Mechanism of the correlation between urban spatial agglomeration and carbon emission levels in Jilin Province

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Abstract

Elucidating the mechanism of the correlation between urban spatial agglomeration processes and carbon emission levels can provide valuable scientific underpinnings for town planning under the constraints of low-carbon goals. This study investigates the characteristics of urban spatial agglomeration in Jilin Province and its association with carbon emission levels. This is achieved by constructing spatial agglomeration indicators, and multiple linear regression models. The findings are as follows: (1) Over the period from 2004 to 2020, the overall trend of urban spatial agglomeration in Jilin Province was characterized by an initial decline, followed by a subsequent increase, but ultimately rising as a whole. (2) A significant negative correlation exists between urban spatial agglomeration and carbon emission levels. Spatial agglomeration in towns exerted a strong influence on changes in regional carbon emission levels.. Specifically, spatial clustering in service industries demonstrated a more pronounced impact on carbon emissions than was the case in production sectors. (3) A regression analysis reveals that the spatial agglomeration of urban population and economic factors has a significant negative impact on both total carbon emissions and carbon emission intensity. The spatial concentration of urban populations is found to have a marked influence in enhancing carbon emission efficiency.

Keywords: Urban spatial agglomeration; Carbon emissions; Associative mechanisms; Spatial Gini coefficient

1. Introduction

Increasing levels of greenhouse gases in the atmosphere are a significant cause of global warming and climate change. Carbon dioxide is the primary constituent of greenhouse gases, and thus, reducing carbon emissions has become an urgent and significant task for the entire world (Zhou et al., 2023). Although China's per capita cumulative carbon emission level is not high from the perspective of the history of human development. However, since 2005, China has been the country with the highest carbon emissions in the world. In 2021, China's carbon emissions accounted for approximately 32.8% of the global total (Tang et al., 2024; Wu et al., 2020). Given the responsibility of reducing carbon emissions in the context of global warming and also considering the resource and environmental constraints of social-economic development, the Chinese government made a commitment at the United Nations General Assembly in 2020 to achieve carbon peaking by 2030 and carbon neutrality by 2060. Under the constraints of these "low carbon" targets, the pressure for emission reduction places practical constraints on the construction of new urbanization in China. How to achieve the country’s carbon peak and carbon neutral commitments has become a realistic issue that the government must face (Zheng et al., 2019). As concentrated areas of population distribution and economic activities, urban spaces have become major sources of carbon emissions and therefore bear the significant responsibility of achieving China’s “low carbon” targets (Liu et al., 2022; Wang et al., 2023).

Spatial agglomeration is a significant geographical characteristic of urbanization development and also serves as an important material foundation for the development of urban spatial forms and the formation of competitiveness (Yu et al., 2022). Urban spatial agglomeration reflects the evolutionary process of production from enterprise agglomeration to industrial agglomeration, and further to urban agglomeration. Various spatially-proximate cities break through traditional administrative boundaries to promote the collective agglomeration economic effects of production factors to produce together. This reflects the scale effect and positive external economic effects of production factor agglomeration (Wang et al., 2023). Urban spaces are major carbon sources, and the correlation mechanism of urban spaces' spatial agglomeration with carbon emissions is unclear. In addition, the agglomeration of various elements of urban space is inevitably accompanied by the reconstruction and transformation of the regional social economy. Does this geospatial transition have a significant impact on carbon emissions? How great is the impact? How can low-carbon urban space agglomeration be achieved? These have become urgent theoretical questions that need to be answered on the road to the green transformation of new urbanization under the background of "low-carbon" goals.

