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Spatiotemporal Evolution of Carbon Emissions in the Chengdu-Chongqing Region

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Abstract

This study analyzes the spatiotemporal dynamics of carbon emissions in the Chengdu-Chongqing urban agglomeration from 2000 to 2022 using nighttime light (NTL) data, Moran's I analysis, and centroid analysis. The results reveal significant regional disparities in carbon emissions, with rapid growth observed in northwestern cities such as Chengdu, Mianyang, and Deyang, while southeastern regions, including Chongqing's urban core, show phase-specific increases. The carbon emission centroid exhibits a general northwestward shift, reflecting the growing contribution of Sichuan's industrial cities, with temporary southeastward movements indicating localized emission surges in Chongqing. Moran's I analysis demonstrates a transition from strong spatial clustering in the early 2000s to spatial dispersion by 2022, driven by urbanization and regional policy interventions.

The study highlights the importance of region-specific strategies to address emission disparities, promote sustainable development, and achieve carbon neutrality. Recommendations include enhancing renewable energy adoption, improving energy efficiency, and strengthening regional coordination. By leveraging spatial tools and dynamic modeling, this research provides valuable insights into carbon emission management in rapidly urbanizing regions like the Chengdu-Chongqing urban agglomeration.

Keywords: carbon emissions, spatiotemporal research, Chengdu-Chongqing urban agglomeration, sustainable development

1. Introduction

1.1 Research Background

Global climate change has become one of the most critical challenges of the 21st century, with its widespread impacts threatening ecosystems, economies, and societal stability worldwide. Reducing carbon dioxide emissions is essential for achieving sustainable development and mitigating the adverse effects of climate change. As the largest developing country and one of the highest carbon emitters, China plays a crucial role in global climate action. In 2015, China submitted its Intended Nationally Determined Contributions (INDC) to the United Nations Framework Convention on Climate Change (UNFCCC), committing to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. These commitments include reducing carbon intensity per unit of GDP by 60%-65% compared to 2005 levels, increasing the share of non-fossil fuels in primary energy consumption to 20%, and expanding forest stock volume by 4.5 billion cubic meters.

At the regional level, urban agglomerations are key to achieving these national objectives due to their high levels of economic activity, energy consumption, and carbon emissions. The Chengdu-Chongqing urban agglomeration, as the economic core of Southwest China, exemplifies these challenges. This region has experienced rapid urbanization and industrialization, resulting in significant carbon emission pressures. Core cities such as Chengdu and Chongqing have seen substantial economic growth and urban expansion, leading to higher emissions, while peripheral areas exhibit slower development and lower emissions. These disparities highlight the need for detailed analysis of carbon emission patterns to address regional differences and support sustainable development.

Existing research has primarily focused on national or provincial levels, often neglecting the spatiotemporal dynamics of carbon emissions within urban agglomerations. However, regions like Chengdu-Chongqing exhibit unique characteristics, including rapid urbanization, uneven energy consumption patterns, and varying levels of economic development, which require closer examination. As a critical area for implementing China's "dual carbon" goals, understanding the spatiotemporal evolution of carbon emissions in the Chengdu-Chongqing region is essential for formulating effective, region-specific strategies to achieve carbon neutrality.

1.2 Significance of the Study

The Chengdu-Chongqing urban agglomeration is a critical region in China's efforts to achieve its "dual carbon" goals of peaking carbon emissions by 2030 and achieving carbon neutrality by 2060. As a rapidly urbanizing and industrializing area, it faces significant challenges in balancing economic growth with environmental sustainability. Understanding the spatiotemporal dynamics of carbon emissions in this region is essential for addressing these challenges and developing effective, region-specific mitigation strategies.

This study provides a high-resolution analysis of carbon emissions using nighttime light (NTL) data, which serves as a reliable proxy for human activity and energy consumption. By leveraging this approach, the research captures the spatial and temporal evolution of carbon emissions, offering valuable insights into emission patterns and their changes over time. Such an analysis is particularly important for regions like Chengdu-Chongqing, where rapid urbanization and uneven development create complex emission dynamics.

In addition, the study addresses a critical gap in existing research, which has often focused on national or provincial levels while neglecting the unique characteristics of urban agglomerations. By examining the spatiotemporal distribution of emissions within the Chengdu-Chongqing region, this research highlights regional disparities and provides a more nuanced understanding of how emissions are distributed and evolve in rapidly developing urban areas.

1.3 Relevant Research

The acceleration of industrialization and urbanization has significantly intensified greenhouse gas emissions, making carbon emission research a critical area of climate change studies. Globally, scholars have developed various methods to estimate carbon emissions, including emission factor methods, material balance methods, life cycle analysis, and biogeochemical modeling (Zhang Deying, 2005; Ren Xiuyan, 2013). Among these, the material balance method, recommended by the IPCC (2006), is widely used for fossil fuel-related emissions due to its reliability in calculating emissions based on the carbon content of fuels and their oxidation rates. However, the accuracy of this method depends heavily on the quality of input data (Ilhan et al., 2010).

From a spatial perspective, significant regional disparities in carbon emissions have been observed globally and within China. Studies have shown that eastern China dominates energy consumption and emissions, while western regions are witnessing a growing share due to industrial expansion (Wang Qianqian et al., 2009). Temporal analyses also reveal dynamic changes in emissions, with most provinces experiencing growth from 1990 to 2009 (Shu Yuqin, 2012). Additionally, spatial autocorrelation methods have identified strong spatial dependencies between emissions and socio-economic factors, emphasizing the need for region-specific mitigation strategies (Fang et al., 2022). However, while these studies highlight important spatial and temporal trends, they often lack detailed analyses at the urban agglomeration level, particularly in regions like Chengdu-Chongqing, where rapid development has created unique emission dynamics.

