

Spatiotemporal Distribution Characteristics and Driving Factors of Carbon Emissions in China

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Abstract. China's unique position as both the largest carbon emitter and a rapidly transitioning economy offers an unparalleled natural experiment in systemic emission mitigation. This study investigates the spatiotemporal evolution and driving mechanisms of carbon emissions across China's 30 provincial regions (2005–2020) through a multidimensional framework integrating demographic, economic, and industrial indicators. Utilizing the Geographical Detector Model, the results reveals three key findings. Temporally, provincial carbon emissions exhibited a phased growth trajectory characterized by accelerated expansion during the initial period (2005–2012) followed by moderated increases post-2012, with interregional disparities transitioning from divergence to convergence. Spatially, persistent emission hotspots emerged in North China, contrasting with stable low-carbon clusters in southwestern and northeastern regions, while dynamic spatial heterogeneity reshaped provincial emission gradients over time. Mechanistically, population agglomeration emerged as the dominant driver, its explanatory power (q-value) surging from 0.2282 to 0.5386, while its synergistic interaction with transportation infrastructure ($q=0.9664$) critically amplified urban carbon differentiation. These findings systematically unravel the nonlinear dynamics of emission patterns and the polycentric interactions among anthropogenic drivers, offering empirical foundations for optimizing China's dual carbon transition strategies.

Keywords: Carbon emissions, Spatiotemporal distribution, Driving factors, Geographical detector model, Multi-dimensional framework

1. Introduction

Under the escalating climate crisis marked by intensifying extreme weather events, accelerated polar ice loss, and unprecedented oceanic warming, anthropogenic carbon release has emerged as a critical driver of planetary-scale environmental transformations. As the principal contributor to global CO₂ emissions and a rapidly evolving economy undergoing structural modernization, China's decarbonization pathway commands particular scientific and policy relevance. The nation's current transition toward innovation-driven sustainable growth presents a unique opportunity to investigate the geospatial heterogeneity and socioeconomic determinants of emission patterns. Empirical analysis is crucial for developing evidence-based strategies to meet carbon targets while sustaining development. Integrating atmospheric chemistry, economic geography, and sustainability science

holds vital significance for understanding the intricate relationships between human activities and earth systems in the Anthropocene epoch.

Research on carbon emissions and their driving factors has become a global academic hotspot. Scholars worldwide have made substantial progress in carbon emission accounting, including top-down methods integrating direct and indirect emissions [1], bottom-up approaches based on energy consumption data [2], and macro-estimation methods using satellite remote sensing data. For instance, Lin Xiaona et al. [3] quantitatively accounted for fossil energy CO₂ emissions in Shanghai from 2000 to 2019 using system dynamics. Yang Peizhi et al. [4] predicted energy demand and CO₂ emissions using the LEAP model. Jinpei Ou et al. [5] and Hongxing Chen et al. [6] established functional equations between nighttime light data and energy-related carbon emissions. Studies on influencing factors have covered economic growth, industrial structure, energy efficiency, and other dimensions. Likang Zhang et al. [7] systematically investigating the coupled effects of demographic expansion, industrial reconfiguration, and innovation capacity alongside economic scaling effects. Mengying Wu et al. [8] provided empirical validation of these dynamics while further delineating urbanization-driven energy metabolisms and technological transition pathways as critical modulators within this complex interdependency framework. Cuiling Zhang et al. [9] highlighted income levels, energy intensity, and population size as direct contributors. Methodologically, Stern [10] developed econometric models to demonstrate significant impacts of economic growth, energy structure, and technological progress on emissions. Dietz and Rosa's STIRPAT model [11], considering nonlinear relationships among population, affluence, and technology, has been widely adopted. Yiming Ma et al. [12] applied neural networks to capture complex interactions, while Hamed Khosravi et al. [13] combined statistical and machine learning techniques. Li Dandan et al. [14] utilized geographically weighted regression (GWR) to study spatiotemporal heterogeneity in provincial carbon emissions. However, existing research often focuses on specific regions, lacks systematic national-scale analysis, overlooks complex interactions among factors, and suffers from limited long-term data, hindering comprehensive assessments of driving mechanisms.

