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REGIONAL INEQUALITY AND INFLUENCING FACTORS OF PROVINCE-LEVEL ENERGY-RELATED CARBON EMISSIONS IN CHINA

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Annotation. This paper estimates carbon emissions from energy consumption in 30 Chinese provinces using the IPCC methodology based on eight types of energy consumption data spanning from 2005 to 2018. Spatial autocorrelation analysis is applied to investigate changes in spatial patterns, while the Geographically Weighted Regression (GWR) model is employed to assess the factors influencing carbon emissions in each province. Three principal findings emerge from the analysis: first, a significant spatial dependency among carbon emissions is observed across the provinces. Provinces with high emissions tend to be geographically clustered with others exhibiting similar levels, forming distinct high-high and low-low agglomeration patterns. However, this spatial dependency has been weakening over time. Second, carbon emissions display significant local spatial clustering, with each province exhibiting unique spatial heterogeneity. Finally, the economic conditions, technological progress, and energy structures vary considerably among provinces leading to differentiated impacts on carbon emissions. Factors such as economic growth, population size and energy structure generally contribute to the rise in carbon emissions,

Keywords: carbon emissions, province-level, spatial pattern, influencing factors.

JEL classification: C23, O23, Q52, Q56, Q58.

Introduction

Energy is one of the critical elements of national development. The use of fossil fuels inevitably results in the emission of large amounts of greenhouse gases, leading to a series of environmental issues. China, undergoing rapid industrialisation and urbanisation, has become a major consumer of energy and an emitter of carbon globally. In this context, the spatialisation of CO_2 emissions is essential for examining the spatial patterns of emissions, which provides the foundational data necessary for reducing CO_2 emissions through spatial pattern optimisation or reconstruction.

To accelerate and improve efforts in reducing CO_2 emissions, the analysis of emissions across different sectors in China has garnered significant academic attention. This paper investigates the distribution

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characteristics of energy-related CO_2 emissions across various regions to facilitate the precise implementation of reduction measures. Precisely, carbon emissions from energy consumption in Chinese provinces from 2005 to 2018 are calculated. The emission patterns and spatial relationships of each province are examined, and the factors influencing these emissions are explored. Ultimately, this analysis serves as a valuable reference for the development of effective and reasonable emission reduction strategies.

In recent years, global initiatives advocating for emission reduction and energy conservation have significantly increased the focus on carbon emissions. Both domestic and international researchers have explored this topic from various perspectives. The existing literature highlights three key areas of focus: the accounting of carbon emissions, the factors influencing emissions and their economic correlations and the spatial patterns as well as evolutionary characteristics of CO_2 emissions.

Simultaneously, recent analyses of energy-related CO_2 emissions have concentrated on three main areas: calculating emissions, examining the relationship between CO_2 emissions and economic growth and identifying influencing factors. The predominant method for estimating energy-related carbon emissions, particularly those from fossil fuels and their derivatives, follows the IPCC guidelines (Zhang, 2020; Zhou *et al*., 2019; Liu *et al*., 2016). Research consistently shows a positive correlation between energy CO_2 emissions and economic growth (Ang, 2008; Lin *et al*., 2016; Zheng, Liu, 2011). Moreover, extensive academic work has identified key determinants of energy consumption and CO_2 emissions, including consumption patterns, lifestyle, urbanisation, population, and economic and technological development Among these, the scale of the economy has been found to exert the most significant influence on CO_2 emission fluctuations (Lin *et al*., 2016; Cheng *et al*., 2014; Jiang, 2011).

1. Literature Review

In the existing literature, factors influencing CO_2 emissions have garnered significant attention. For instance, Li *et al*. (2011) highlighted that China's GDP and industrial sector are the most prominent drivers of CO_2 emissions. Similarly, Pao *et al*. (2010) reported that energy consumption significantly impacts CO_2 emissions under the Environmental Kuznets Curve (EKC) hypothesis. In a study of twelve Middle Eastern economies, Al-Mulali (2012) confirmed that foreign direct investment (FDI) and primary energy consumption are key determinants of emissions. Andreoni *et al*. (2016) and Xiao *et al*. (2017) reached similar conclusions in their respective studies. Likewise, Wang *et al*. (2013) argued that various factors, including per capita GDP, urbanisation and population, are correlated with CO_2 emissions in China. Additionally, Jayanthakumaran *et al*. (2012) assessed the short- and long-term relationships between per capita income, structural changes, energy consumption, and carbon emissions in India and China. Ang *et al*. (1998) explored the factors driving changes in energy demand and carbon emissions from the perspective of China, Korea and Singapore.