Nighttime light (NTL) data, captured by remote sensing satellites such as the Visible Infrared Imaging Radiometer Suite (VIIRS) and the Operational Linescan System (OLS), have emerged as a valuable tool for studying human activities. Early studies (Elvidge et al., 1997; Doll et al., 2000) established strong correlations between NTL intensity and socio-economic indicators such as GDP, electricity consumption, and greenhouse gas emissions. Over time, NTL data have been increasingly used to analyze urbanization, economic development, and environmental changes (Li Yuanting et al., 2023).

In the context of carbon emission research, NTL data have proven effective for estimating and detecting emissions. For example, Doll et al. (2000) demonstrated the utility of NTL data in studying global CO2 distributions. More recent studies have extended this application to analyze spatiotemporal emission dynamics at county and city levels (Tang et al., 2025; Wang et al., 2024). In the Chengdu-Chongqing region, NTL data have been used to track urban expansion and its impact on emissions (Wang Han et al., 2022). Compared to traditional statistical datasets, NTL data offer unique advantages, such as real-time monitoring and the ability to fill gaps in regions with limited ground-based measurements (Zhao Yu et al., 2022). However, challenges remain in improving the accuracy of NTL-based estimates, particularly in low-light rural areas where emission activities are less detectable.

Despite these advancements, several gaps remain in the current literature. First, most studies focus on national or provincial scales, often overlooking the spatiotemporal dynamics of emissions within urban agglomerations. This is particularly relevant for the Chengdu-Chongqing region, where rapid urbanization and uneven development have created complex emission patterns that require detailed analysis. Second, while NTL data have been widely applied for estimating emissions, their potential for capturing fine-scale spatiotemporal variations in emissions within urban agglomerations remains underutilized.

This study builds on previous research by employing NTL data to analyze the spatiotemporal evolution of carbon emissions in the Chengdu-Chongqing urban agglomeration from 2000 to 2022. Unlike earlier studies, which often focus on broader spatial scales or rely solely on statistical datasets, this research leverages the high-resolution capabilities of NTL data to capture intra-regional disparities and emission dynamics. By focusing on the unique characteristics of the Chengdu-Chongqing region, the study provides new insights into emission patterns and offers a scientific basis for developing tailored strategies to achieve China's "dual carbon" goals.

1.4 Research Design

This study investigates the spatiotemporal dynamics of carbon emissions in the Chengdu-Chongqing urban agglomeration from 2000 to 2022, employing an integrated methodological framework to analyze temporal trends, spatial patterns, and spatiotemporal shifts. By combining these analytical approaches, the research aims to provide a comprehensive understanding of emission dynamics and offer insights for addressing regional disparities and supporting carbon neutrality strategies in this rapidly urbanizing region.

To analyze temporal trends, a slope analysis is applied to quantify the rate of change in carbon emissions over the study period. This method calculates the slope of annual carbon emissions for each spatial unit, identifying areas experiencing growth, decline, or stability in emissions. By detecting temporal heterogeneity across the Chengdu-Chongqing urban agglomeration, this analysis highlights regions with rapid emission growth or reductions, providing a foundation for understanding how emissions have evolved over time.

The spatial patterns of carbon emissions are examined using Moran’s I and local Moran’s I (LISA) statistics. Moran’s I measures the degree of spatial autocorrelation, revealing whether emissions are clustered, dispersed, or randomly distributed across the region. Local Moran’s I further identifies specific clusters or outliers of high and low emissions, uncovering regional disparities and spatial dependencies. This spatial analysis is essential for understanding the geographic distribution of emissions and their relationship to urbanization and development within the region.

To integrate spatial and temporal perspectives, a centroid analysis is conducted to track the movement of the carbon emission centroid over the study period. This method provides insights into the shifting geographic focus of emissions, reflecting the changing contributions of different subregions to overall emissions. The trajectory of the centroid highlights the dynamic interplay between urbanization, economic development, and emission patterns, offering a detailed understanding of how emissions evolve across both time and space.

By combining these analytical methods, the research design ensures a robust investigation of carbon emission dynamics in the Chengdu-Chongqing urban agglomeration. This integrated approach captures the complexity of emission trends, spatial dependencies, and dynamic shifts, enabling the development of targeted strategies for achieving sustainable development and supporting China’s “dual carbon” goals.

2. Method

This study employs a combination of quantitative methods to analyze the spatiotemporal evolution of carbon emissions in the Chengdu-Chongqing region. The methods include trend analysis using the slope method, spatial autocorrelation analysis, and centroid analysis. The following sections detail the data sources and methodologies used in this study.

2.1 Data Sources

The carbon emission data used in this study are derived from the Open-source Data Inventory for Anthropogenic CO2 (ODIAC), a high-resolution global dataset for CO2 emissions. ODIAC integrates fossil fuel CO2 emissions from point sources (e.g., power plants), national emission totals, and satellite-based nighttime light data to allocate emissions spatially. Its 1 km × 1 km grid-level resolution makes it particularly suitable for analyzing intra-regional disparities and trends in carbon emissions. This dataset serves as the primary source for carbon emission data in the Chengdu-Chongqing region.

The spatial boundary data for the Chengdu-Chongqing region are obtained from vector maps provided by the Ministry of Natural Resources of China. These maps offer detailed geographic and administrative boundary information, which is essential for spatial analysis and visualization of carbon emission patterns and trends.