This study integrates multiple methods to analyze the spatiotemporal effects of carbon emissions and their influencing factors in China. During data processing, multicollinearity tests were conducted to mitigate variable correlation issues. Carbon emissions were estimated using the apparent emission accounting method from the China Carbon Accounting Database (CEADs), ensuring accuracy and authority. A multi-dimensional indicator system and the Geo-detector model was used to comprehensively assess influencing factors. Innovations include: (1) introducing the geographical detector model to directly quantify the explanatory power of factors and their interactions, offering new insights into carbon emission mechanisms; (2) analyzing dynamic evolution patterns of driving factors using long-term data, providing timely and targeted scientific support for policymaking.

2. Methods and data

2.1. Data collection and processing

An objective, systematic, and quantifiable evaluation indicator system for carbon emissions was constructed based on existing research [15–16]. Seven dimensions were selected: population, population agglomeration, economic development, industrial structure, energy structure, transportation, and openness (Table 1).

Table 1. Indicator selection and meaning

Index	Meaning	Unit
X1(Population)	Population size	Person
X2(Population agglomeration)	Urban population density	Person/km ²
X3(Economic development)	Per capita regional GDP	Yuan/person
X4(Industrial)	Proportion of the added value of the secondary industry in GDP	%
X5(Energy)	Proportion of coal consumption in total energy consumption	%
X6(Transportation)	Highway passenger volume	Ten thousand persons
X7(openness)	Total investment of foreign-invested enterprises	Million dollars

This analysis incorporates panel data spanning quadrennial intervals (2005-2020) from 30 Chinese provincial administrations, excluding Tibet and special administrative regions due to data availability constraints. Apparent carbon metrics were sourced from provincial CO₂ inventories in the China Emission Accounts and Datasets (CEADS; <https://www.ceads.net>), while demographic variables were derived from the LandScan High-Resolution Global Population Dynamics suite (<https://landscan.ornl.gov>) [17-18]. Socioeconomic indicators - including urban population density, per capita GDP, secondary industry contribution, coal consumption share, highway transit volumes, and foreign investment - were acquired from the National Bureau of Statistics (<https://www.stats.gov.cn>). Temporal discontinuities in provincial records were resolved through linear interpolation, maintaining dataset integrity across the 15-year observational window.

In order to prevent high correlation between independent variables, multicollinearity test is performed on variables. In Table 2, the VIF value and tolerance of each variable can be obtained through linear regression analysis. Diagnostic metrics revealed variance inflation factors (VIF) consistently below 5 alongside tolerance values exceeding 0.1 across all predictors, effectively ruling out substantial multicollinearity concerns within the model framework.

Table 2. Linear regression analysis results

	Collinearity diagnosis	
	VIF	Tolerance
Population size	4.262	0.235
Urban population density	1.111	0.9
Per capita regional GDP	2.293	0.436
Proportion of the added value of the secondary industry in GDP	1.346	0.743
Proportion of coal consumption in total energy consumption	1.698	0.589
Highway passenger volume	4.232	0.236
Total investment of foreign-invested enterprises	3.122	0.32

Note: Dependent variable=apparent carbon emissions.

2.2. Carbon emission estimation

This study estimates carbon emission data using the apparent emission accounting method. Based on energy consumption data, the method calculates CO₂ emissions by multiplying the consumption of various energy types (coal, oil, natural gas, etc.) by their corresponding carbon emission coefficients

(determined by international standards and domestic conditions), and summing them up. This approach fully accounts for carbon emission differences across energy sources during combustion, featuring high accuracy and reliability, which is widely used in domestic and international carbon emission research.

