Interdisciplinary
Research perspective

Investigating Spatial Spillover Effects of Urban Carbon Emission Intensity under Low-Carbon Transition: Evidence from Chinese Cities

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Abstract: The problem of global warming caused by the increase in carbon emissions poses a serious challenge to the sustainable development of human society, and the search for reasonable methods of carbon reduction has become an important issue around the world.This study employs kernel density estimation to dynamically analyze the temporal evolution patterns of carbon emissions across 249 Chinese cities from 2005 to 2018. Spatial autocorrelation analysis is utilized to characterize and interpret the spatiotemporal dynamics of carbon emissions. Additionally, both Traditional Markov Chain and Spatial Markov Chain models are applied to investigate the spatial-temporal transition pathways of urban carbon emissions.The carbon emission levels of most Chinese cities show a convergence trend, and the emission intensities of some cities significantly deviate from the main distribution intervals. Global spatial autocorrelation results show significant spatial heterogeneity of carbon emissions in 249 cities in different years. Spatial Markov Chain analysis shows that the transfer of carbon emission intensity is closely related to the region, and there is a spatial spillover effect, and the regional background strengthens the "club convergence effect", and the neighboring state has a guiding effect on the direction of carbon emission transfer. The study of the spatio-temporal evolution law and spatial spillover effect of carbon emission intensity will be conducive to the further development of carbon emission reduction measures.

Keywords: Carbon Emission; Kernel Density Estimation; Spatial Autocorrelation Analysis;Spatial Markov Chain

1. Introduction

Since the Industrial Revolution, the development of human society has been heavily reliant on fossil fuels. The large-scale consumption of fossil energy has generated substantial carbon dioxide and other greenhouse gas emissions, thereby intensifying the phenomenon of global warming. This climate change has led to rising sea levels and frequent extreme weather events, presenting formidable challenges to the survival and development of human civilization.As an emerging economy, China's carbon emissions trajectory reached a historic turning point in 2006, when it surpassed the United States to become the world's largest carbon emitter for the first time

[1].Driven by urbanization and industrialization, cities have exchanged rapid economic growth for a reduction in the carrying capacity of environmental resources, and have begun to experience problems such as imbalance in energy structure, underutilization of resources and insufficient protection of ecological fundamentals.To this end, the Chinese Government has adopted a series of comprehensive measures to promote carbon emission reduction on all fronts. In terms of industrial restructuring, it has promoted the transformation of traditional industries in the direction of greening and low-carbonization through technological innovation and process upgrading. In the energy sector, China has continued to promote the low-carbon transformation of its energy structure and reduce the proportion of high-carbon energy in its energy consumption structure. However, China's energy consumption structure shows a pattern dominated by coal, which accounts for up to 70% of energy consumption and is difficult to fundamentally adjust in the short term [2]. While pursuing economic growth, carbon emissions have not been completely decoupled from economic development, and the contradiction between economic development and environmental protection is still prominent, which makes China face a great challenge in realizing carbon emission reduction targets. Cities are a major source of greenhouse gas emissions, and according to the International Energy Agency (IEA), urban areas account for approximately 67% of global energy consumption and 71% of global carbon emissions [3]. The importance of carbon intensity research at the urban scale is thus emphasized.In the new stage of high-quality development, China is facing the problem of dynamic balance between economic growth and carbon emission reduction.Therefore, analyzing the development pattern of carbon emissions in different cities in China and understanding the mobility of carbon emissions among cities are conducive to the targeted formulation of carbon emission reduction policies in each city. Based on this, it is necessary to explore the non-homogeneity of carbon emissions of cities in different regions, and accurately grasp the distribution characteristics of carbon dioxide emissions of cities in different regions, as well as the long-term evolution trends and patterns of regional differences. The systematic deconstruction of the spatial and temporal characteristics and driving mechanism of carbon emission intensity as a core indicator for measuring the effectiveness of low-carbon transformation is crucial for solving the paradox of “development-emission reduction” and constructing a regional differentiated policy system. This is not only a prerequisite for cities to scientifically formulate carbon emission reduction tasks, but also an important basis for Chinese cities to formulate low-carbon development strategies and related policies in the future. This study focuses on the following aspects: (1) Based on kernel density estimation (KDE), this study systematically investigates the dynamic temporal evolution of carbon emissions across Chinese cities, revealing distinct trajectory clustering and regional divergence patterns from 2005 to 2018.(2) Based on spatial autocorrelation analysis (Moran's I index), this study systematically investigates the spatiotemporal evolution and clustering patterns of carbon emissions, revealing significant high-high (HH) and low-low (LL) agglomerations with distinct spatial spillover effects.(3) Based on Traditional Markov Chain model (TMC) and Spatial Markov Chain models (SMC), this study systematically investigates the spatiotemporal transition pathways of urban carbon emissions, constructing transition probability matrices to quantify state persistence and leapfrogging dynamics while incorporating spatial adjacency effects to reveal neighborhood-driven path dependence.The structure of the article is organized as follows: Section 1 provides an overview of the research background and related literature; Section 2 describes the sources of carbon emission data and the main methods used to investigate the spatial and temporal characteristics of carbon emissions and the spatial and temporal transfer paths; Section 3 discusses and analyzes the main results of the experiments; and Section 4 gives the conclusions.