In the context of spatial effects, Burnett (2013) investigated the influence of economic activities on state-level emissions in the US. Using a similar approach, Zhao *et al*. (2014) examined the mechanisms influencing carbon emissions at the provincial level in China, finding that population density and per capita GDP growth can somewhat reduce carbon emission intensities. Wang *et al*. (2015) identified economic development as the most significant factor driving the increase in carbon emissions, with energy structure being the second most prominent factor in China. While economic growth is the primary factor influencing carbon emissions, national strategies have also altered China's carbon emission patterns, with carbon intensity playing an increasingly important role (Pan *et al*., 2018). Wang *et al*. (2018) studied the effects of energy consumption, urbanisation and economic growth on carbon emissions, suggesting that income levels and development stages are critical considerations for policymakers aiming to reduce carbon emissions. In line with this, Xu *et al*. (2014) identified energy structure and population size as equally essential factors influencing energy-related CO_2 emissions. Timmons *et al*. (2016) confirmed that population size directly and indirectly impacts CO_2 emissions, while urban living in the US typically corresponds to lower CO_2 emission levels. Shahbaz *et al*. (2019) also demonstrated that FDI and energy consumption increase carbon emissions, whereas trade openness reduces them. Similarly, Kivyiro and Arminen (2014) found that FDI positively affects carbon emissions in some economies and negatively affects others. Different approaches have been incorporated to scrutinise the possible impact of CO_2 discharges. Taking China's Xinjiang as a case, Huo *et al*. (2015) adopted a STIRPAT model to scrutinise the potential effect of socio-economic development on carbon discharges. Conversely, Yao & Sun (2012) employed the Ward approach to carry out an in-depth analysis of CO_2 emissions across diverse areas, highlighting that the intensity of carbon discharges is primarily subject to coal consumption, energy intensity, and the degree to which the heavily polluting industries are saturated. In particular, the EKC serves as a critical theory as it triggers the changing trend between the per capita GDP and pollution in order to demonstrate the influences of economic development (Jebli, Youssef, 2015). From the carbon intensity's perspective, the EKC is used extensively to illustrate that carbon intensity shall persistently heighten in the initial phase of economic development. However, it will decline with the advancement in economic development. Though several studies examine the influential mechanism of carbon emission from diverse viewpoints, little is known regarding the comparative significance of these contributing factors among various levels.

From the perspective of regional disparities in CO_2 emissions, studies have primarily been categorised into two main types based on research techniques such as the Theil index and the Gini coefficient (Mussini, Grossi, 2015; Grunewald *et al*., 2014). Some researchers have adopted these inequality indices to assess regional disparities in CO_2 emissions and identify their sources (Wang *et al*., 2020). Wang and Zhou (2018) applied the IDA model and the Theil index to analyse global disparities in carbon emissions from 1995 to 2009, concluding that these disparities primarily originate from emerging economies, particularly India and China. Similarly, Pakrooh *et al*. (2020) highlighted provincial differences in carbon emissions within Iran's agricultural sector and analysed their driving factors. In the same vein, Bianco *et al*. (2019) examined potential inequality in carbon emissions and energy usage within the EU, finding that while carbon emission disparities remained relatively stable, GDP was the key driver. Other studies explored the spatiotemporal variations in CO_2 emissions (Wang *et al*., 2021; Li *et al*., 2021). However, merely quantifying the inequality in carbon emissions offers limited insights. Therefore, researchers and policymakers are actively investigating the underlying causes of these disparities to develop practical strategies for addressing them.

A growing number of scholars have focused on the dynamic changes and factors influencing CO_2 emissions. Prominent methods include structural decomposition analysis (SDA; Sajid, 2021), index decomposition analysis (IDA; Zhang *et al*., 2021) and STIRPAT-based regression models (Fang *et al*., 2022). Su and Ang (2017) utilised a structural decomposition method to introduce an intensity indicator for detecting carbon emissions from a demand perspective. Similarly, Wang *et al*. (2016) employed a multi-regional SDA model to investigate the drivers of carbon emissions at both national and global levels. However, the input-output tables required for SDA have long update cycles, making it difficult to obtain recent data. In contrast, IDA allows continuous, time-series analysis (Liu *et al*., 2021). Afterwards, Su and Ang (2016) defined two core categories of decomposition, namely SDA and TDA. With the regional differences' expansion, certain researchers aimed to explore heterogeneity related to the factors impacting CO_2 discharges on the basis of SDA (Wang, Zhou, 2018). For example, using the spatial IDA in China from regional and national standpoints, Li *et al*. (2017) investigated the evaluation of CO_2 discharges' drivers, confirming that the economic scale and energy efficiency act as the major drivers behind regional disparity in carbon discharges. Likewise, Song *et al*. (2019) discovered regional variances in CO_2 discharges as well as the dynamics of affecting factoring by utilising temporal-spatial IDA using the panel data from the provinces of China from 2000 to 2015.