2.3. Statistical analysis

Geospatial heterogeneity constitutes a fundamental attribute of territorial systems. The Geographical Detector Model (GDM) provides a robust analytical framework for quantifying spatial variance in environmental phenomena while identifying underlying mechanisms through factor interaction diagnostics. This methodology enables rigorous assessment of individual drivers' explanatory capacity regarding observed spatial patterns and evaluation of nonlinear synergies between covariates. Extensively validated in ecological, socioeconomic, and climatological studies, GDM's application to China's CO₂ emission dynamics offers distinct advantages: it circumvents inherent multicollinearity limitations present in Geographically and Temporally Weighted Regression (GTWR) approaches while simultaneously resolving both main effects and higher-order interactions among emission determinants. The basic principle is shown in formula (1) - (3):

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{K \sigma^2} = 1 - \frac{SSW}{SST} \quad (1)$$

$$SSW = \sum_{h=1}^L K_h \sigma_h^2 \quad (2)$$

$$SST = K \sigma^2 \quad (3)$$

Where K is the total sample size, σ^2 is the variance, N_h and σ_h^2 are the sample size and variance of stratum h. A higher q value indicates stronger explanatory power.

3. Results and discussion

3.1. Temporal distribution of carbon emissions

Pronounced regional disparities in economic output gradients, manufacturing concentration, energy mix composition, and urban expansion dynamics across China's provincial administrations manifest as spatiotemporal divergence in CO₂ emission trajectories, with Figure 1 quantifying these heterogeneous provincial emissions through comparative visualization.

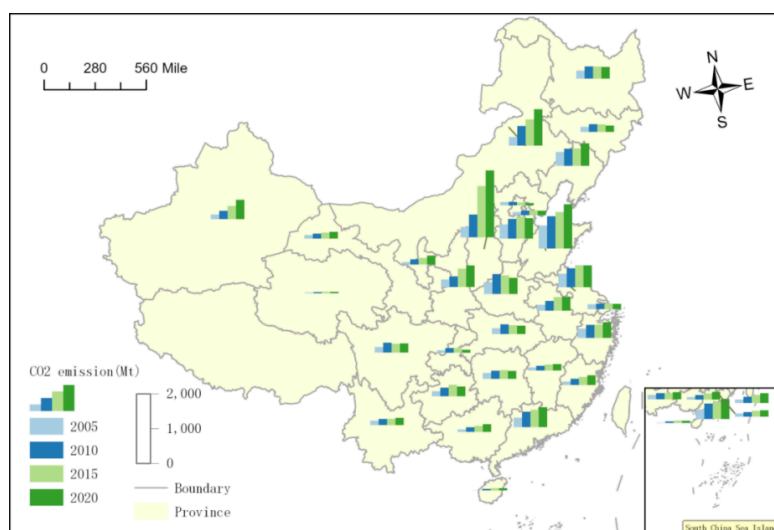


Figure 1. Characteristics of the spatial and temporal distribution of carbon emissions in China

This paper studies the temporal changes of carbon emissions in 30 provinces and cities in China except Hong Kong, Macao, Taiwan and the Tibet Autonomous Region: the carbon dioxide emissions of all provinces showed an upward trend from 2005 to 2020. From 2005 to 2010, the carbon emissions of provinces and cities gradually increased, and the regional differences gradually expanded. From 2010 to 2020, the growth rate of most provinces and cities slowed down and tended to be stable, but Shanxi Province showed a significant growth and continued to rise after 2010, and the carbon emissions of Shandong Province and Inner Mongolia Autonomous Region were also increasing significantly.

The gradual increase in carbon emissions and the widening regional disparities between 2005 and 2010 can be attributed to several factors. During this period, China experienced rapid economic growth and accelerated industrialization. To boost economic development, provinces and cities heavily invested in infrastructure and industrial manufacturing, leading to a sharp rise in energy demand. At the time, coal and other fossil fuels were the primary energy sources, and their extensive use resulted in increased carbon emissions. Additionally, the varying industrial structures, levels of economic development, and degrees of industrialization across different provinces and cities contributed to the growing regional differences.

