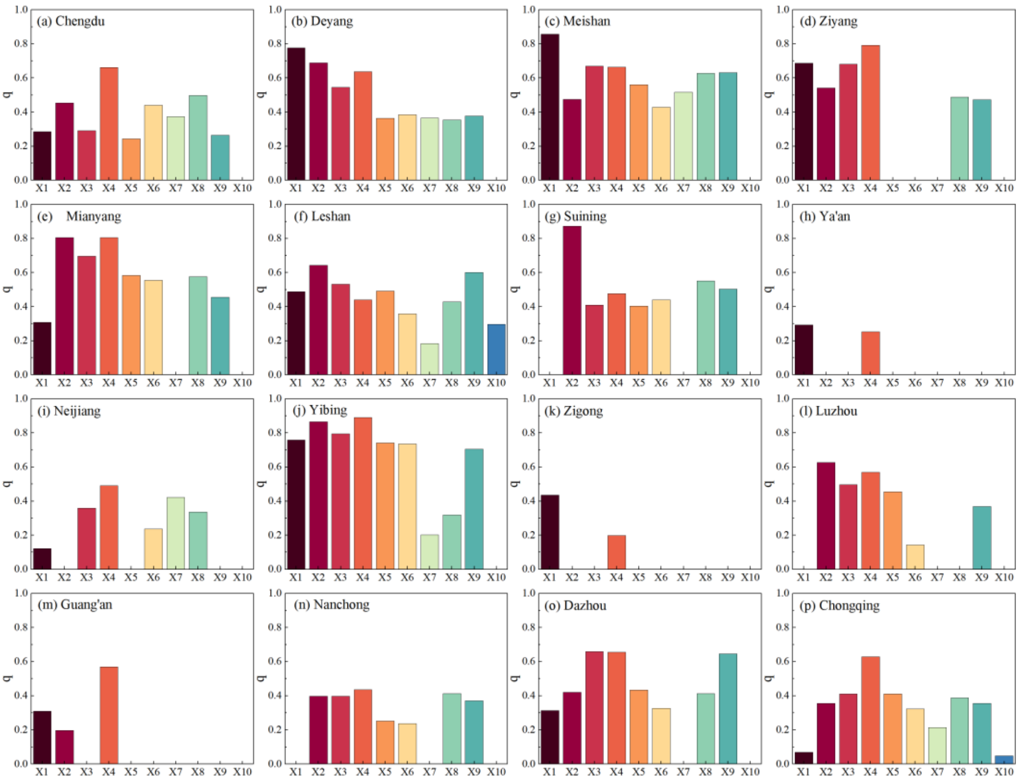


Figure 6. Distribution of the influence of each influence factor on carbon emission in Chengdu and Chongqing region from 2005 to 2017 ($p < 0.05$).

(1) Population size influence type: The regions with strong X_1 influence on carbon emissions include Meishan (0.86), Deyang (0.78), Yibin (0.76), Ziyang (0.69), Leshan (0.49), Zigong (0.44), Dazhou (0.31), Guang 'an (0.31), Mianyang (0.31) and nine other cities.

(2) Influence type of urbanization rate: The regions where carbon emissions are greatly affected by X_2 include Suining (0.87), Yibin (0.87), Mianyang (0.81), Deyang (0.69), Leshan (0.64), Luzhou (0.63), Ziyang (0.54), Meishan (0.47), Chengdu (0.45), Dazhou (0.42), Nanchong (0.40), Chongqing (0.35) and another 12 cities.

(3) Economic development influence type: The regions where carbon emissions are heavily affected by X_3 include 12 cities, Yibin (0.80), Mianyang (0.70), Ziyang (0.68), Meishan (0.67), Dazhou (0.66), Deyang (0.55), Leshan (0.53), Luzhou (0.50), Suining (0.41), Chongqing (0.41), Nanchong (0.40) and Neijiang (0.36).

(4) Industrial structure influence type: The regions where carbon emissions are strongly influenced by X_4 include Yibin (0.89), Mianyang (0.81), Ziyang (0.79), Meishan (0.66), Chengdu (0.66), Dazhou (0.66), Deyang (0.64), Chongqing (0.63), Guang'an (0.57), Luzhou (0.57), Neijiang (0.49), Suining (0.48), Leshan (0.44), South Chong (0.44) and another 14 cities.

Depending on the number of dominant factors, the Chengdu–Chongqing region can be divided into single-factor, double-factor and multiple-factor influence regions. Of these, Zigong belongs to the single-factor influence region; Chengdu, Neijiang and Guang'an belong to the double-factor influence region; and Suining, Luzhou, Nanchong, Chongqing, Deyang, Meishan, Ziyang, Mianyang, Leshan, Yibin and Dazhou belong to the multi-factor influence region, as shown in Figure 7. Overall, the Chengdu–Chongqing region has two factors as the center and multiple factors as the main body that together affect the total county-level carbon emissions.