2. Related Work

With regard to the spatial and temporal evolution of carbon emissions, scholars have carried out a lot of research using several methods.Chen et al.[4] systematically analyse the spatial differentiation mechanism of carbon emission intensity in China based on the Terrell index decomposition and spatial autocorrelation model. It is found that the spatial imbalance of carbon emission intensity from 2000 to 2019 is characterised by the dominant intra-regional differences.Yang et al.[5] revealed the spatial and temporal evolution of carbon emissions in Chinese cities by constructing a county-scale spatial panel model: the total amount of carbon emissions shows a non-equilibrium evolution path of “falling in the north and rising in the south, with an east-west gradient intensifying”, and the spatial spillover effect of carbon emissions is asymmetric. The spatial spillover effect of carbon emission is asymmetric. Xiao et al.[6] used kernel density estimation and spatial autocorrelation modelling to systematically deconstruct the spatial and temporal patterns of carbon emissions in the counties of Hubei Province from 2000 to 2020. The study shows that the intensity of carbon emission shows the gradient differentiation feature of core-edge, and the intensity of carbon emission shows the gradient differentiation feature of core-edge. Based on kernel density estimation combined with spatial autocorrelation analysis, Tian et al.[7] revealed the spatial and temporal variability of agricultural carbon emissions in China. The study shows that, from the time dimension, the carbon emission intensity shows a non-linear fluctuation trend of overall decreasing - phased oscillation. Wu et al.[8] deconstructed the spatial and temporal patterns of agricultural carbon emissions at the provincial level in China. The study shows that from the time dimension, the total agricultural carbon emissions show a three-stage evolution trajectory of rapid growth - slowdown - accelerated emission reduction. Xie et al.[9] adopted the DEA method to compare the carbon emission allocation amount and actual emissions in Chinese provinces, and concluded that the carbon emission utilization rate gradually increases from east to west regions. Existing methodologies predominantly focus on endogenous development patterns of individual regions, while overlooking the geographical proximity effects and spatial spillover characteristics inherent in carbon emissions. To address this research gap, this study employs a Spatial Markov Chain transition probability matrix framework, which systematically captures the spatio-temporal evolution patterns of carbon emission intensity within urban clusters and their adjacent regions. This approach enables dynamic quantification of inter-regional carbon linkage effects through three-dimensional analysis of state transfer probabilities, spatial lag mechanisms, and temporal persistence characteristics.

3. Materials and Methods

3.1. Study Areas and Data

Carbon emission data are derived from the county-level inventories in the China Carbon Accounting Database [10], which use the particle swarm optimization-backpropagation (PSO-BP) algorithm to estimate county-level carbon emissions in China from 1997-2017. Limited by the availability of carbon emission data, 249 prefecture-level cities in China were selected as the study module to investigate the formulation and implementation of regional carbon emission reduction policies. As the basic analytical module for policy formulation, these cities cover different geographic regions, city sizes and levels of economic development, which to some extent ensures the comprehensiveness and representativeness of the study. The spatial distribution of the study area is shown in Figure 1, which using the latest administrative boundaries of the city.