The issue of carbon emissions in urbanized areas has long been a focus of academic attention. Since the 1990s, numerous studies have investigated the worldwide relationship between urbanization and carbon emissions. As an important carrier of urbanization, urban spaces and their carbon emission issues have also become key areas of concern in both domestic and international academic circles. In summary, existing research findings are mainly reflected in the following three aspects:

Firstly, research has been conducted on the spatiotemporal pattern characteristics of carbon emissions in urban spaces. Such research aids in scientifically understanding regional differences and evolution trends in carbon emissions. These studies also provide a basis for the formulation of low-carbon development strategies (Zeng et al., 2024; Cui et al., 2020). With breakthroughs in methods for calculating carbon emission data, such as remote sensing image inversion, continuous carbon emission data across multiple scales and over time have been obtained in urban areas (Zhang et al., 2025). The academic community has conducted extensive research on the spatiotemporal pattern characteristics of carbon emissions in urban areas. The primary focus has been on the spatiotemporal variation in the geospatial distribution of carbon emissions (Ren et al., 2024; Zhang et al., 2023) and the spatial network pattern characteristics of carbon emissions (Chen et al., 2023; Yang et al., 2024). There have also been studies on the spatial correlation or spillover characteristics of carbon emissions (Zhou et al., 2023), among other aspects. Furthermore, some scholars have measured the degree of carbon emission efficiency in urban areas by establishing models, such as IPCE, SBM-DEA, and STIRPAT, and analyzed the characteristics of the carbon emissions' spatial patterns (Liu et al., 2022; Yu et al., 2020).

Secondly, research has been conducted on the correlation characteristics between the evolution of urban spatial structure and carbon emissions. Related research is mainly reflected in two aspects. One focus is on studying the relationship between the evolution of urban internal spatial structure and carbon emissions. Many studies, for example, have analyzed the correlation characteristics between urban spatial structure and carbon emissions by establishing spatial correlation models, such as spatial coupling degree models and spatial statistical models. Also discussed have been the correlation characteristics of urban spatial structure and evolution (Yin et al., 2023; Wang et al., 2022), scale and density change (Ma et al., 2021), morphological feature changes (Bibri et al., 2020; Wang et al., 2019), and spatial agglomeration and diffusion (Liu et al., 2022) with carbon emissions. The second focus is on studying the relationship between the overall process of urbanization and carbon emissions. Most studies indicate that in the initial stages of urbanization, as population and economic scale increase, carbon emissions in the region will rise significantly. However, as urbanization reaches a higher level, the growth in carbon emissions tends to stabilize, and carbon emission efficiency per capita will increase significantly (Liu et al., 2019; Shahbaz et al., 2016; Yu et al., 2020). Moreover, some scholars have also focused on the impact of regional integration or coordinated regional development on carbon emissions, pointing out that regional integration or coordinated regional development can enhance urban carbon emission efficiency (Sun et al., 2024; Feng et al., 2023).

Thirdly, there has been research on the impact mechanisms of carbon emissions in urban areas and countermeasures for low-carbon development. The research outcomes have been based on theories such as using the Kuznets environmental curve to construct models (like the STIRPAT model and spatial panel regression models) to explore influencing factors. Most studies have identified significant impacts on carbon emissions during the process of urban spatial agglomeration. These impacts have come from economic development (Chen et al., 2023; Wang et al., 2023), population growth (Gao et al., 2022), changes in industrial structure (Guo et al., 2024), changes in household consumption (Cheng et al., 2024), green technological innovation (Tang et al., 2024; Du et al., 2019), and the development of the digital economy (Chen et al., 2024; Li et al., 2024). These studies have further explained the mechanisms through which each influencing factor affects carbon emissions through mathematical analysis. Subsequently, low-carbon development strategies have been proposed from the perspective of the spatial organization of urbanization factors. In addition, some scholars have constructed difference-in-differences (DID) models and slack-based measure (SBM) models, among others, to discuss the impact of low-carbon pilot city policies on carbon emission efficiency (Zou et al., 2024; Wen et al., 2022; Yu et al., 2021; Zhang et al., 2022). In-depth analyses have been conducted of the mechanisms through which China's low-carbon pilot policies affect carbon emissions, and the results have provided theoretical support for the promotion of low-carbon policies.