In general, hierarchy and scale are significant for effectively understanding the complexity of regional socio-economic inequality in China, including carbon emissions (Li, Wei, 2010; Geist, Lambin, 2010). Findings from one spatial scale are not applicable to another, as socio-economic development is subject to scale changes. Many scholars have suggested that geographical phenomena exhibit varying developmental trends at different spatial scales. Consequently, the issue of scale has become a common challenge in geography-oriented research (Guagliardo, 2004). As a form of socio-economic indicator, CO_2 emissions also demonstrate spatial heterogeneity and multi-scale patterns, exhibiting a hierarchical structure with non-linear processes across spatial scales. However, most prior research has been conducted at either a single city or single spatial scale, often within different geographical and political contexts (Cai, 2014; Wang *et al*., 2018). Studies investigating and comparing the spatiotemporal variance of CO_2 emissions and their drivers across different levels remain scarce, primarily due to the lack of precise local-scale carbon emissions data (Shi *et al*., 2018).

Further analysis is necessary to examine the regional variations and evolutionary pathways of China's CO_2 emissions. In most studies on China, total carbon emissions are used to indicate the extent of emissions. However, regional differences within China should be analysed through the lens of carbon emissions intensity. Additionally, existing studies often focus on national or regional contexts, which reveal trends in carbon emissions at the national level but fail to capture disparities among Chinese provinces. Given the pronounced regional inequality in a country like China, exploring provincial-level differences in carbon emissions is of practical significance. Moreover, the evolutionary pathways of province-level carbon emissions should be examined from a spatiotemporal perspective to accurately assess the emissions intensity of each province.

To address this, the present study utilises spatial autocorrelation to reflect regional disparities by examining changes in the spatial patterns of carbon emissions. Additionally, the factors influencing carbon emissions in each province are analysed using geographically weighted regression (GWR). This study aims to determine whether carbon emissions in China are sensitive to spatial scale and whether the multi-faceted mechanisms driving CO_2 emissions exhibit a hierarchical spatiotemporal structure influenced by socio-economic development patterns.

2. Data and Methodology

2.1 Estimation of Carbon Emission

This paper focuses on estimating carbon emissions from non-renewable fossil fuels and their primary derivatives. Using data from the China Energy Statistics Yearbook, eight types of energy – coke, coal, crude oil, gasoline, kerosene, natural gas, fuel oil, and diesel – were selected for carbon emissions calculations.

Table 1. Various Fuels' Emission Coefficient Estimates

Types	*NCVi* [kJ /kg or kJ/m^3]	*CCi* [kg/GJ]	*COFi*
Coal	20934	26.37	0.90
Coke	28470	29.5	0.90
Crude oil	41868	20.1	0.98
Gasoline	43124	18.90	0.98
Kerosene	43124	19.60	0.98
Diesel	42705	20.20	0.98
Fuel oil	41868	21.1	0.98
Natural gas	38931	15.32	0.99

Notes: The net calorific value (NCVi) is sourced from the General Principles of Comprehensive Energy Consumption Calculation (GB/T 2589-2020). The carbon content (CCi) references the Guidelines for Compiling Provincial Greenhouse Gas Inventories. Meanwhile, the carbon oxidation factors (COFi) are derived from the Greenhouse Gas Inventory Guide Study.

Source: own calculations.

In accordance with the 2006 IPCC National Greenhouse Gas Inventory Guidelines, a formula for estimating carbon emissions has been developed. The specific mathematical expression for calculating carbon emissions from energy consumption is provided in Eq. (1):

$$E_{e1} = \sum_i AC_i \times NCV_i \times CC_i \times COF_i \times 44/12 \tag{1}$$

In this expression, E represents the carbon emissions generated by energy consumption in each province, measured in kilograms. Here, i denotes the energy type; AC_i is the amount of fuel i consumed, measured in cubic meters or kilograms. NCV_i represents the net calorific value of fuel i, expressed in *kJ/kg* or *kJ/m^3*. COF_i refers to the carbon oxidation factor for fuel i, and 44/12 is the conversion factor used to convert carbon into CO_2. These data are obtained from national statistical yearbooks and the General Rules for Calculation of Comprehensive Energy Consumption compiled by China.

Table 1 presents the estimated emission coefficients for various fuels.

2.2 Spatial Correlation Analysis

Spatial autocorrelation, which is frequently used to examine regional spatial distribution differences and associations of elements, is divided into global and local spatial autocorrelation. Global spatial autocorrelation captures the overall characteristics of spatial dependency across the entire area and is typically measured using the Global Moran's I index. In contrast, local spatial autocorrelation focuses on spatial variations relative to a specific unit and its surroundings, with the Local Moran's I index serving as the common metric.