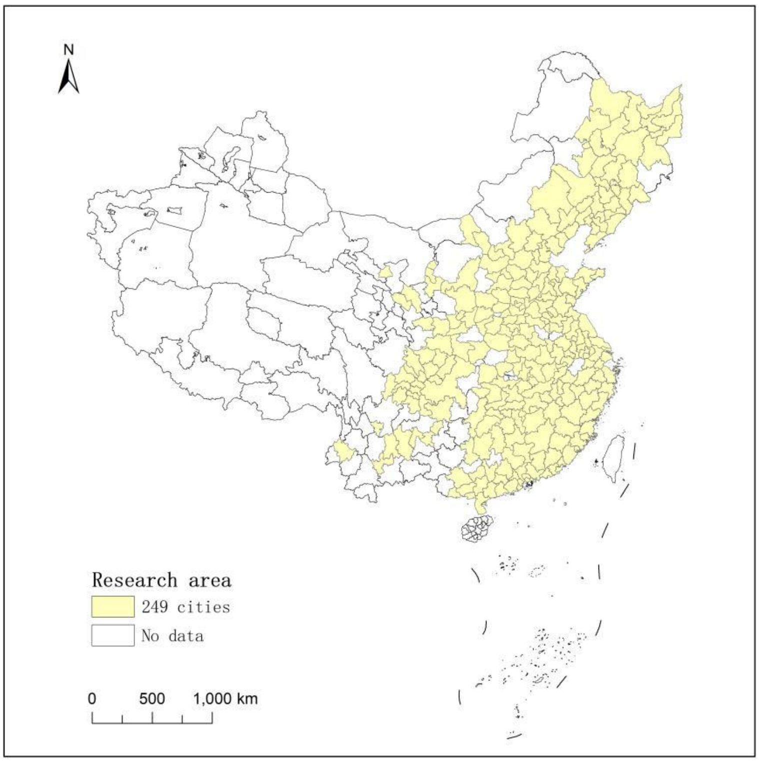

Figure 1. Spatial distribution of the study cities in China.

3.2. Kernel Density Estimation

Kernel Density Estimation (KDE), as a nonparametric statistical technique for probability density estimation, is mathematically formalized as follows: Let $Y_1, Y_2, \cdots Y_n$ be independent and identically distributed random variables drawn from a population characterized by an unknown probability density function *f(y)*. Based on the observed sample $\{y_1, y_2, \cdots, y_n\}$, KDE constructs a nonparametric density estimator by applying localized smoothing effects through a kernel function *K(·),* The mathematical formulation is expressed as:

$$f(y) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{y - Y_i}{h}\right) \tag{1}$$

where the sample size is denoted as *n*, and the kernel function *K(·)*, whose influence range is governed by the bandwidth parameter *h*, serves as the smoothing operator. The mathematical essence of this method lies in parameterizing the kernel function's shape around each data point, thereby constructing *n* localized density distribution functions centered at individual observations.

3.3. Spatial Autocorrelation Model

The First Law of Geography emphasizes the autocorrelation of geospatial data. Global spatial autocorrelation models can effectively reflect the static spatial distribution of carbon emissions in Chinese cities. In this study, the global spatial autocorrelation Moran's I represents the degree of spatial correlation of carbon emissions across regions. The calculation formula is as follows:

$$Moran's\ I = \frac{n}{\sum_i \sum_j w_{ij}} \times \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_j (x_i - \bar{x})^2} \tag{2}$$

where *n* is the sample size, w_{ij} is the spatial weight matrix, x_i and x_j are the attribute values of spatial units *i* and *j*, $\bar{x}$ is the average of the attribute values.