2.2 Methodology

2.3.1 Temporal Analysis of Carbon Emissions Using the Slope Method

Along with the description of subjects, give the mended size of the sample and number of individuals meant to be in each condition if separate conditions were used. State whether the achieved sample differed in known ways from the target population. Conclusions and interpretations should not go beyond what the sample would warrant.

To analyze the temporal trends of carbon emissions across cities, the Slope Method is applied. This method establishes a univariate linear regression model between carbon emissions and time to reflect their changing trends. The formula is as follows (Lu Hui & Shi Jiancheng, 2012):

$$SLOPE = \frac{\sum_{i=1}^{n} X_i T_i - (\sum_{i=1}^{n} X_i) \times \frac{(\sum_{i=1}^{n} T_i)}{n}}{\sum_{i=1}^{n} T_i^2 - \frac{(\sum_{i=1}^{n} X_i)^2}{n}} \tag{1}$$

In this study, n represents the total number of years, T_i denotes the i-th year, and X_i corresponds to the carbon emission value in the i-th year. The slope (SLOPE) is used to indicate the trend of carbon emissions. When the SLOPE value is greater than zero (SLOPE > 0), it indicates an increasing trend in carbon emissions. Conversely, when the SLOPE value is less than zero (SLOPE < 0), it indicates a decreasing trend in carbon emissions.

To classify the growth types of carbon emissions, the calculated slope values are divided into levels based on the mean ($\bar{C}$) and standard deviation (s), as shown below (Su Yongxian, 2015):

Table 1. Carbon Growth Level

Growth Type	Slow Growth	Moderate Growth	Medium Growth	Fast Growth	Rapid Growth
Slope Value	$< \overline{C} - 0.5s$	$\overline{C} - 0.5s \sim \overline{C} + 0.5s$	$\overline{C} + 0.5s \sim \overline{C} + 1.5s$	$\overline{C} + 1.5s \sim \overline{C} + 2.5s$	$\overline{C} > 2.5s$

2.3.2 Spatial Autocorrelation Analysis

Spatial autocorrelation analysis is used to examine the degree of clustering or dispersion of carbon emissions within the Chengdu-Chongqing region. This method includes both Global Moran's I and Local Moran's I (LISA) indices.

The Global Moran's I Index evaluates the overall spatial clustering of carbon emissions. The formula is:

$$I = \frac{\sum_{i=1}^{n} (x_i - \overline{x}) \sum_{j=1}^{n} W_{ij} (x_j - \overline{x})}{s^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} \tag{2}$$

Where, n represents the total number of spatial units, while x_i and x_j denote the attribute values of spatial units i and j, respectively. The term W_{ij} refers to the spatial weight matrix that defines the adjacency relationship, and s^2 represents the variance of x.

The value of Moran's I generally falls between -1 and 1, and the spatial correlation is categorized as follows (Anselin, 2008):

Table 2. Spatial Correlation

I Value	$I < 0$	$I \to 0$	$I > 0$
Spatial Correlation	Negative	No correlation	Positive
Spatial Pattern	Dispersed Pattern	Random Distribution	Clustered Pattern

Note. The closer I is to -1, the stronger the negative correlation; the closer it is to 1, the stronger the positive correlation.

To identify local clusters or spatial outliers, the Local Moran's I Index is applied. The formula is:

$$I_i = (x_i - \overline{x}) \sum_{j=1}^{n} W_{ij} (x_j - \overline{x}) / s^2 \tag{3}$$

Substituting s^2, the formula becomes:

$$I_i = n\,(x_i - \overline{x}) \sum_{j=1}^{n} W_{ij}\big(x_j - \overline{x}\big) \Big/ \sum_{i=1}^{n} (x_i - \overline{x})^2 = Z_i' \sum_i W_{ij} Z_j' \quad (4)$$

If $I_i > 0$*, there is a strong positive spatial autocorrelation, indicating local clustering of carbon emissions.*

If $I_i < 0$*, there is a strong negative spatial autocorrelation, indicating local dispersion of carbon emissions.*

2.3.3 Centroid Analysis of Carbon Emissions

The concept of a "centroid" is used to represent the spatial balance point of carbon emissions within the region. This study employs the weighted centroid method, which considers the magnitude of carbon emissions, giving greater weight to high-emission areas. The calculation formulas are:

$$X = \frac{\sum x_i c_i}{\sum c_i} \; Y = \frac{\sum y_i c_i}{\sum c_i} \quad (5)$$

Where, X and Y represent the coordinates of the centroid. x_i and y_i denote the coordinates of the i-th point, and c_i represents the carbon emission value at the i-th point.

The distance of centroid movement reflects the dynamic trend of overall carbon emissions in the Chengdu-Chongqing region. The formula for calculating the movement distance is:

$$D = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2} \quad (6)$$

Where, D represents the Euclidean distance of centroid movement. X_1 and Y_1 denote the coordinates of the centroid before and after the movement.

3. Analysis of Carbon Emissions in the Chengdu-Chongqing Urban Agglomeration

This section explores the spatiotemporal dynamics of carbon emissions in the Chengdu-Chongqing urban agglomeration using nighttime light (NTL) data. The analysis is organized into three parts: (1) classification of carbon emission growth trends, (2) spatial patterns of emissions, and (3) the spatiotemporal evolution of emission distribution.