From 2010 to 2020, the growth rate of most provinces and cities slowed and stabilized due to several factors: economic restructuring and industrial upgrading led to the decline of high-energy, high-emission traditional industries, while the share of emerging industries grew, slowing energy demand; improvements in energy technology enhanced efficiency, and the use of clean energy sources like solar, wind, and hydropower increased, reducing reliance on fossil fuels such as coal; some provinces and cities shifted to an intensive economic growth model, decreasing energy dependence and stabilizing carbon emissions. The significant growth of carbon emissions in Shanxi, Shandong, and Inner Mongolia can be attributed to the following: Shanxi Province, a major coal production base in China, has seen its coal output rise due to increased domestic demand, leading to higher carbon emissions. The economy heavily relies on the coal industry, which contributes to its single industrial structure. In Shandong and Inner Mongolia, rapid industrial development, particularly in high energy consumption and high emission industries, has also resulted in a substantial increase in carbon emissions.

3.2. Spatial distribution of carbon emissions

Select the data of 2005, 2010, 2015 and 2020 respectively, and use the natural breakpoint method to divide China's provincial-level carbon emission levels (low value area, low and medium value area, medium and high value area, high value area) as shown in Figure 2.

Overall, CO₂ emissions in various regions of China are gradually increasing, with the spatial distribution pattern constantly evolving. High-value regions are primarily concentrated in North China, including Shanxi, Hebei, Shandong, and Inner Mongolia, while low-value regions are consistently found in Qinghai Province. In 2005, North China and East China had relatively high carbon emissions. High-value areas were mainly in Hebei, Shandong, and Jiangsu, while medium to high-value areas were in Shanxi, Henan, and Inner Mongolia. In 2010, Shanxi, Henan and Inner Mongolia joined the high-value regions, while the coverage of medium and high-value regions shrank. By 2015, both high-value and median regions had become less extensive. Hebei, Henan, Inner Mongolia and Jiangsu dropped out of the high-value category and were reclassified as medium-high-value regions. Meanwhile, most provinces and cities in Southwest and Southeast China transitioned from median regions to medium-low-value regions. In 2020, Inner Mongolia re-entered the high-value ranks, creating a spatial distribution where North China has high carbon emissions, while Northeast and Southwest China exhibit low carbon emissions.