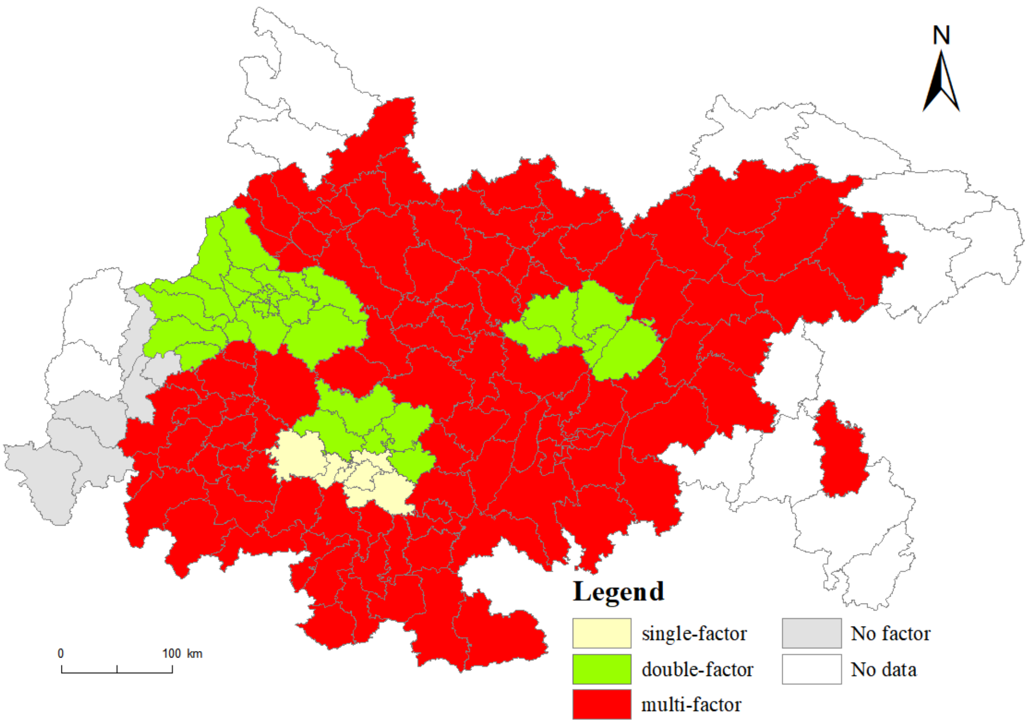


Figure 7. The dominant factor subdivision of carbon emission of each city in Chengdu–Chongqing region.

4. Discussion

4.1. Spatial and Temporal Distribution of Carbon Emissions

From the spatio-temporal variation characteristics of carbon emissions, the carbon emissions in the Chengdu–Chongqing region are dominated by the "dual core" of Chengdu and Chongqing, and the spatial dependence is strong. Chengdu and Chongqing not only have a high level of economic development, but also top the list of carbon emissions, which is consistent with the study of Wang et al. [51]. The central region is more likely to concentrate and consume more energy, resulting in more carbon emissions. In contrast, the southern cities such as Ya 'an and Leshan, which are near the western Sichuan Plateau, are relatively far away from the two core cities, so it is difficult to receive the technology, capital and other resources spillover from the center and maintain low development, forming the low-emission hinterland between the polar core. Mianyang, Deyang, Ziyang, Meishan and other surrounding districts and counties have relatively high carbon emissions, which is consistent with Peng et al. [52]. This is because cities such as Mianyang and Deyang are geographically close to each other, and are obviously influenced by the two major central cities. In addition, the Chengdemei Capital is supported by the policy of urban development, which has a good economic foundation and a high level of urbanization, thus increasing carbon emissions. With the economic development and population gathering, the energy demand is constantly increasing, the carbon emission level of the main urban areas of Chengdu and Chongqing and their surrounding districts and counties will become more prominent, and the "core-edge" structure of carbon emission will become more prominent. It is worth noting that, during the study period, the Qingyang District of Chengdu and Dadukou District of Chongqing changed from the high-high cluster area to the low-high cluster area, which is closely related to the industrial transfer of the main urban area. For example, Heavy Steel Group moved from Dadukou in 2007 and lasted 5 years [53].