3.1 Classification of Carbon Emission Growth Trends

Using the Slope Method, the cities within the Chengdu-Chongqing urban agglomeration are categorized into five distinct groups according to their carbon emission growth rates over the period from 2000 to 2022 (Table 1). This classification underscores the heterogeneous nature of carbon emissions across the region, reflecting underlying disparities in industrial structures, energy consumption patterns, and stages of economic development.

Using the Slope Method, this study classifies cities within the Chengdu-Chongqing urban agglomeration into four categories based on their carbon emission growth rates from 2000 to 2022. The Slope Method calculates the rate of change in carbon emissions over time, providing a standardized measure to compare growth trends across cities. The results are summarized in Figure 1.

3.1.1 Classification of Carbon Emission Growth Trends

Cities classified under the slow growth type exhibit minimal growth in carbon emissions, as indicated by their low slope values (less than 400). This reflects relatively stable energy consumption and industrial activity, often associated with slower economic development or a transition toward low-carbon industries. These cities are typically characterized by limited industrial expansion and a focus on maintaining environmental sustainability. Examples of cities in this category include Dadukou (166.42), Dianjiang (291.94), Fengdu (263.34), Jiangbei (394.80), Liangping (315.62), Nanchuan (398.31), Qianjiang (334.05), Rongchang (386.85), Yunyang (299.71), Yuzhong (7.01), and Zhongxian (289.28).

Cities in the moderate growth type demonstrate steady growth in carbon emissions, with slope values ranging from 400 to 2000, which are close to the regional mean. This reflects balanced economic development and energy use, often driven by gradual industrialization and urbanization. These cities maintain moderate energy consumption levels and exhibit a stable trajectory of carbon emissions. Cities in this category include Banan (1014.35), Beibei (699.31), Bishan (649.46), Changshou (715.30), Dazu (770.03), Fuling (848.48), Guang'an (1825.93), Hechuan (716.79), Jiangjing (1119.12), Jiulongpo (692.38), Kaizhou (466.86), Leshan (2087.83), Nan'an (423.55), Neijiang (1597.09), Qijiang (623.38), Shapingba (754.54), Suining (1794.49), Tongliang (610.40), Tongnan (467.21), Wanzhou (508.21), Ya'an (1212.08), Yongchuan (714.76), Yubei (1425.37), Zigong (1330.50), and Ziyang (1291.49).

Cities classified under the medium growth type experience relatively rapid growth in carbon emissions, as indicated by slope values ranging from 2000 to 4000. This growth is often driven by increased industrial activity and energy consumption, particularly in cities with expanding manufacturing sectors and energy-intensive industries. Examples of cities in this category include Dazhou (2375.85), Deyang (2388.85), Luzhou (2240.58), Meishan (2353.03), Mianyang (2913.02), Nanchong (3227.10), and Yibin (2750.37).

Chengdu is the only city classified under the rapid growth type, with an exceptionally high slope value of 11232.15. This reflects its rapid growth in carbon emissions, driven by its role as the economic and industrial core of the Chengdu-Chongqing urban agglomeration. Chengdu's carbon emission growth is fueled by its rapid urban expansion, high-energy-consuming industries, and significant economic development, making it a unique case within the region.

3.1.2 Analysis of Carbon Emission Growth Trends

The analysis reveals significant regional disparities in carbon emission growth rates between cities in Sichuan Province and Chongqing Municipality. Generally, cities in Sichuan exhibit higher growth rates, particularly those classified under the medium and rapid growth types, such as Dazhou, Mianyang, and Chengdu. This disparity can be attributed to differences in industrial structures, with Sichuan cities relying more heavily on energy-intensive industries, while Chongqing cities tend to maintain a more balanced industrial structure, resulting in slower or moderate growth in emissions.

Chengdu stands out as the dominant contributor to carbon emissions in the region, with an exceptionally high growth rate that places it in the rapid growth category. As the economic and industrial core of the Chengdu-Chongqing urban agglomeration, Chengdu's rapid urban expansion and energy-intensive industries drive its emissions. This highlights both its critical role in regional development and the challenges it faces in transitioning toward low-carbon growth.

Inter-city variations are also evident, with most cities falling into the moderate growth category, reflecting steady but controlled increases in emissions driven by gradual industrialization and urbanization. However, a few cities, such as those in the medium growth category (e.g., Nanchong and Yibin), exhibit relatively rapid growth, reflecting the uneven distribution of emissions across the region. In contrast, cities in the slow growth category, such as Dadukou and Yuzhong, demonstrate minimal growth, often due to stable energy consumption and a focus on environmental sustainability.

This classification of cities into growth types provides a nuanced understanding of the spatiotemporal dynamics of carbon emissions in the Chengdu-Chongqing urban agglomeration. It highlights the need for targeted policy interventions that address regional disparities, support low-carbon transitions in high-growth cities, and promote balanced development to achieve carbon peaking and neutrality goals.

3.2 Spatial Analysis of Carbon Emissions

To examine the spatial clustering characteristics of per capita carbon emissions in the Chengdu-Chongqing urban agglomeration, this study employs Moran's I analysis. The global Moran's I index is used to evaluate the overall spatial autocorrelation of per capita carbon emissions, while the local Moran's I (LISA) identifies specific spatial clustering patterns and their evolution over time. This analysis provides insights into the spatial dependencies and clustering dynamics of carbon emissions across the region from 2000 to 2022.

3.2.1 Global Moran's I Analysis

The global Moran's I index results for per capita carbon emissions from 2000 to 2022 are presented in Table 3. The Moran's I values exhibit a gradual decline over the study period, indicating a transition from significant positive spatial autocorrelation to a more dispersed spatial distribution. This trend reflects the evolving spatial dynamics of carbon emissions in the Chengdu-Chongqing urban agglomeration.