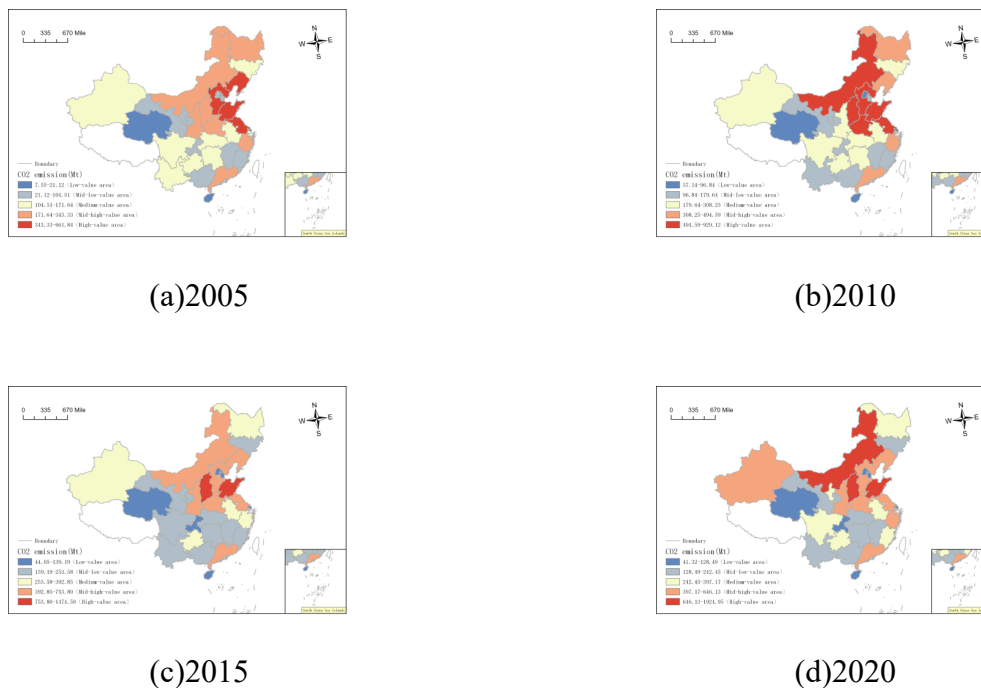


Figure 2. The spatial pattern of carbon emissions in China

North China has long remained a high-value region for carbon emissions primarily due to the fact that Shanxi and Inner Mongolia serve as major coal-producing areas in China. With a high concentration of energy mining and chemical industries, these regions exhibit intense carbon emission levels. Hebei and Shandong are also major energy and industrial provinces. The high density of population and the high concentration of industries lead to more carbon dioxide emissions. The reason for the relatively low carbon dioxide emissions in the northeast and southwest regions is that the energy utilization efficiency in the northeast region is low, which means that the

carbon emissions may be relatively low in the process of energy consumption [19]; Southwest China is rich in natural gas reserves, and using natural gas is cleaner than using fossil fuels such as coal or oil, so carbon emissions are relatively low.

3.3. Driving factors of carbon emissions

This study employs geographical detectors to analyze the influence of the following factors on carbon emissions: population (X1), population agglomeration (X2), economic development (X3), industrial structure (X4), energy structure (X5), transportation (X6) and openness (X7).

3.3.1. Single factor analysis

According to the single factor detection results of the geographical detector (Table 3), it is found that the seven factors of population (X1), population agglomeration (X2), economic development (X3), industrial structure (X4), energy structure (X5), transportation (X6) and openness (X7) have significant effects on carbon emissions ($p < 0.01$).

Table 3. Single factor detection result

Influencing Factors	2005	2010	2015	2020	p value
X1	0.4729	0.4622	0.4488	0.3550	0.000
X2	0.2282	0.3978	0.4501	0.5386	0.000
X3	0.4076	0.5765	0.3526	0.3558	0.000
X4	0.3934	0.2045	0.5170	0.4872	0.000
X5	0.3125	0.6076	0.3038	0.3564	0.000
X6	0.4849	0.2101	0.3696	0.1657	0.000
X7	0.4998	0.5348	0.2678	0.4238	0.000

From the temporal variation of influencing factors, X1 q value trended downward, indicating weakened direct effect of population growth on carbon emissions; X2 q value increased significantly, indicating that the driving effect of population concentration on carbon emissions grew during urbanization; X3 q value peaked in 2010 and then declined, suggesting that the driving effect of economic growth on carbon emissions has mitigated since 2010; X4 q value fluctuates greatly, reflecting the phased impact of industrial structure adjustment; X5 q value sharply declined after peaking in 2010, suggesting a significant reduction in the contribution of coal dependence to carbon emissions post-2010; X6 q value showed a continuous decline, suggesting that the carbon emission pressure in the transportation sector was gradually alleviated; X7 q value was relatively high in 2010, and recovered after declining in the later period. This fluctuation suggests that attention should be paid to the structure of foreign capital. Overall, around 2010 marked a crucial turning point for the driving factors of carbon emissions. The impact of X3 (economic development) and X5 (energy structure) weakened after 2010, while the role of X2 (population agglomeration) increased significantly.

Based on the single-factor detection results of geographical detectors, this paper conducts an in-depth analysis of the mechanisms of carbon emission influencing factors: Chen Xiangyang [20] holds the view that the expansion of population size will drive the growth of carbon emissions, but with the development of society, the mode of population growth will gradually change, and the quality of population will improve, which will gradually diminish the direct effect of population on