3.4. Spatial Markov Model

The Traditional Markov Chain has the advantages of randomness, stability and no posteriority, etc. It classifies the carbon emission intensity of each spatial unit from 2005 to 2018 according to the value size of the corresponding year, so as to form k types, and then constructs a k×k matrix reflecting the probability of the state transfer, and records the probability distribution of the carbon emission intensity transferring from one type to another, so as to describe the whole process of spatial and temporal transfer of regional carbon emission intensity. Then a k×k matrix reflecting the state transfer probability is constructed to record the probability distribution of carbon emission intensity transferring from one type to another, thus describing the whole process of spatial and temporal transfer of regional carbon emission intensity. The expression is:

$$M_{ij} = \frac{n_{ij}}{n_i} \tag{3}$$

where M_{ij} represents the element of the k×k state transition probability matrix, where the numerator n_{ij} denotes the total number of spatial units whose carbon emission intensity transitions from state *i* in year *t* to state *j* in year *t+1* across the study period, and the denominator n_i corresponds to the cumulative count of spatial units in state *i* throughout the entire study duration. The Spatial Markov Chain explicitly incorporates spatial spillover effects from neighboring units on the attributes or states of target units, enabling the analysis of spatial state transition patterns in geographical phenomena. Its mathematical formulation is expressed as:

$$\mathrm{Lag} = \sum_{i=1}^{n} y_i w_{ij} \tag{4}$$

where *Lag* denotes the spatial lag value, *n* represents the total number of spatial units, y_i corresponds to the observed value of spatial unit *i*, and w_{ij} signifies the adjacency-based spatial weight matrix constructed under the Queen contiguity rule.

The modelling software for this study is ArcMap 10.8.1.

4. Results

This study further analyses the spatial and temporal evolution of carbon emissions in 249 cities in China during the study period, mainly from the two aspects of the dynamic temporal evolution trend of carbon emissions based on kernel density estimation and spatial autocorrelation, as well as the analysis of the spatial and temporal transfer paths of carbon emissions based on the traditional Markov and spatial Markov. In this study, the natural breakpoint grading method of ArcGIS 10.8 is used to divide the carbon emission intensity of Chinese cities into optimal intervals. The initial state transfer probability matrix is constructed, and the carbon emission intensity of cities is classified into four emission classes: low intensity (k=1), medium-low intensity (k=2), medium-high intensity (k=3) and high intensity (k=4).

Firstly, the kernel density curves for all observed years exhibit a unimodal and right-skewed distribution with pronounced right-tailed characteristics, indicating that the majority of cities cluster within lower emission ranges, while a minority form high-emission outliers significantly exceeding the mean. Morphologically, the curves transition from a sharp-peaked and narrow-based profile in 2005 to a flattened and broad-based configuration by 2018, which indicates that the overall level of carbon emissions is on an upward trend, the variance of carbon emissions between cities has increased, and the differences in carbon emissions have been widening year by year.