Table 3. Global Moran's I Results for Per Capita Carbon Emissions (2000–2022)

Year	Moran's I	Z-Value
2000	0.180212014	2.53616415
2001	0.171684803	2.39514018
2002	0.19957198	2.523764292
2003	0.150985165	2.015607159
2004	0.139911304	1.976127496
2005	0.182019684	2.441830427
2006	0.177385691	2.463539237
2007	0.173731287	2.349795689
2008	0.168996674	2.299064791
2009	0.103270196	1.551468551
2010	0.141412761	2.195130426
2011	0.155448977	2.01092138
2012	0.147727893	2.035875927
2013	0.141085772	1.887742352
2014	0.136255568	1.832998513
2015	0.130954379	1.828792979
2016	0.127770611	1.651067146
2017	0.106851727	1.579959917
2018	0.120316817	1.874194151
2019	0.118775619	1.68335593
2020	0.093137036	1.441037534
2021	0.090764365	1.363630933
2022	0.089453774	1.354871612

The results indicate three distinct phases of spatial clustering evolution:

2000–2010: Strong Spatial Clustering

During this period, Moran's I values ranged between 0.15 and 0.20, with Z-values consistently exceeding 2.0, indicating statistically significant positive spatial autocorrelation. This suggests that cities with similar levels of per capita carbon emissions tended to cluster geographically. High-emission cities were concentrated in Chongqing's central urban areas, while low-emission cities formed clusters in peripheral regions.

2010–2016: Weakening Spatial Clustering

From 2010 to 2016, Moran's I values declined to approximately 0.13, reflecting a reduction in spatial clustering. High-emission clusters in Chongqing's urban core became less prominent, and low-emission clusters began to disperse. This trend indicates a gradual decentralization of carbon emissions, likely driven by urban expansion and industrial restructuring.

2016–2022: Spatial Dispersion

By 2022, Moran's I values had dropped below 0.10, with Z-values falling below 1.65, indicating a transition to spatial dispersion. The spatial distribution of per capita carbon emissions became increasingly random, reflecting the decentralization of emissions and the diminishing influence of spatial clustering.

3.2.2 Local Moran's I Analysis

The local Moran's I analysis, visualized through LISA cluster maps, seen in figure 2, provides a more detailed understanding of the spatial clustering patterns of per capita carbon emissions at the city level. The results reveal distinct spatial clustering patterns that evolved over time, corresponding to the trends observed in the global

Moran’s I analysis.

High-High Clusters

High-high clusters were primarily concentrated in Chongqing’s central urban areas during the early stages of the study period. These clusters represent cities with high per capita carbon emissions surrounded by other high-emission cities, reflecting the concentration of energy-intensive industries and urban activities in Chongqing’s core.

Low-Low Clusters

Low-low clusters were observed in peripheral areas surrounding Chongqing’s urban core. These clusters represent cities with low per capita carbon emissions surrounded by other low-emission cities, often located in less industrialized or rural areas.

Low-High Clusters

Low-high clusters persisted in northeastern Chongqing, indicating cities with relatively low per capita carbon emissions surrounded by high-emission cities. This pattern highlights the spatial heterogeneity of carbon emissions in this region, where localized factors such as industrial activity and energy consumption differ significantly from surrounding areas.

The LISA results reveal three distinct phases of local clustering evolution:

2000–2010: Strong Local Clustering

During this phase, high-high clusters were prominent in Chongqing’s central urban areas, while low-low clusters were concentrated in peripheral regions. Low-high clusters were also observed in northeastern Chongqing, reflecting localized disparities in carbon emissions.

2010–2016: Weakening Local Clustering

The prominence of high-high clusters in Chongqing’s urban core diminished during this period, reflecting a reduction in the concentration of high-emission areas. Low-low clusters also became less significant, indicating a more dispersed distribution of low-emission cities.

2016–2022: Local Dispersion

By the final phase, the spatial clustering of per capita carbon emissions had largely dissipated. High-high clusters in Chongqing’s central urban areas further weakened, and low-low clusters in peripheral regions became less pronounced. The low-high clusters in northeastern Chongqing persisted but became less significant, reflecting a general trend toward spatial dispersion.

3.2.3 Spatial Patterns

The results of the Moran’s I analysis reveal dynamic spatial patterns of per capita carbon emissions in the Chengdu-Chongqing urban agglomeration. Over the study period, the transition from strong spatial clustering to greater spatial dispersion reflects the combined effects of urbanization, industrial restructuring, and regional policy interventions. These changes suggest that while carbon emissions remain concentrated in specific areas, the spatial distribution is becoming more balanced as development progresses across the region.

In the early stages, Chongqing’s central urban areas were characterized by high-high clusters, indicating their significant contribution to regional carbon emissions. This dominance reflects the city’s role as a major economic and industrial hub. However, the weakening of these clusters over time suggests progress in decentralizing emissions, likely driven by industrial relocation, improved energy efficiency, and policy measures aimed at reducing emissions in urban cores. In contrast, low-high clusters have persisted in northeastern Chongqing, highlighting localized disparities in carbon emissions. These areas, with relatively low emissions surrounded by higher-emission regions, may require targeted interventions to address the underlying causes of these disparities, such as uneven development or limited access to cleaner energy sources.

The findings emphasize the importance of region-specific strategies to reduce spatial disparities in carbon emissions and promote balanced development. High-emission areas, particularly in Chongqing’s urban core, should prioritize energy efficiency measures, industrial restructuring, and the adoption of cleaner technologies to curb emissions. Meanwhile, low-emission areas should focus on sustainable development practices to prevent future emission growth as they continue to urbanize and industrialize. These tailored approaches are essential for achieving the region’s carbon reduction goals while maintaining economic and social development.