Existing researches have systematically explored the spatio-temporal characteristics of carbon emissions in urban spaces and analyzed the influencing factors of carbon emissions in urban spaces from multiple perspectives. Those researches have provided extensive models and methodologies for this study to draw upon and emulate. However, three areas in existing research still require further expansion. Firstly, relatively speaking, research on the associative characteristics between the dynamic geospatial process of urban spatial agglomeration and carbon emissions has been neglected. Most existing studies on the carbon emission effects of urban spaces have focused on static patterns and their correlation analyses. The agglomeration process of urban spatial elements has a significant impact on regional carbon emissions. Secondly, existing theoretical research on the correlation between urban spatial evolution and carbon emission is still not sufficiently systematic. Previous research on carbon emissions in urban spaces has predominantly focused on specific aspects, such as spatial patterns, emission efficiency, and associative characteristics. This has hindered the necessary comprehensive understanding of the carbon emission mechanisms associated with urban spatial agglomeration. Currently, very few studies have explicitly proposed development models for urban spatial agglomeration in the context of low-carbon goals. Thirdly, most existing research has either been conducted at the national scale or has selected highly-populated and economically-developed regions, such as the Yangtze River Economic Belt, the Beijing-Tianjin-Hebei region, and the Pearl River Delta urban agglomeration in China as case studies. However, relatively scant attention has been paid to the carbon emission issues during the urbanization process of old industrial bases. Due to their unique development histories and heavy industrial structures, old industrial bases exhibit certain peculiarities in carbon emissions during the urbanization process. Discussing the carbon emission effects of urban spatial evolution in these areas can help further tap into the potential for carbon reduction.

In view of the above, this study selects Jilin Province of China, an old industrial base with high carbon emission intensity, as a case study. The focus is on analyzing the interactive impact between the dynamic geospatial process of urban spatial agglomeration and carbon emissions. By constructing various spatial agglomeration models and spatial correlation model systems, this study systematically analyzes the mechanism underlying the association between urban spatial agglomeration and carbon emissions. In addition, low-carbon development models for urban spaces are further explored. The innovations of this study are embodied in the following two aspects: Firstly, this article investigates the association mechanism between the dynamic process of urban spatial agglomeration – a holistic regional phenomenon – and carbon emissions, thereby providing a new perspective for studying the resource-environmental effects of urban spatial structure evolution. Secondly, this study analyzes the impact process of urban spatial agglomeration on carbon emissions and explores low-carbon models of urban spatial agglomeration. The results can provide references for planning low-carbon models during the process of urban spatial transformation against the backdrop of China's "low carbon" goals.

The research framework of this paper is as follows (Figure 1):