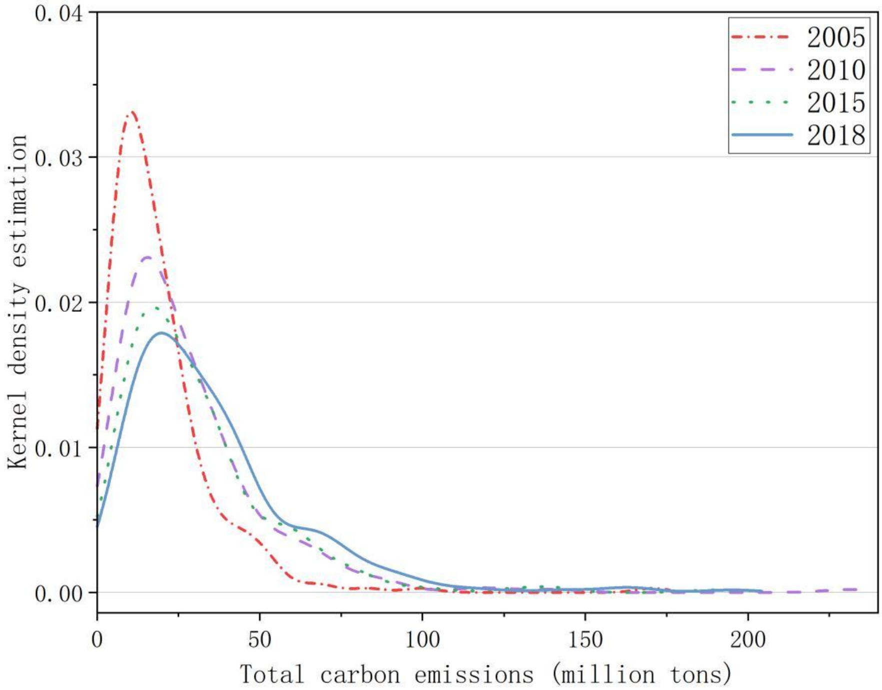

Figure 2. Estimated kernel density for 249 cities in China

Next, we calculate the Moran's I index of global carbon emissions of 249 Chinese cities in 2005, 2010, 2015 and 2018. As shown in Table 1, the Moran's I values are all greater than 0, and the P-values all pass the significance test at the 1% level, indicating that there is a significant positive spatial correlation of carbon emissions in 249 Chinese cities.

Table 1. Global spatial correlation test results of carbon emissions in 249 Chinese cities.

Year	2005	2010	2015	2018
Moran' I index	0.195	0.210	0.208	0.198
Z score	4.781	9.061	8.819	8.371
P value	0.000	0.000	0.000	0.000

Finally, the traditional Markov transfer probability matrix was calculated based on the city-level carbon emission levels in China from 2005 to 2018, and according to the type of carbon emission intensity, the city carbon emission intensity was divided into four types: low intensity, lower intensity, higher intensity and higher intensity, corresponding to k=1, 2, 3 and 4, respectively. For comparison, this study firstly calculated the traditional Markov transfer probability matrix, based on which the spatial lag term is added to calculate the spatial probability transfer matrix.

Table 2. Traditional Markov Transfer Probability Matrix for Carbon Emissions in 249 Cities.

t\t+1	n	1	2	3	4
1	1335	0.9318	0.0681	0	0
2	952	0.0147	0.8855	0.0997	0
3	321	0	0.0654	0.7383	0.1962
4	629	0	0	0.0127	0.9872

From the traditional Markov probability matrix, it can be seen that (1) the steady state probabilities of the four state diagonals are 93.18%, 88.55%, 73.83% and 98.72%, respectively, with the probabilities of upward shifts ranging from 6.81% to 19.62%, and the probabilities of downward shifts ranging from 1.27% to 6.54%. (2) The probability of diagonal shift is greater than the probability of non-diagonal shift, and each city maintains its original state of carbon emission intensity rather than easily shifting to other states, which has a strong stability characteristic. (3) The carbon emission intensity of cities shows the characteristic of 'bipolar stability', with the probability of maintaining the original state of high and low carbon emission intensity cities being 93.18% and 98.72%, which is higher than that of the middle two categories of cities, namely 'higher' and 'lower', and the probability of maintaining the original state of high and low carbon emission intensity cities is 93.18% and 98.72%, respectively. Low' two types of cities, by talent and technology and other factors, the formation of a sustained Matthew effect, showing a "high always high, low always low" long-term trend of differentiation. (4) The upward transfer probability is greater than the downward transfer probability, indicating that the stability of high-intensity carbon emission agglomeration cities is significantly stronger than that of low-intensity carbon emission agglomeration cities. The transfer probabilities between non-neighbouring levels are all zero, indicating that the evolution of urban carbon emission intensity follows a gradual adjustment pattern, avoiding the extreme cases of high-emission cities directly crossing over to low-emission cities or low-emission cities suddenly changing to high-emission cities. In addition, the highest non-diagonal transfer probability is 19.62%, which is much lower than the diagonal transfer probability, which further emphasises the need for Chinese cities to adopt the strategy of 'gradual change' to achieve gradual optimisation through continuous factor mobility to promote technological innovation and carbon emission efficiency.