4.2. Factors Influencing County-Level Carbon Emissions

From the perspective of the influencing factors of carbon emissions, eight factors, including industrial structure, economic development, investment level, financial situation, social consumption and urbanization rate, all have strong positive driving effects on carbon emissions. In addition, the influence of the scale of three industries on carbon emissions shows an increasing trend year by year, and the other influencing factors basically show a trend of increasing first and then decreasing. Each factor will have an enhanced effect on carbon emissions after spatial superposition with other factors, which is consistent with the studies of Wang et al. and Han et al. [54,55].

The positive driving effect of industrial structure is the largest, and the interactive enhancement effect of the scale of the secondary industry and tertiary industry also increased from 0.49 in 2005 to 0.88 in 2017, indicating that the internal changes of industrial structure play an increasingly important role in carbon emissions, which is similar to the conclusion obtained by Wei et al. [56]. As an important industrial town in the Sichuan province, Yibin has a large scale of secondary industry, resulting in the greatest impact of industrial structure on carbon emission. Ya 'an is an underdeveloped city with a relatively small secondary industry, low energy consumption and little impact on carbon emissions. However, Chengdu and Chongqing, which have a high output value of the secondary industry, pay attention to the upgrading of the internal structure of the industry and promote the sustainable and healthy development of the industry, so the positive impact of the industrial structure is not the largest.

The positive impact of economic development is followed by $X_3 \cap X_{10}$(0.88), which is always the dominant interaction factor, indicating that promoting technological innovation and promoting high-quality economic development will be an important path to reduce carbon emissions in the Chengdu–Chongqing region in the future. In the process of promoting economic development, cities such as Yibin, Mianyang, Ziyang and Meishan constantly expand construction land and develop heavy industry, increasing energy demand and leading to a rapid increase in carbon emissions, which is consistent with the research of Xu et al. [57]. Chengdu, with a high level of economic development, focuses on optimizing the energy structure, attracting talents and promoting technological progress, resulting in a high energy utilization rate, but is not affected by carbon emissions. In addition to industries with high energy consumption, there are also other pillar industries such as the tourism and wine industries in Zigong and Luzhou. Economic development is not strongly dependent on industry, so the impact of carbon emissions is relatively low.

The positive influence of investment level is also strong, which is similar to Li et al. [58]. This is mainly due to the fact that some high-carbon-emission enterprises are moving from the eastern region with higher economic development level to the western region. However, as environmental awareness increases and high-carbon projects are strictly controlled, the impact of investment levels begins to decline. At the same time, the interaction between investment level and the other nine factors also showed a change characteristic of first rising and then falling, indicating that the government has great potential to reduce carbon emissions in the Chengdu–Chongqing region by strengthening the macro-control of fixed asset investment.

Counties are economically active and have high tax revenue, which may lead to higher carbon emissions [59]. However, the economic development in the Chengdu–Chongqing region is not balanced, and, coupled with the policy support of the western development and Chengdu–Chongqing twin city economic circle, transfer payments are at a high level. Increasing the expenditure of public environmental and health services is conducive to the optimization of the social and economic environment [60]. Therefore, they should seize the national strategic opportunity, make good use of financial transfer payments, and give full play to the advantages of regional latecomers. This plays an important role in realizing green and low-carbon transformation in the Chengdu–Chongqing region.

Although social consumption showed a trend of increasing first and then decreasing, the interactive influence with the scale of secondary industry and tertiary industry showed a trend of increasing. In the context of expanding consumption to boost domestic demand, the impact of consumption on carbon emissions will become stronger and stronger [61]. Therefore, changing residents' consumption concept, advocating moderate consumption, low-carbon consumption and green consumption, guiding residents to use clean energy and improving energy consumption structure are important links of low-carbon industrial transformation and upgrading in the Chengdu–Chongqing region.

The urbanization rate has a strong positive impact on Suining, Yibin, Mianyang and other cities, which may be due to the low urbanization rate and small urban population in these areas, resulting in the inadequate operation of public facilities and infrastructure, relatively dispersed and low concentration of transportation, construction and energy-intensive industries, and a higher dependence on energy equipment, resulting in a continuous increase in carbon emissions. This is consistent with the research results of Zhang et al. [62]. With the improvement of the urbanization level, urban population agglomeration may lead to a high operating degree of public facilities, industrial agglomeration, and a substantial increase in production efficiency and the energy utilization rate, thus reducing the impact on carbon emissions [30]. Therefore, Chengdu and Chongqing are relatively less affected by urbanization.

Population size has a small impact on carbon emissions in Chengdu–Chongqing region, but it has a relatively large impact on Meishan, Deyang and Yibin, which may be because the increasing population size and energy consumption and demand lead to an increase in carbon emissions. However, Chengdu and Chongqing, which have a large population, may be less affected by the population size because the population concentration degree is higher, which is conducive to the centralized supply of energy and improves the efficiency of energy.