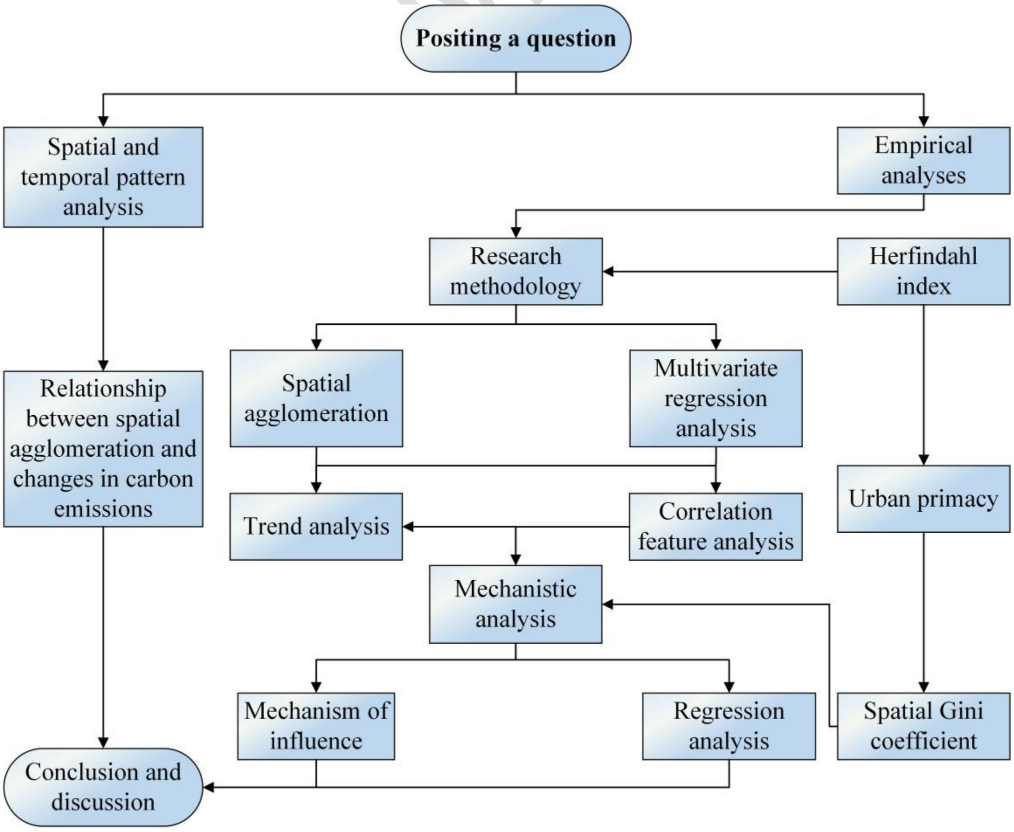

Figure 1. Research framework and technological roadmap

2. Scope of the study, data sources and research methods

2.1 Scope of the study

Located in Northeast China, Jilin Province is a typical old industrial base, characterized by an early initiation of urbanization, a heavy industrial structure, and a generally high level of carbon emissions. The development of urbanization in Jilin Province of China relies more on the development of traditional heavy industries, and the process of interaction between urbanization and carbon emissions is relatively typical. Discussing the relationship between spatial agglomeration characteristics of cities and towns and carbon emissions in Jilin Province of China as an example is representative and the conclusions of the study are of generalization value. As of 2023, Jilin Province in China had a population of 23,394,100, a GDP of RMB 1,353,119 million, and a territorial area of 187,400 square kilometers. The province administers eight prefecture-level cities, one autonomous prefecture, 20 county-level cities, and 19 counties. This study will discuss the characteristics of urban spatial agglomeration and its correlation mechanism with carbon emissions during the period from 2004 to 2020. The data come from a total of 47 research units, including the municipal districts of the abovementioned eight prefecture-level cities, 20 county-level cities, and 19 counties in Jilin Province (Figure 2).