2.2.1 Global Spatial Autocorrelation

The global spatial autocorrelation method quantitatively analyses the correlation and differences between elements in regional space by the Global Moran's I index. The specific formula is as follows:

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

$$=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \quad i=1,2,\dots,n \tag{2}$$

$$S^2=\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\ ;\bar{x}=\frac{1}{n}\sum_{i=1}^{n}x_i \tag{3}$$

In this expression, x_i and x_j represent the carbon emissions from energy consumption in provinces i and j, respectively. $\bar{x}$ denotes the mean carbon emissions across the 30 provinces under study. The total number of provinces is represented by n, while ω_{ij} signifies the elements of the spatial weight matrix, and S represents the standard deviation. Moran's I values range from -1 to 1. A positive Moran's I (I>0) indicates a positive spatial correlation, suggesting stronger spatial dependence and smaller overall spatial variance. Conversely, a negative Moran's I (I<0) implies a negative spatial correlation, indicating greater spatial disparities. A value of zero (I=0) suggests randomness or no spatial correlation.

2.2.2 Local Spatial Autocorrelation

The local spatial autocorrelation is used to measure the degree of differences in research elements between local regions. The formula for calculating the Local Moran's I index is:

$$I_i=\frac{(x_i-\bar{x})}{S^2}\sum_{j=1}^{n}\omega_{ij}(x_j-\bar{x}) \tag{4}$$

In this expression, a positive I_i suggests a minimal spatial disparity between province i and its neighbouring province j. Conversely, a negative I_i indicates a pronounced spatial difference between the two provinces. By utilising the Local Moran's I index, Z-score, and LISA values, spatial patterns can be categorised into four distinct types. The Low-High (LH) type is characterised by a positive local Moran's I index, a negative Z-score, and a negative LISA value, representing high values surrounded by lower ones. The High-High (HH) type features positive values for the Local Moran's I index, Z-score, and LISA, indicating clusters of high values. The Low-Low (LL) type, with negative values for the Local Moran's I index and Z-score but a positive LISA value, signifies clusters of low values. Lastly, the High-Low (HL) type displays negative values for the Local Moran's I index, Z-score, and LISA, denoting low values surrounded by higher ones.

2.3 Geographically Weighted Regression (GWR) Model

The GWR model enhances the conventional linear regression model by incorporating the spatial location of data points into the regression equation. This allows the data from neighbouring provinces to be used for local estimation. The corresponding expression is:

$$y_i=\beta_0(u_i,v_i)+\sum_i\beta_k(u_i,v_i)x_{ik}+\varepsilon_i \qquad i=1,2,\dots,n \tag{5}$$

In this model, y_i represents the carbon emissions from energy consumption in each province. x_{ik} denotes the k-th influencing factor of carbon emissions and energy consumption in the province i. The tuple (u_i, v_i)specifies the spatial coordinates of the i-th province. β_0 is the constant of the linear regression at the specific location(u_i , v_i), while β_k represents the spatially varying regression coefficient for the k -th influencing factor in the province i . ε_i denotes the random error component. The regression coefficients of the explanatory variables in the GWR model vary with spatial location. Applying this model to analyse the regional variations in factors influencing energy consumption and carbon emissions across Chinese provinces allows for a more detailed examination of spatial characteristics and a more accurate investigation of the data's spatial non-stationarity.

2.4 Data Source

This study utilises spatial vector data obtained from the GIS database of the Resource and Environmental Science and Data Centre at the Chinese Academy of Sciences. Province- and region-specific data were primarily sourced from the China Statistical Yearbook (2006–2019), the China Energy Statistical Yearbook (2005), and various provincial statistical yearbooks (National Bureau of Statistics, Department of Energy Statistics, and China Energy Statistical Yearbook, 2016). Calculations of total carbon emissions in each province are based on energy usage data reported in the China Energy Statistical Yearbook, following the methods outlined in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

Due to limited data availability in Macao, Taiwan, Hong Kong, and Tibet, the empirical analysis of spatial carbon emissions measurement is confined to the remaining 30 provinces, autonomous regions, and municipalities. The emission factors and heat conversion coefficients for various fossil fuels used in this analysis are sourced from the General Principles for the Calculation of Comprehensive Energy Consumption, the Guidelines for the Preparation of Provincial Greenhouse Gas Inventories, and the 2007 Research on Greenhouse Gas Inventories.

3. Spatial Correlation Analysis

3.1 Global Spatial Autocorrelation

Using ArcGIS 10.5, the Global Moran's I index for China's carbon emissions was calculated based on data from 2005 to 2018. The results are presented in *Table 2*.