3.3 Spatiotemporal Evolution Analysis of Carbon Emissions

Report any other analyses performed, including subgroup analyses and adjusted analyses, indicating those that were pre-specified and those that were exploratory (though not necessarily in the level of detail of primary analyses). Consider putting the detailed results of these analyses on the supplemental online archive. Discuss the implications, if any, of the ancillary analyses for statistical error rates.

To further explore the dynamic spatiotemporal evolution of carbon emissions in the Chengdu-Chongqing urban agglomeration, this study employs the centroid analysis method. Widely used in geographic research, centroid analysis provides a quantitative approach to examining the spatial distribution changes of carbon emissions over time. By calculating the weighted centroid coordinates, this method reveals the key regions of carbon emissions and their movement trajectories, offering insights into the dynamic evolution of carbon emission patterns in both time and space. These findings serve as a scientific basis for regional carbon emission management and policy formulation, contributing to a better understanding of the interplay between regional development and environmental coordination.

This section analyzes the spatiotemporal dynamics of carbon emissions in the Chengdu-Chongqing region from 2000 to 2022 using the weighted centroid method. The analysis focuses on the direction, distance, and characteristics of centroid movement, while also considering the regional economic and urbanization background to identify the driving factors and phase-specific features of carbon emission changes. The results and analysis are presented in Figure 3 and Figure 4.

3.3.1 Trajectory and Dynamics of Carbon Emission Centroid

The movement trajectory of the carbon emission centroid for the Chengdu-Chongqing urban agglomeration from 2000 to 2022 reveals distinct spatial patterns and variations in the distribution of carbon emissions over time. These patterns reflect the combined effects of urbanization, industrial restructuring, and regional policy interventions, offering valuable insights into the shifting focus of carbon emissions within the region.

Overall, the carbon emission centroid exhibits a general northwestward movement trend over the study period. This indicates a gradual shift in emissions toward the northern and western parts of the region, particularly in cities such as Chengdu, Mianyang, and Deyang in Sichuan Province. This northwestward trend highlights the growing contribution of these cities to regional carbon emissions, driven by rapid industrialization and urban expansion. However, deviations from this trend are observed in certain years, where the centroid temporarily shifts southeastward or southward. These deviations suggest short-term increases in emissions from Chongqing's central urban areas and neighboring regions, reflecting localized changes in economic activities or energy consumption patterns.

The movement distance of the centroid further illustrates the dynamics of carbon emission distribution. In most years, the centroid exhibited short-distance movements, typically ranging from 0.01 to 0.5 kilometers. These minimal shifts suggest relatively stable spatial distribution patterns of carbon emissions during these periods, with no significant changes in the regional carbon emission intensity. However, in specific years such as 2001, 2002, 2004, and 2020, the centroid experienced significant movements exceeding 1 kilometer. These larger shifts indicate notable changes in the regional distribution of emissions, likely driven by major economic events, industrial restructuring, or the implementation of significant policy measures during these years.

Together, the trajectory and movement dynamics of the carbon emission centroid provide a comprehensive picture of the spatiotemporal evolution of emissions in the Chengdu-Chongqing urban agglomeration. These findings underscore the importance of understanding regional shifts in emissions to inform targeted policy interventions and promote balanced, low-carbon development across the region.

3.3.2 Regional Dynamics and Influencing Factors of Carbon Emissions

The movement of the carbon emission centroid highlights significant regional disparities and influencing factors shaping carbon emission patterns within the Chengdu-Chongqing urban agglomeration. These dynamics reflect the interplay of industrialization, urbanization, and seasonal variations, offering a deeper understanding of the spatial and temporal evolution of emissions across the region.

The northwestern and northern regions, particularly cities such as Chengdu, Mianyang, and Deyang, have emerged as dominant contributors to carbon emissions. These cities have experienced rapid growth in emissions due to their roles as major industrial and economic hubs in Sichuan Province. The northwestward movement of the carbon emission centroid over the study period underscores the increasing influence of these cities in the region's carbon emission landscape, driven by industrial expansion and economic development.

In contrast, the southeastern regions, including Chongqing's central urban areas and surrounding districts, have shown significant growth in carbon emissions during specific years. This is reflected in the southeastward shifts of the centroid in years such as 2004, 2005, and 2020. These shifts suggest temporary increases in emissions from energy-intensive industries and urban activities in Chongqing, highlighting the region's evolving role in the spatial distribution of emissions. Such phase-specific growth underscores the need for targeted interventions to address emissions in these areas during periods of heightened activity.

Additionally, seasonal variations in carbon emissions have been observed within the Chengdu-Chongqing urban agglomeration. In most years, the centroid exhibited southeastward shifts during specific months, particularly from April to June and from November to January. These seasonal variations are likely influenced by climatic differences across the region, which affect energy consumption patterns, such as increased heating demands in winter and cooling demands in summer. Understanding these seasonal dynamics is crucial for designing policies that address short-term fluctuations in emissions while maintaining long-term sustainability goals.

Together, these regional and seasonal dynamics provide valuable insights into the factors driving carbon emissions in the Chengdu-Chongqing urban agglomeration. They emphasize the importance of region-specific and time-sensitive strategies to manage emissions effectively and promote balanced, low-carbon development across the region.