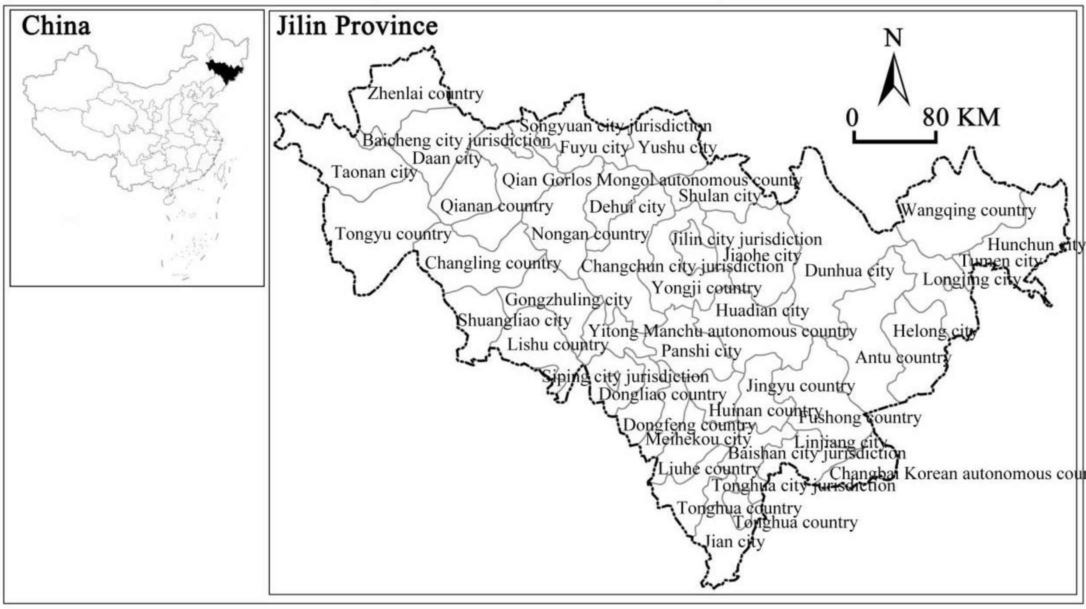

Figure 2. Study areas and study units

2.2 Data sources

Urban population and economic data are primarily sourced from the Jilin Statistical Yearbook for the years 2005 to 2021, as well as the corresponding annual statistical bulletins on the national economic and social development of Jilin Province. Carbon emission data are derived from county-level and provincial-level data provided by the "China Emission Accounts and Datasets" website (CEADs, https://www.ceads.net.cn/). These data are inverted from DMSP/OLS and NPP/VIIRS nighttime remote sensing data and cover multiple scales of carbon emission data, including provincial and county/city levels. This method has the advantages of uniform caliber and strong continuity. Missing data were filled in using interpolation.

2.3 Research methods

2.3.1 Spatial agglomeration degree

In this study, three spatial agglomeration measurement models, namely the Herfindahl index, spatial Gini coefficient, and urban primacy (Table 1) models were selected to measure the spatial agglomeration characteristics of the cities and towns in Jilin Province. Five factors were used, namely: population, GDP, output value of the secondary industry, output value of the tertiary industry, and retail sales of consumer goods. The spatial agglomeration characteristics reflected by the three abovementioned models are each unique. The Herfindahl index reflects the spatial agglomeration caused by absolute internal individual differences, thereby characterizing agglomeration due to individual variability. The spatial Gini coefficient reflects the spatial agglomeration characteristics that arise from the accumulation of individual differences, thereby reflecting the agglomeration characteristics caused by the overall difference. Urban primacy reflects the agglomeration caused by the gaps between the largest towns and other towns, thereby reflecting agglomeration characteristics due to differences in the size structure of the locality.

Table 1. Spatial agglomeration measurement model formulation and implications for cities and towns

Indicator name	Formula	Implication
Herfindahl index	$H=\sum_{i=1}^{n}\left(S_i^2\right)=\left(\frac{X_i}{X}\right)^2$ i=1, 2, 3, ⋯⋯, n (1)	Where H represents the Herfindahl index, n is the number of research units, X_i denotes the value of a specific type of element in the i-th unit, and X signifies the total sum of that specific type of element across all research units.
Spatial Gini coefficient	$G=1-\sum_{i=1}^{n}\left(y_i+y_{i-1}\right)\left(x_i-x_{i-1}\right)$, i=1, 2, 3, ⋯⋯, n (2)	Where G represents the spatial Gini coefficient, x_i denotes the code for the i-th cell, y_i signifies the value of a specific type of element in the i-th study cell, and n is the total number of study cells
Urban primacy	$S=\frac{x_{\max}}{\sum_{i=1}^{n}x_i-x_{\max}}$ i=1, 2, 3, ⋯⋯, n (3)	Where S represents the urban primacy, $x_{\max}$ denotes the maximum value of a specific type of element across all cells, x_i signifies the value of that specific type of element in the i-th cell, and n is the number of study cells