4.3. Limitations

As the "fourth pole" of China's economic growth, the Chengdu–Chongqing region must realize low-carbon and green transformation while developing its economy. Therefore, this paper can provide some reference for the future development planning of the Chengdu–Chongqing region. Inevitably, this paper also has certain limitations:

(1) Due to the difficulty of data acquisition at the county level, the impact factor indexes selected in this paper are not comprehensive and accurate. For example, energy utilization data at the county level is lacking, and energy-consumption-related indexes have not been considered. Technological progress should be represented by additional or comprehensive indicators such as the number of patents. Future research can be combined with regional development status, expand data collection sources, advance screen impact factors and update part of the data set to improve the timeliness of the research.

(2) The geographical detector model is based on the analysis of spatial variance, and the continuous independent variables need to be discussed and converted into classification variables. The classification methods commonly used include equidistant segmentation, natural segmentation, quantile segmentation, geometric segmentation and standard deviation segmentation. This study discretized each influence

factor according to the natural breakpoint method of conformity selection, which is characterized by making the difference between different types as large as possible. However, the results of the spatial discretization of continuous variables are related to the distillation method [34,63], and arbitrary zoning methods may mislead the actual relationship between geographical phenomena and their influence factors. Future research will also consider the regeneration effect, compare and analyze different discrete methods such as the natural breakpoint method, equidistant breakpoint method and quantile method, and also select the best personalization method suitable for the analysis of carbon emission impact factors in the Chengdu–Chongqing region.

5. Conclusions

This paper takes county carbon emissions in the Chengdu–Chongqing region from 2005 to 2017 as the research object. Firstly, the spatial and temporal distribution pattern of carbon emissions is analyzed. Secondly, the spatial autocorrelation model is used to identify the spatial aggregation characteristics of carbon emissions. The main conclusions and suggestions are as follows:

(i) Carbon emissions generally showed an annual growth trend of "first fast and then slow" with 2010 as the boundary. The average carbon emissions of the counties increased from 172 million tons to 283 million tons, with an annual growth rate of 4.24%. In terms of spatial distribution, the main urban areas of Chengdu and Chongqing show a circular pattern, in which the main urban areas of Chengdu and Chongqing are high-carbon-emission areas, the southern districts and counties are low-carbon-emission areas, and the central and northern regions are transition zones between high-carbon-emission areas and low-emission areas. Therefore, the economically developed areas and counties such as the main urban areas of Chengdu and Chongqing, as the key areas of carbon reduction, drive the surrounding areas and counties to gradually seek the path of low-carbon development to narrow the economic and social gap with the developed areas, so as to achieve the overall emission reduction target.

(ii) Carbon emissions showed a significant spatial positive autocorrelation, the adjacent districts and counties mostly presented the spatial agglomeration characteristics of "high-high" or "low-low", the number of high-high and low-low aggregation districts and counties was increasing, gradually spreading to the surrounding districts and counties, and the agglomeration state had a trend of strengthening. Therefore, high-carbon-emission areas such as the main urban areas of Chengdu and Chongqing should give full play to the coordination and spillover effect between neighboring districts and counties to carry out co-reduction and co-governance. Low-carbon-emission areas such as Ya 'an City, Meishan City, Leshan City, Neijiang City, Zigong City, Yibin City and Luzhou City can learn from each other and demonstrate together.

(iii) The influencing factors of carbon emission change significantly over time, and the influence of single factors is as follows in descending order: industrial structure > economic development > investment level > financial situation > social consumption > urbanization rate > technological progress > population size. The influence of the interaction factors was significantly higher than that of the single factor. However, the change trends of the influence of the single factor and the interaction factor were similar, and most of them had a trend of increasing first and then decreasing. Therefore, the key to realize the overall carbon emission reduction is to make full use of the regional social economy and resource endowment, give play to the advantages of late development, rationally regulate social and economic factors, and take the low-carbon and circular development road with the characteristics of the Chengdu–Chongqing region.

(iv) There are obvious regional differences in the influencing factors of carbon emissions. County carbon emissions of 9 cities, such as Meishan, are of the population size influencing type; the district and county carbon emissions of 12 cities, such as Suining, Yibin and Mianyang, are of the urbanization rate influencing type; the district and county carbon emissions of 12 cities, such as Yibin, are of the economic development influencing type. Yibin City, Mianyang City and another 14 cities are affected by the industrial structure, showing a two-factor influence as the core, and the county carbon emission in the Chengdu–Chongqing region is affected by multiple factors. Therefore, the formulation and implementation of carbon emission reduction policies should consider the stage differences of regional development, pay attention to the mutual integration of various influence factors, and promote resource integration, so as to achieve regional carbon emission reductions.

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