Table 2. Global Moran's I of Energy Carbon Emissions in China, 2005-2018

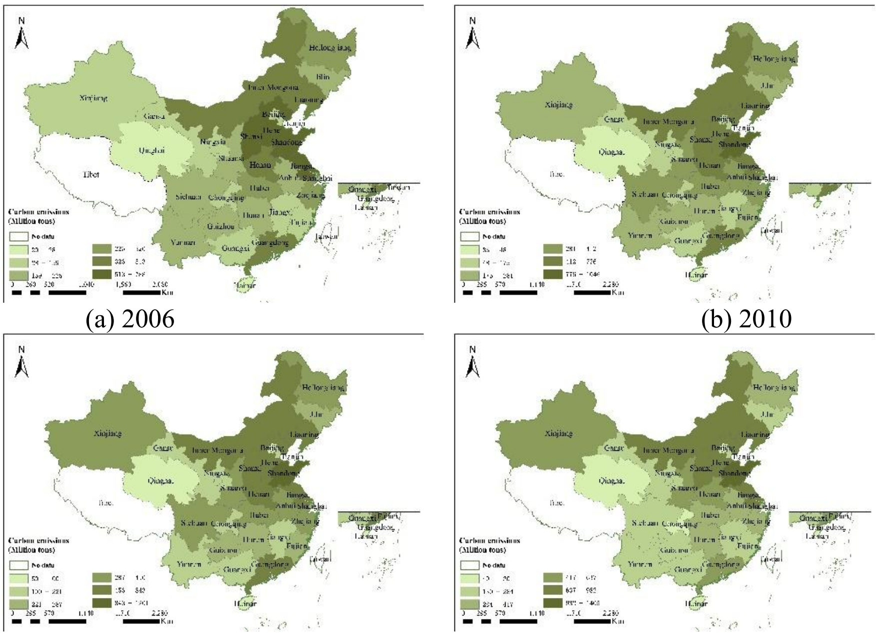
Years	Moran's I	z	p
2005	0.353	3.404	0.001
2006	0.353	3.395	0.001
2007	0.351	3.400	0.001
2008	0.366	3.546	0.000
2009	0.356	3.463	0.001
2010	0.350	3.413	0.001
2011	0.358	3.452	0.001
2012	0.344	3.349	0.001
2013	0.340	3.466	0.001
2014	0.329	3.390	0.001
2015	0.334	3.475	0.001
2016	0.317	3.336	0.001
2017	0.303	3.202	0.001
2018	0.310	3.240	0.001

Source: own calculations.

The Global Moran's I values for energy consumption-related carbon emissions across 30 Chinese provinces (2005-2018) were positive, with a significance level of 1% (*Table 2*). This indicates that the carbon emissions of each province were not spatially independent but exhibited significant spatial dependence. In other words, provinces with high energy-related carbon emissions were relatively close to other provinces with similarly high emissions. Likewise, regions with low energy carbon emissions were also clustered together, displaying a clear high-high and low-low clustering pattern.

Over time, Moran's I values show a downward trend from 2005 to 2018, suggesting that the spatial dependence of energy consumption and carbon emissions in China has been weakening. As spatial spillover effects significantly impact CO_2 emissions in each province, neighbouring provinces tend to have similar carbon emissions.

Four key time nodes, 2006, 2010, 2014 and 2018, are selected to describe the energy consumption's CO_2 discharges in China. The distribution of CO_2 discharges in China was drawn by ArcGIS10.5, as shown in *Figure 1*.



(a) 2006 (b) 2010

(c) 2014 (d) 2018

Source: created by the authors.

Figure 1. ***Distribution of Carbon Emissions in China***

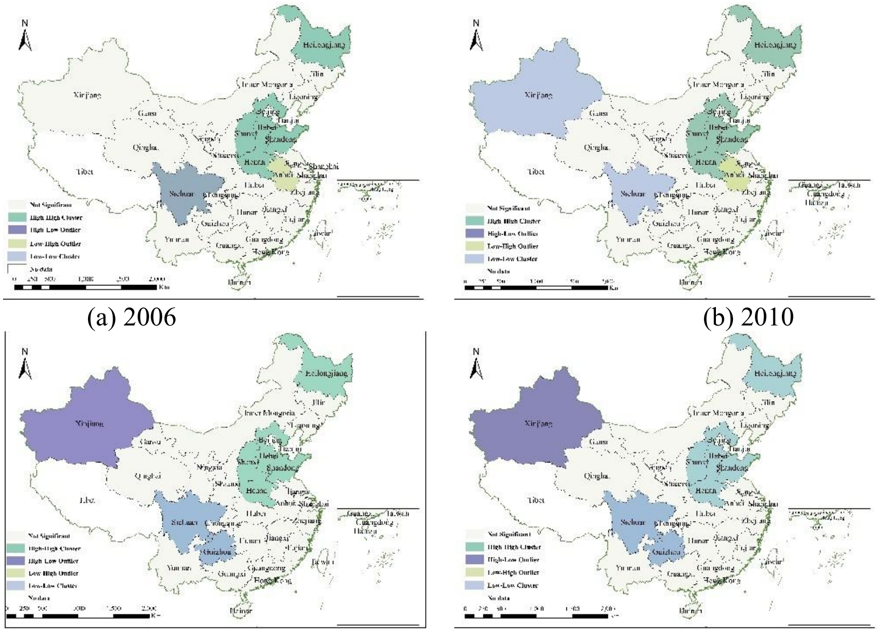
In China, CO_2 emissions vary significantly across regions. Carbon emissions in the eastern zone are greater compared to those in the western zone, and emissions in the northern zone are higher than in the southern zone, particularly in the Bohai Bay Economic Circle in the northeast.