2.3.2 Multivariate regression analysis

Taking the level of carbon emissions (total amount, intensity, and efficiency) as the dependent variable and urban spatial agglomeration indicators as the independent variables, this paper analyzes the mechanism through which urban spatial agglomeration influences carbon emissions. The model formula is as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + \mu_i \qquad i=1, 2, 3, \cdots\cdots, n \qquad (4)$$

In this formula, Yi represents the dependent variable, X_{1i}, X_{2i}, $\cdots$, X_{ki} represent the independent variables, and μ_i is the random interference term. Then, β_0 is the intercept term, which represents the expected value of Y_i when all X_{1i}, X_{2i}, $\cdots$, X_{ki} are 0. Finally, β_i represents the partial regression coefficient, which reflects the amount of change in the explained variable caused by each unit change in the corresponding explanatory variable if the rest of the explanatory variables are held constant, normally, $\beta_0 > 0$, $0 < \beta_i < 1$.

3. Analysis of spatial agglomeration characteristics and carbon emission trends of cities and towns in Jilin Province

3.1 Characteristics and trends of spatial agglomeration of towns in Jilin province

The Herfindahl index, the spatial Gini coefficient, and an urban primacy model are applied to measure the spatial agglomeration level of the following: population (*POP*), gross domestic product (*GDP*), output value of the secondary industry (*SSI*), output value of the tertiary industry (*TSI*), and the total retail sales of social consumer goods (*SST*) of 47 spatial units in Jilin Province, China, respectively (Figure 3). The results show some similarity between the three model measurements. Changes in spatial agglomeration of cities and towns as reflected in the three indicators show a decreasing and then increasing trend. However, there are slight differences in the trends and magnitude of changes in the indicators. The tendency for the level of spatial agglomeration, as reflected in the spatial Gini coefficient, to first decrease and then increase is more pronounced.

Specifically, over the period 2004 - 2020, the spatial agglomeration of towns and cities as reflected in the main economic indicators in Jilin Province, China, shows a trend of first decreasing, then increasing, but ultimately rising as a whole. The results show that there was a slow decrease from 2004 to 2016, followed by a rapid increase from 2016 to 2020. Since 2003, the Chinese government has been implementing a large-scale "Northeast Revitalization" strategy, intensifying investments in the Northeast region. This has brought rare development opportunities to the Northeast region, which includes Jilin Province. On this basis, the socio-economic development of Jilin Province entered a period of rapid growth spanning approximately 10 years. The relatively abundant investments led to a favorable momentum in local economic development. However, despite this positive economic momentum, the spatial agglomeration of towns and cities has not been pronounced, and the degree of spatial agglomeration has even slightly decreased. Since 2014, a new round of decline in Northeast China, primarily characterized by population loss and low economic growth, has once again garnered widespread attention from all sectors of society. The economic development of the Northeast region, including Jilin Province, has once again fallen into a downturn. In this context, leveraging limited production factors to create economic growth poles and then stimulate the development of surrounding areas has become a helpless choice for the regional economic development of Jilin Province. Consequently, various development plans have emerged. For example, some have advocated for the development of the central Jilin city cluster and Changchun metropolitan area with Changchun, the provincial capital city as the core. This new plan promoted the development of the primary city, Changchun, resulting in a rapid increase in the level of urban spatial agglomeration in Jilin Province during the period from 2016 to 2020. The overall level of urban spatial agglomeration, reflected in the population indicators of Jilin Province over the period from 2004 to 2020, exhibited a slight increase. This indicates that, compared with various economic indicators, the degree of urban population agglomeration remains relatively low. Furthermore, the issue of non-coordination between urban population and economic factors during the process of spatial agglomeration is notably prominent.