4. Discussion

4.1 Summary

This study provides a comprehensive analysis of the spatiotemporal dynamics of carbon emissions in the Chengdu-Chongqing urban agglomeration from 2000 to 2022, revealing significant regional disparities, evolving spatial clustering patterns, and dynamic shifts in the carbon emission centroid. The findings highlight the complex interplay between industrialization, urbanization, and policy interventions in shaping the region's carbon emission trends.

Key results indicate pronounced regional disparities, with northwestern and northern cities such as Chengdu, Mianyang, and Deyang experiencing rapid emission growth driven by industrialization and economic development. In contrast, southeastern regions, including Chongqing's urban core, exhibit phase-specific increases in emissions during certain years, reflecting localized surges in energy consumption and industrial activity. The northwestward movement of the carbon emission centroid underscores the growing dominance of Sichuan's industrial cities, while temporary southeastward shifts highlight localized emission growth in Chongqing. Additionally, the weakening of spatial clustering, as revealed by Moran's I analysis, suggests progress in decentralizing emissions through industrial restructuring and urbanization. Seasonal variations in emissions, particularly during April–June and November–January, further emphasize the role of climatic differences in influencing energy consumption patterns.

To address these challenges, several policy recommendations are proposed. High-emission cities in the northwest should prioritize industrial restructuring, energy efficiency, and the adoption of renewable energy to reduce emissions. Southeastern regions, particularly Chongqing's urban core, require localized interventions, such as stricter regulations on energy-intensive industries, improved urban planning, and the promotion of green infrastructure. Regional coordination between Sichuan and Chongqing is essential to balance development and emission reduction, with joint initiatives like cross-regional carbon trading and collaborative clean energy projects offering promising solutions. Promoting sustainable development through green urbanization, renewable energy transitions, and circular economy models can further support the region's carbon neutrality goals while ensuring economic growth and social equity.

4.2 Contributions and Limitations

This study provides valuable insights into the spatiotemporal dynamics of carbon emissions in the Chengdu-Chongqing urban agglomeration, offering a foundation for region-specific strategies to achieve carbon peaking and neutrality. However, several limitations remain. The analysis focuses primarily on spatial and temporal trends, with limited exploration of the socioeconomic drivers, such as GDP, population density, and industrial output, that influence emission patterns. Incorporating such data in future studies could provide a more comprehensive understanding of the factors driving emissions.

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Appendix

Supplementary Figures

This appendix provides supplementary figures referenced in the main text to support the analysis of carbon emission dynamics in the Chengdu-Chongqing urban agglomeration. These figures offer additional visual insights into the spatiotemporal patterns, local spatial clustering, and centroid movement trajectories discussed in the study.

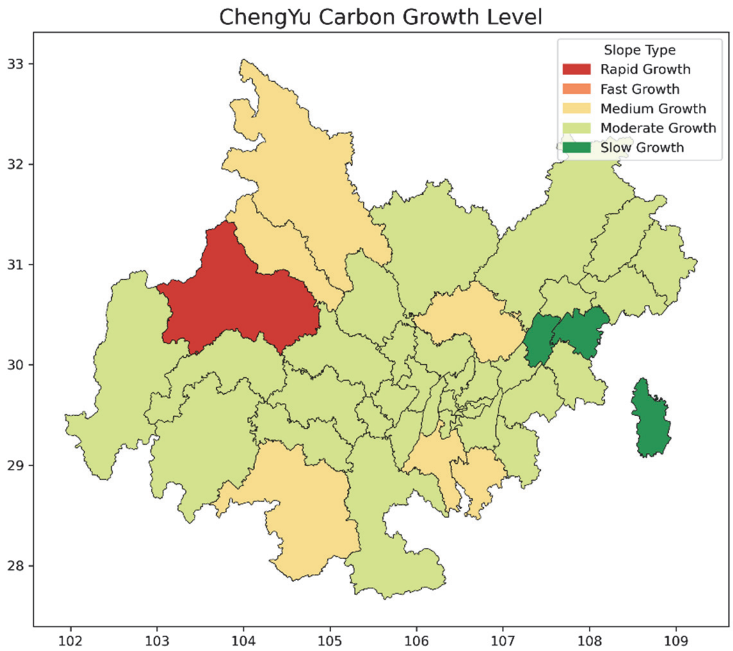

Figure 1. ChengYu Carbon Growth Level

This figure illustrates the slope of carbon emission changes across the Chengdu-Chongqing urban agglomeration, highlighting areas with significant increases or decreases in emissions over the study period. The slope map provides a detailed spatial representation of emission trends, aiding in the identification of regions with rapid growth or decline in emissions.