Figure 1 clearly illustrates the substantial regional disparities in China's carbon emissions. Specifically, the eastern regions exhibit higher emissions than the western regions, and the northern regions exceed the southern regions in terms of emissions, with particularly elevated levels in the Bohai Bay Economic Circle in the northeast.

3.2 Local Spatial Autocorrelation

The Local Spatial Autocorrelation conducts a detailed analysis of regional variations in spatial autocorrelation by examining the local spatial autocorrelation of energy consumption and carbon emissions across 30 Chinese provinces. Key years – 2006, 2010, 2014 and 2018 – were selected for analysis from 2005 to 2018. The Moran's I scatter plot, showing the spatial distribution of carbon emissions from energy consumption, was generated using ArcGIS 10.5, as shown in *Figure 2*. The carbon emissions in China exhibit significant local spatial agglomeration characteristics.

In the four key years of 2006, 2010, 2014 and 2018, eight provinces displayed significant spatial autocorrelation. In 2006, the HH regions were primarily Hebei, Shanxi, Shandong, Henan, and Heilongjiang, with Sichuan as an LL region and Anhui as an LH region. In 2010, the HH regions remained Hebei, Shanxi, Shandong, Henan, and Heilongjiang, while Xinjiang and Sichuan were LL regions, and Anhui was an LH region. By 2014, the HH regions still included Hebei, Shanxi, Shandong, Henan, and Heilongjiang, with Guizhou and Sichuan classified as LL regions and Xinjiang as an HL region. In 2018, the HH regions continued to consist of Hebei, Shanxi, Shandong, Henan, and Heilongjiang, with Sichuan and Guizhou as LL regions and Xinjiang as an HL region.



(a) 2006 (b) 2010

(c) 2014 (d) 2018

Source: created by the authors.

Figure 2. **The Moran's I Scatter Point Spatial Distribution of Carbon Discharges**

The HH regions, characterised by high carbon emissions, primarily encompass areas such as the Bohai Bay Economic Circle, the North China Plain, and Heilongjiang, excluding Beijing and Tianjin. These areas feature advanced economic development, established industries, or abundant natural resources. Coupled with rapid urbanisation and industrialisation, this leads to significant fossil fuel consumption and a sharp rise in carbon emissions. Moreover, regions like Shanxi and Henan, which serve as considerable energy hubs in China, exhibit high carbon emissions due to their reliance on energy-intensive economic growth.

The LL category is predominantly found in the southwest. Despite the Western Development Strategy promoting economic growth and increased carbon emissions, these regions still lag behind their eastern counterparts. Over these four years, Xinjiang transitioned from a low-significance LL region to an HL type. Located in northwest China, Xinjiang's initially low economic levels have experienced substantial growth driven by national development strategies, leading to increased energy consumption and, consequently, higher carbon emissions compared to other western provinces.

Anhui has also experienced shifts in its emission levels over the years, typically characterised by high carbon emissions due to its location in the central inland region. Rapid industrialisation and urbanisation have driven increased energy consumption and carbon emissions in the province. Notably, in 2014, the secondary industry dominated Anhui’s economy. By 2018, the share of the secondary industry had aligned with that of the tertiary sector, which generally produces lower carbon emissions, contributing to the observed changes.

Research and analysis indicate that spatial heterogeneity characterises carbon emissions across different Chinese provinces, with spatial factors significantly influencing overall emissions.

Table 3. Estimation Results of GWR Model

Index	2006	2010	2014	2018
R2	0.715	0.763	0.759	0.627
Adjusted R2	0.594	0.653	0.641	0.484
AICc	665.278	673.372	682.526	701.942

Source: own calculations.

4.2.2 Factor Analysis

1. Population

Analysis of the regression coefficients reveals that the population variable exhibits positive coefficients in most provinces for 2006, 2010, 2014 and 2018, although some provinces show negative coefficients. High levels of urbanisation in the central and eastern zones typically lead to a significant increase in carbon emissions as the population grows. In contrast, the western provinces, characterised by lower technological advancement, less industrialisation and lower energy efficiency, tend to consume more energy, thus generating higher carbon emissions. Additionally, the substantial economic scale of certain provinces involves numerous workers in economic activities, which further increases energy consumption. Notably, Xinjiang and Qinghai exhibit the most pronounced suppressive impact of population growth on carbon emissions.

2. Energy structure

Across all provinces in China, the energy structure has contributed to the rise in CO2 emissions. Spatially, the impact of energy structure on carbon emissions generally diminishes from west to east (2006 to 2018). Temporally, the influence of energy structure on carbon emissions has been progressively increasing. This trend is primarily driven by rapid urbanisation, which has led to significant increases in overall energy and coal consumption, thereby escalating carbon emissions.