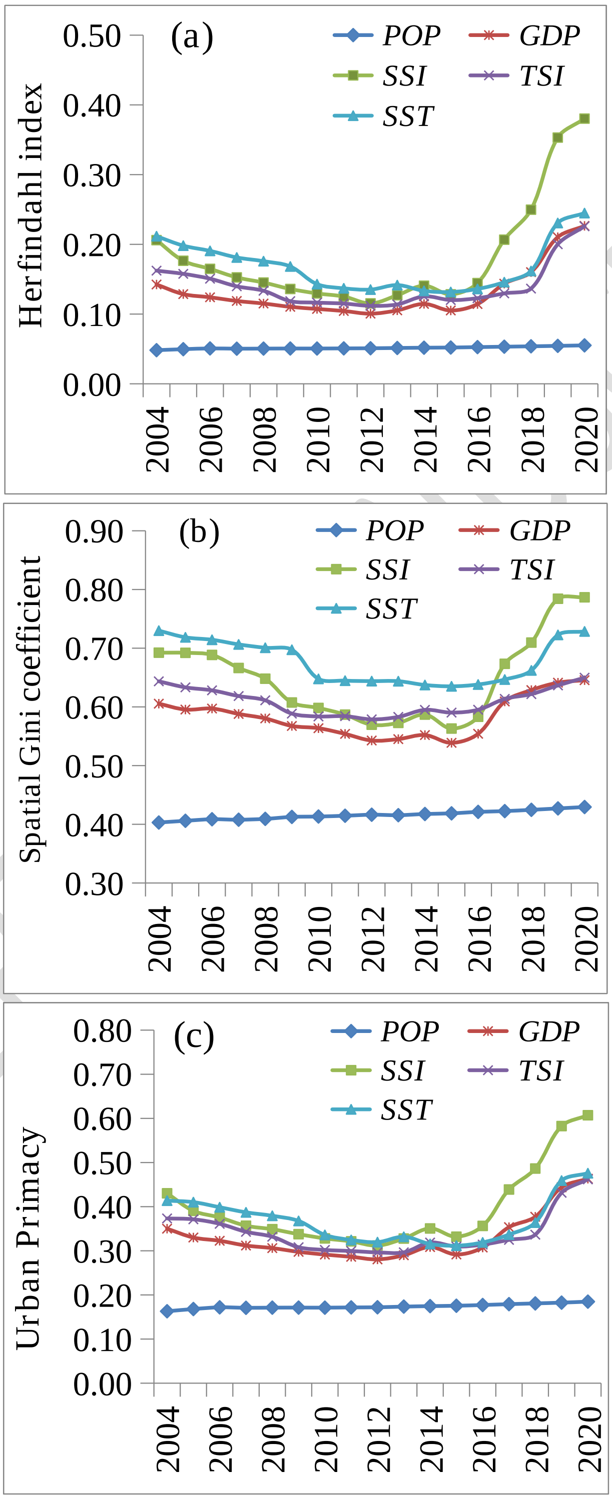

Figure 3. Trends in indicators of spatial agglomeration of urban factors in Jilin Province, 2004-2020

3.2 Trends in total carbon emissions, intensity, and efficiency in Jilin Province

During the period from 2004 to 2020, the total carbon emissions in Jilin Province exhibited a trend of initial increase, followed by a decrease; overall, there was a slight increase (Figure 4a). Specifically, from 2004 to 2011, the emissions showed a steady and rapid growth trend, increasing from 123.66 million tons in 2004 to 264.67 million tons in 2011, representing an average annual growth rate of 13.52%. In 2012, carbon emissions reached 265.30 million tons, slightly higher than the emissions in 2011. During this period, the Northeast region of China was undergoing rapid local economic development under the "Revitalization of Northeast China" strategy. This led to significant investments in infrastructure construction and consequently, a rapid increase in carbon emission levels. The primary reasons for this phenomenon can be attributed to the following: Firstly, during this period, Jilin Province's economic development was impacted by a new wave of decline affecting Northeast China. That decline resulted in a slowdown or even recession in economic growth, which in turn led to a reduction in carbon emissions. Secondly, in recent years, the Chinese government has thoroughly implemented the concept of green and low-carbon development. Rectification measures have been conducted with regard to high-emission and high-pollution industries, thereby effectively reducing regional carbon emissions.