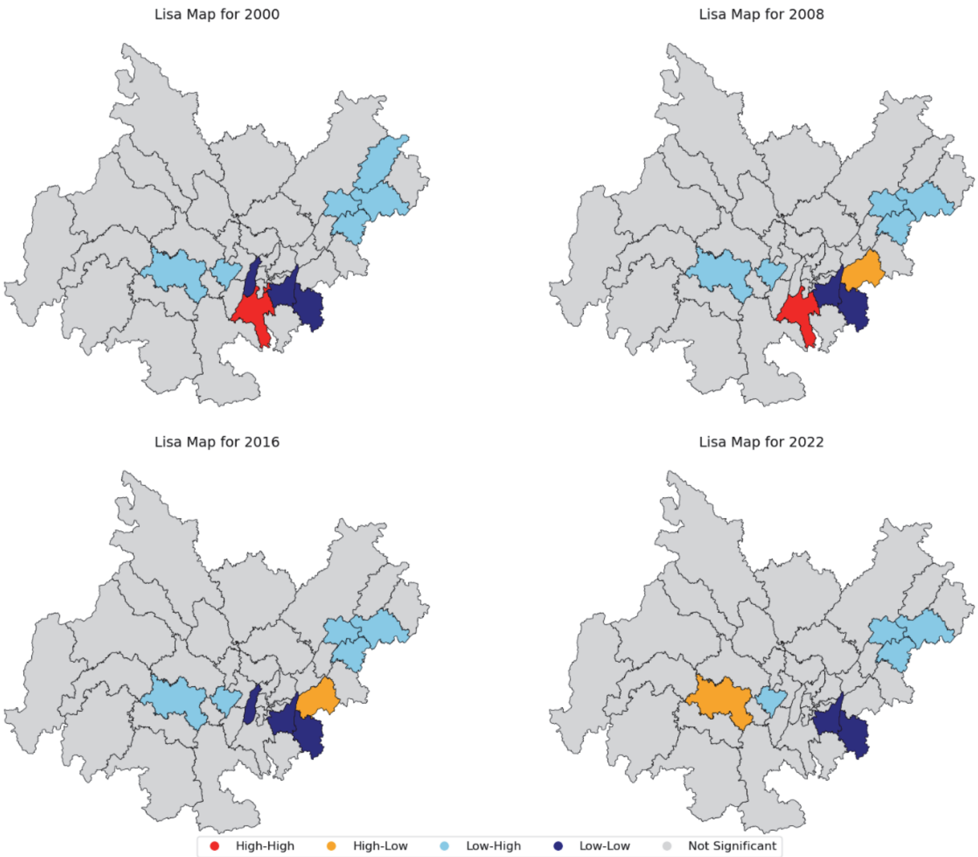

Figure 2. Local Moran's I Cluster Map

This figure presents the results of the Local Moran's I analysis, identifying spatial clusters of high and low per capita carbon emissions. The map highlights high-high, low-low, high-low, and low-high clusters, offering insights into the spatial clustering and disparities in carbon emissions across the region.

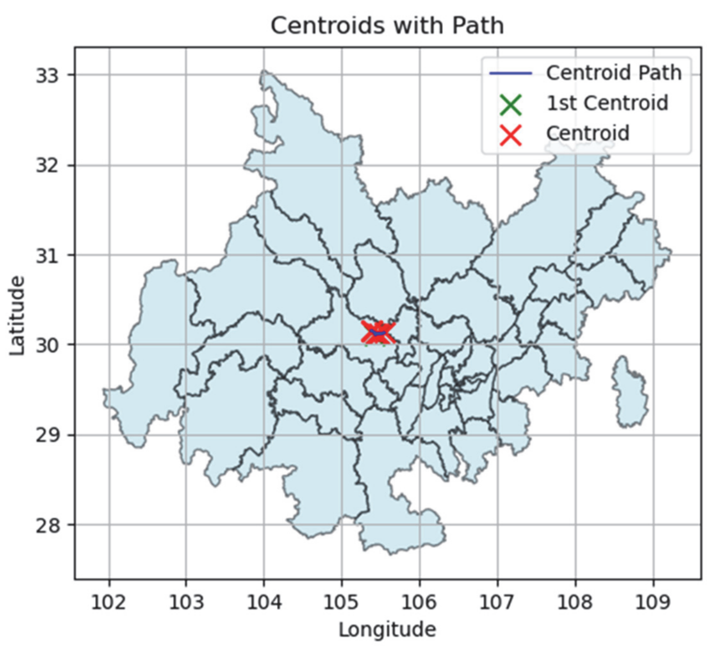

Figure 3. Centroid Movement Trajectories

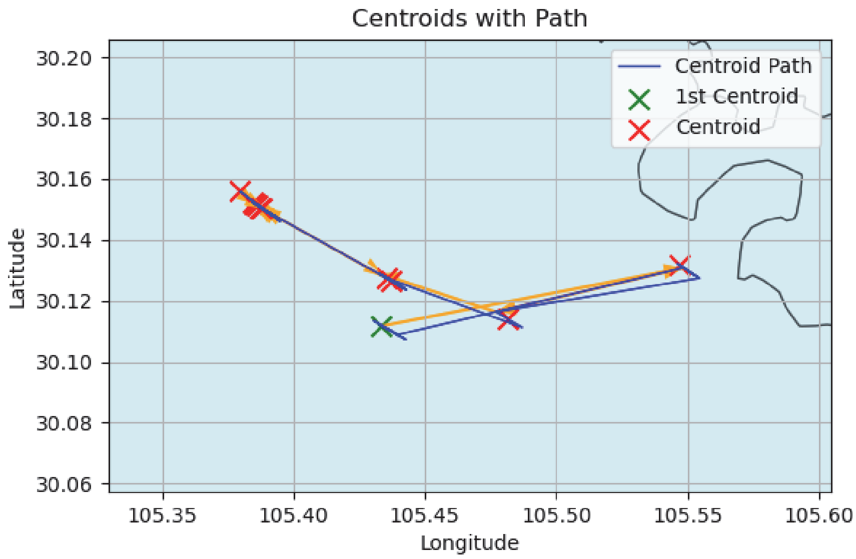

Figure 4. Centroid Movement Trajectories(Zoomed)

These figures depict the movement trajectories of the carbon emission centroid from 2000 to 2022. Figure 3 shows the overall trajectory of the centroid, reflecting the shifting spatial focus of carbon emissions over time. Figure 4 provides a detailed view of the annual movements, highlighting years with significant shifts and their corresponding directions.