Table 3 shows the Markov transfer probability matrices for the carbon intensity types of Chinese cities.Carbon emission intensity in Chinese cities has significant spatial correlation characteristics, and its intensity change is often influenced by multiple factors such as economic development, resource deployment and policy intervention, and shows obvious path-dependent characteristics spatially, with spatial locking effect occurring easily in the high carbon emission urban agglomeration area, while the low emission area shows a trend of agglomeration enhancement. This study incorporates the spatial lag effect into the Traditional Markov chain to explore the degree of influence of different geographic domain types on the transition of carbon emission status. In this section Table 3-5 shows the spatial Markov shift probability matrix of carbon emission intensity types in Chinese cities.

Table 3. Spatial Markov Transfer Probability Matrix for Carbon Emissions in 249 Cities

Type	t\t+1	n	1	2	3	4
1	1	663	0.9592	0.1407	0	0
	2	131	0.0129	0.9083	0.1687	0
	3	8	0	0	0.75	0.25
	4	4	0	0	0	1
2	1	571	0.9054	0.0945	0	0
	2	526	0.0152	0.9030	0.0817	0
	3	121	0	0.0578	0.6859	0.2561
	4	174	0	0	0.0172	0.9827
3	1	68	0.9411	0.0588	0	0
	2	159	0.0006	0.8930	0.1006	0
	3	89	0	0.0337	0.8539	0.1123
	4	119	0	0	0	1
4	1	33	0.9881	0.1818	0	0
	2	136	0.0147	0.7867	0.1985	0
	3	103	0	0.1067	0.6990	0.1941
	4	332	0	0	0.0150	0.9849

The results of the Spatial Markov model show that (1) the steady-state probabilities of the diagonal are 95.92%, 90.83%, 75% and 100% when the carbon emission neighbourhood type is low intensity, with a range of probabilities of upward shifts from 14.07% to 25%, and a range of probabilities of downward shifts from 0 to 1.29%. At lower intensities of carbon emission neighbourhood type, the diagonal steady state probabilities were 90.54%, 90.3%, 68.59% and 98.27%, with a range of upward shifts from 8.17% to 25.61% and downward shifts from 1.52% to 5.78%. At carbon emission neighbourhood type of higher intensity, the diagonal steady state probabilities are 94.11%, 89.3%, 85.39% and 100%, the probability of upward shift ranges from 5.88% to 11.23% and the probability of downward shift ranges from 0 to 3.37%. When the carbon emission neighbourhood type is high intensity, the steady state probabilities of the diagonal are 98.81%, 78.67%, 69.9% and 98.79%, with a range of upward transfer probabilities from 18.18% to 19.85% and downward transfer probabilities from 1.47% to 10.67%. (2) The dynamic transfer process of urban carbon emissions and regional geographic characteristics show significant spatial coupling effects, and the probability of the spatial Markov transfer path is different from that of the traditional Markov transfer path, indicating that there is a spatial spillover effect of urban carbon emissions, and the strength of the spatial spillover effect in different geographic regions shows differences. (3) Compared with the Traditional Markov Chain transfer probability, the diagonal probability value of the Spatial Markov Chain transfer matrix is still significantly higher than the non-diagonal probability value, even though the model incorporates a spatial lag term, indicating that the probability of maintaining the original state in each city is still significantly higher than the probability of transferring to other states, and that the maintenance state has strong stability. The non-diagonal transfer probability is generally low, no discontinuous transfer phenomenon occurs across more than two levels, and all the distal transfer probabilities are zero, and there is a spatial locking effect and path-dependent effect on the intensity of urban carbon emissions. (4) The geographical proximity effect significantly strengthens the ‘Matthew effect’ and ‘club convergence effect’ of urban carbon emission intensity, and the probability of maintaining the high emission status of a high carbon emission city increases from 98.72% to 98.79% when the high carbon emission city is adjacent to the same type of city; similarly, the probability of maintaining the high emission status of a high carbon emission city increases from 98.72% to 98.79%. 98.79%; similarly, the probability of a low carbon emitting city maintaining a low emission level increases from 93.18% to 95.92% in a low carbon neighbourhood environment. Cities in high-carbon emitting regions may develop upstream and downstream industrial chains towards cities in neighbouring regions due to similar energy industry structures, while low-carbon emitting regions consolidate their competitive advantages through talent and technology aggregation, etc., forming the phenomenon of path dependence. For example, developed city clusters along the eastern coast have smaller differences in carbon emission intensity due to the convergence of industrial structures, while the differences within city clusters in central and western China that are dominated by heavy industry also show a convergence trend. (5) After considering the geographic proximity effect, the range of probability of upward transfer of carbon emission intensity is further larger than the range of probability of downward transfer of carbon emission intensity, which indicates that the spatial effect of cities with high carbon emission intensity on their neighbouring cities has a significant impact. High-carbon emission regions often exhibit rigid constraints in energy infrastructure, such as the technological lock-in effects of heavy industries in Northeast China's old industrial bases. Such lock-ins diffuse to neighboring regions through upstream and downstream industrial linkages, leading to regional-level path dependence. For instance, in the Jin-Shan-Meng Energy Basin (encompassing Shanxi, Shaanxi, and Inner Mongolia), coal-dependent industries have formed technologically synergistic networks with surrounding cities. Geographical proximity accelerates the spatial spillover of these technological paradigms, driving adjacent cities to converge in energy structures and industrial layouts.