3. Gross regional product

Economic activity has been a major driver of increased carbon emissions across all Chinese provinces. During periods of rapid economic growth and substantial investment, carbon emissions tend to rise. However, as economic development reaches higher levels, greater emphasis is placed on environmental issues, leading to enhanced awareness and continuous technological improvements, which can eventually reduce CO_2 emissions. The positive regression coefficients of GDP in this study over the past four years suggest that the relationship between economic growth and CO_2 emissions in all provinces is still intensifying. Historically, economic growth has led to an increase in carbon emissions.

4. Influencing Factors and Results

4.1 Selected Factors

There are significant differences in economic level, energy structure, and technological development among Chinese provinces, which result in varying impacts on carbon emissions across different regions. CO_2 emissions are influenced by a variety of factors, including energy consumption intensity, urbanisation level, population, energy structure, economic development, and energy efficiency (Wang *et al*., 2015; Jing, 2015; Su *et al*., 2018; Qing *et al*., 2023). In this study, three independent variables were selected: the gross regional product, year-end population, and energy structure of 30 provinces in China in 2006, 2010, 2014 and 2018. These variables are used to construct the GWR model to investigate the spatial heterogeneity of factors influencing China's carbon emissions. Collinearity among the selected factors was examined using SPSS 22.0, and the results indicate no multicollinearity between the variables, confirming the suitability of the GWR model.

4.2 Estimation Results and Factors Analysis

4.2.1 GWR Estimation

Using data from 2006, 2010, 2014 and 2018 for 30 Chinese provinces, this study employs ArcGIS 10.5 to analyse the spatial variability of factors influencing energy consumption and carbon emissions in each province. The regression estimates are presented in *Table 3*, demonstrating a satisfactory model fit.

5. Discussion

The carbon emissions of each province were not spatially independent, meaning that Chinese provinces with high CO_2 emissions were generally located near other provinces with similarly high emissions, and vice versa. Furthermore, the spatial dependence of energy consumption and CO_2 emissions in China exhibited a downward trend from 2005 to 2018. Neighbouring provinces displayed similar carbon emission levels, as spatial spillover effects significantly influenced CO_2 emissions in each province. Similarly, CO_2 emissions in the western zone were lower than those in the eastern zone. In comparison, emissions in the northern zone were higher compared to the southern zone, particularly in the northeast, including the Bohai Bay Economic Circle.

In China, CO_2 emissions exhibit significant local spatial agglomeration characteristics. Spatial heterogeneity defines CO_2 emissions across different provinces, with spatial factors influencing overall emissions. The HH region, characterised by high CO_2 emissions, predominantly includes areas such as the North China Plain, the Bohai Bay Economic Circle, and Heilongjiang, excluding Tianjin and Beijing. These areas have established industries and advanced economic development, which, combined with rapid industrialisation and urbanisation, have led to substantial fossil fuel consumption and sharply rising CO_2 emissions. Additionally, regions like Henan and Shanxi, key energy hubs in China, show high CO_2 emissions due to their heavy reliance on energy-intensive economic growth.

The LL category is primarily located in the southwest. Despite the Western Development Strategy promoting economic growth and increased CO_2 emissions, these areas still lag behind the eastern regions. Over the years, Xinjiang has transitioned from a low-significance LL category to an HL category. Initially characterised by low economic levels, Xinjiang has seen noticeable growth, leading to higher energy consumption and CO2 emissions than other western provinces. Similarly, Anhui (an LH region) has experienced shifts in its emission levels, typically marked by high CO_2 emissions due to its location in the central inland zone. Rapid urbanisation has further increased energy consumption and CO_2 emissions in Anhui.

There are notable differences in GDP, population growth, and energy structure across Chinese provinces, resulting in diverse impacts on carbon emissions. From the perspective of influencing factors, the population shows positive coefficients in most provinces for 2018, 2014, 2010 and 2006, though some provinces display negative coefficients. High levels of urbanisation in the eastern and central zones generally lead to significant increases in carbon emissions as the population grows. In contrast, the western provinces, with less industrialisation, lower energy efficiency and slower technological advancement, tend to consume more energy, leading to higher CO_2 emissions. Furthermore, the energy structure contributes to the rise in CO_2 emissions across all Chinese provinces. Spatially, the impact of energy structure on carbon emissions tends to decrease from west to east. Over time, this effect has gradually intensified, driven by urbanisation and population growth. Finally, GDP remains a key driver of increasing CO_2 emissions across all Chinese provinces, with its influence continuing to escalate nationwide.