carbon emissions; With the acceleration of urbanization, massive population aggregation in cities and the expansion of urban scale lead to a substantial rise in energy consumption, thereby gradually increasing the impact on carbon emissions. This finding aligns with the analysis by SUN Meng et al. [21]; Before 2010, China's rapid economic growth depended on high-energy consumption industries, so it had a significant impact on carbon emissions, which was consistent with the analysis of Sarkodie et al. [22]. However, due to the transformation of China's economic development model, the optimization and upgrading of industrial structure, and the reduced reliance of economic growth on high-energy-consuming industries, the impact of economic growth on carbon emissions has gradually weakened; As industrial structure adjustment is a complex dynamic process, the influence of industrial structure on carbon emissions shows significant fluctuations; After 2010, China has vigorously promoted energy transformation and encouraged the development of clean energy. The reduction in the proportion of coal in energy consumption has significantly diminished the contribution of energy structure to carbon emissions, consistent with the findings of Liu Yiwen et al. [23]; Public transport has been continuously improved, the construction of urban subway, light rail and other public transport has been accelerated, and the development of new energy vehicle technology has replaced some fuel vehicles, reducing the pressure of carbon emissions in the field of transportation; The growth of foreign investment will further expand production scale, leading to higher energy and resource consumption, and thus exacerbating the impact of openness on carbon emissions. This conclusion aligns with the findings of Shen Yang et al. [24].

3.3.2. Interaction analysis

Table 4 reports the multi-year average value of q value of the interaction of carbon emission impact factors from 2005 to 2020, and the interaction of each impact factor shows double factor enhancement or nonlinear enhancement. On the whole, the q value of the two-factor interaction effect on carbon emissions is higher than that of the single-factor effect. The top three factor combinations of the multi-year average of the interaction q value are $X2 \cap X6$, $X1 \cap X2$, $X1 \cap X5$, respectively, indicating that population and the population agglomeration play a dominant role in the spatial differentiation of urban carbon emissions.

The results of two-factor detection clearly indicate that the interaction of each influencing factor exhibits two-factor enhancement or nonlinear enhancement, which offers a fresh perspective for a deeper understanding of carbon emissions, and can more comprehensively reveal the complex mechanism affecting carbon emissions, so as to provide a more targeted basis for policy-making. First, the interaction between population agglomeration and transportation has the most significant impact on the spatial differentiation of carbon emissions. This is because areas with high population agglomeration tend to have greater demand for transportation, so the interaction between the two has a strong impact on carbon emissions, which is consistent with the research results of Tian Ze [25]. Second, the interaction between population and population agglomeration takes the second place. The analysis of David Satterthwaite [26] shows that both population growth and urbanization exert a significant influence on carbon emissions. Third, the interaction between population and energy structure also has a substantial impact on the spatial differentiation of carbon emissions. Specifically, the expansion of population size significantly boosts energy consumption, thereby driving the growth of carbon emissions. This finding aligns with the research outcomes of Birdsall [27].

Table 4. Interactive detection results

	X1	X2	X3	X4	X5	X6	X7
X1	0.4347						
X2	0.9559	0.4037					
X3	0.9123	0.9014	0.4231				
X4	0.9156	0.9256	0.8914	0.4006			
X5	0.9367	0.8787	0.8331	0.9046	0.3951		
X6	0.8898	0.9664	0.8582	0.8679	0.9088	0.3076	
X7	0.8686	0.8690	0.7722	0.8635	0.8460	0.8783	0.4315

4. Conclusions

This research uses the geographical detector model to analyze the spatio-temporal distribution and drivers of China's carbon emissions. From 2005 to 2020, emissions in 30 provinces showed an overall upward trend: growing rapidly with widening regional gaps before 2010, then slowing post-2010. Spatially, high-value areas remained concentrated in North China despite evolving patterns. The model identified 2010 as a critical turning point: population agglomeration intensified its impact on emissions, while economic development and energy structure influences weakened. Population factors dominated spatial differentiation of urban emissions.

The study's findings provide essential theoretical and practical support for China's carbon peaking and neutrality goals. By defining carbon emissions' spatio-temporal patterns and drivers, it enables targeted policy-making and strategic adjustments to industries and energy structure. However, the geographical detector model cannot determine factor interaction directions, and the indicator system may be incomplete. Future research should expand time-series data, deepen cross-regional comparisons of emission drivers, and explore collaborative reduction mechanisms.

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