5. Conclusions

5.1. Policy Implications

To address regional carbon governance, this study proposes the following integrated strategies: Firstly, establish a differentiated collaborative governance mechanism by developing a three-tier zoning system (high, medium, and low carbon emission spillover zones), implementing cross-jurisdictional joint control and a unified regulatory platform for high-spillover zones, while imposing ecological compensation fees on high-carbon cities with negative spillovers and allocating fiscal transfers to low-carbon cities demonstrating positive spillovers. Secondly, refine industrial policies through spatial restructuring of supply chains, subsidizing low-carbon technology firms undertaking cross-regional relocation. Thirdly, optimize spatial resource allocation via a carbon-equivalent trading mechanism for talent mobility and mandatory carbon lock-in assessments for infrastructure projects. Finally, innovate governance tools by creating a real-time monitoring platform for spatial Markov transition probability matrices, with automated threshold-triggered alerts to enable dynamic policy interventions.

5.2. Conclusions and Limitations

The study first introduces the research area and dataset, followed by the core methodologies: Kernel Density Estimation (KDE), Spatial Autocorrelation Analysis, and the Spatial Markov Model (SMC). Specifically, KDE is utilized to characterize the distribution and evolution of emission intensities, Spatial Autocorrelation Analysis identifies spatial dependencies, while the Spatial Markov Model quantifies transitional probabilities of emission levels under spatial spillover effects. Conclusions include: (1)The carbon emission levels of most Chinese cities show a convergence trend, and the emission intensities of some cities significantly deviate from the main distribution intervals. (2) Global spatial autocorrelation results show significant spatial heterogeneity of carbon emissions in 249 cities in different years. (3) Spatial Markov Chain analysis shows that the transfer of carbon emission intensity is closely related to the region, and there is a spatial spillover effect, and the regional background strengthens the ‘club convergence effect’, and the neighboring state has a guiding effect on the direction of carbon emission transfer. The study of the spatial and temporal evolution of carbon emission intensity and the spatial spillover effect is conducive to scientifically grasping the law of carbon emission growth and spatial expansion, and provides a basis for scientifically formulating policies on ecological protection and low-carbon sustainable development.

This study still has a few shortcomings: Firstly, this study currently focuses on the spatial spillover effects of carbon emissions in Chinese cities but lacks an analysis of the impacts of urban energy structures and economic development levels on carbon emissions. Future research may benefit from incorporating socioeconomic variables to further validate the findings and enrich the existing body of knowledge. Furthermore, the Spatial Markov Model assumes that spatial dependencies are determined by fixed weight matrices, which may lead to model deviations under complex spatial interactions. Additionally, the model ignores spatial heterogeneity. Future studies could further investigate the spatially heterogeneous impacts of urban carbon emissions by integrating advanced approaches such as Geographically Weighted Regression (GWR).

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