Conclusions

Following the methodology outlined by the IPCC, this study calculates the carbon emissions from energy consumption in China. It then applies global and local spatial autocorrelation techniques to conduct an empirical analysis, elucidating the spatio-temporal evolutionary patterns of carbon emissions across the country. Several key findings emerge: First, the Global Moran's I indicates a decreasing trend from 2005 to 2018, suggesting a weakening spatial dependency of carbon emissions among provinces. Notably, regions with high emission values are primarily located in the Bohai Bay Economic Circle and Heilongjiang, among others. Second, the influence of population, energy structure, and GDP on carbon emissions exhibits significant temporal variation, with their regression coefficients varying markedly across different provinces, all contributing to an increase in carbon emissions.

Policy Implications

The study presents several implications for policymakers in developing effective strategies for CO_2 mitigation in China. The scale and geographical context of China must be considered to significantly reduce carbon emissions, which is in line with the multi-scale and heterogeneous nature of emissions. Policymakers should adopt strategies tailored to local conditions, as the factors influencing carbon emissions vary across different spatial and temporal levels. At the provincial level, optimising the economic structure is a core measure for significantly lowering emissions. State authorities must focus on upgrading traditional industries while extensively supporting the financial and services sectors, which have lower carbon emissions since many Chinese provinces rely heavily on energy-intensive industries.

Moreover, carbon mitigation strategies should also emphasise technological advancements, such as carbon sequestration technologies and alternative energy sources. Given that carbon-related technology in China remains at a relatively low level, the state should prioritise investments in research and development. Additional efforts should be directed toward expanding renewable energy development and improving the efficient utilisation of coal technologies. Promoting innovation and the development of carbon capture and storage technologies through location-specific measures is essential for controlling carbon emission intensity.

Furthermore, it is crucial to enhance coordination between developed and underdeveloped regions in China. This includes focusing on optimising energy structures, supporting sustainable urbanisation, and managing population size in particular megacities. Local authorities should also establish a robust intellectual property system to facilitate the diffusion of low-carbon technologies, which would not only help mitigate carbon emissions but also improve public environmental awareness and encourage households to adopt low-carbon consumption practices. Finally, stricter environmental regulations should be enacted to raise the threshold for market entry in heavily polluting industrial sectors.

Study Limitations

There are certain limitations associated with this study. For instance, the spatial autocorrelation approach used here does not fully capture the frictional effects of explanatory variables influencing carbon emissions. Future research could focus on a more comprehensive selection of indicators to thoroughly investigate the mechanisms affecting carbon emissions at finer spatial scales. Additionally, the analysis in this study is limited to provincial-level geographical units due to data constraints, highlighting the need for future studies to conduct analysis at the city level or smaller units.

Furthermore, given the significant variations in factors affecting carbon emissions across different industries, conducting analyses specific to various sectors would be more appropriate, thereby improving the precision of energy reduction strategies in the industrial sector. Finally, the time span of this study covers the years 2005 to 2018. Future studies can also be carried out over a broader time period, including the latest possible years.

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PROVINCIJŲ REGIONINĖ NELYGYBĖ IR SU ENERGIJA SUSIJUSIO ANGLIES DIOKSIDO IŠMETIMO ĮTAKOS VEIKSNIAI KINIJOJE

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Santrauka. Straipsnyje, remiantis aštuonių rūšių energijos suvartojimo 2005–2018 m. duomenimis, pasitelkus TKKK metodiką apskaičiuotas dėl energijos vartojimo 30 Kinijos provincijų išmetamo anglies dioksido kiekis. Siekiant ištirti erdvinių dėsningumų pokyčius, atlikta erdvinės autokoreliacijos analizė, o geografiškai srovinės regresijos modelis pritaikytas vertinant anglies dioksido išmetimo kiekvienoje provincijoje veiksnius. Atlikus analizę suformuluotos trys pagrindinės išvados. Pirma, nustatyta didelė anglies dioksido išmetimo provincijose erdvinė priklausomybė. Provincijos, kuriose išmetama daug anglies dioksido, yra geografiškai sujungtos su kitomis provincijomis, kuriose išmetamas panašus kiekis, todėl susidaro skirtingi didelio ir mažo kiekio aglomeracijos modeliai. Tačiau ilgainiui ši erdvinė priklausomybė silpnėja. Antra, išmetamo anglies dioksido kiekis pasižymi dideliu vietiniu erdviniu susitelkimu, o kiekvienai provincijai būdingas unikalus erdvės heterogeniškumas. Galiausiai, ekonominės sąlygos, technologinė pažanga ir energetikos struktūros provincijose labai skiriasi, o tai lemia skirtingą poveikį išmetamam anglies dioksido kiekiui. Tokie veiksniai kaip ekonomikos augimas, gyventojų skaičius ir energetikos struktūra paprastai prisideda prie anglies dioksido išmetimo didėjimo.

Reikšminiai žodžiai: išmetamo anglies dioksido kiekis; provincijos lygmuo; erdvinis modelis; įtaką darantys veiksniai.