From the perspective of the trend in carbon emission intensity (Figure 4b), both per capita carbon emissions and carbon emissions per unit area underwent a process of first increasing and then decreasing during the sampled years. This trend is primarily correlated with total carbon emissions. The carbon emission intensity per unit of production reflects the efficiency of carbon emission controls in production activities. During the study period, a continuous decreasing trend was observed, indicating that the practice of low-carbon development models in industrial development in Jilin Province during those years was quite effective. The carbon emissions required to produce each unit of GDP became increasingly smaller, and carbon emission efficiency gradually improved.

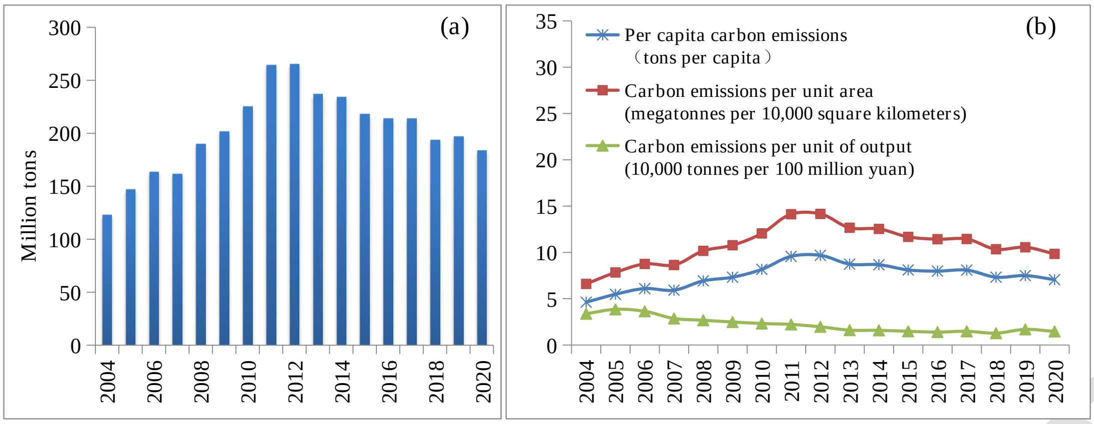

Figure 4. Trends in total carbon emissions (a) and per capita, land, and production carbon emissions (b) in Jilin Province, 2004-2020

4. Analysis of the correlation characteristics between urban spatial agglomeration and carbon emissions in Jilin Province

During the analysis of the correlation characteristics and mechanisms between urban spatial agglomeration and carbon emissions, the differences among the three spatial agglomeration indicators – the Herfindahl index, spatial Gini coefficient, and primary city index – were not significant. Relatively speaking, the relevant laws between the spatial Gini coefficient of various urban elements and carbon emission indicators are clearer. On this basis, this study selects the spatial Gini coefficient to discuss the correlation characteristics and mechanisms between urban spatial agglomeration and carbon emissions.

Analysis using the Pearson correlation coefficient indicates that, during the period from 2004 to 2020, an overall negative correlation existed between the spatial Gini coefficient of various urban elements, total carbon emissions, and carbon emission intensity in Jilin Province (Table 2). To a certain extent, this can be interpreted as a high level of urban spatial agglomeration corresponding to a lower level of carbon emissions. However, this negative correlation varies significantly among different urban element indicators. Specifically, the spatial agglomeration of the service industry represented by the total value of the tertiary industry (*TSI*) and the total retail sales of social consumer goods (*SST*) has a significant negative correlation with the total carbon emissions and carbon emission intensity. For example, the Pearson correlation coefficients between the spatial Gini coefficient of total retail sales of consumer goods (*G-SST*) and total carbon emissions, per capita carbon emissions, and carbon emissions per unit of land area were -0.819, -0.817, and -0.819, respectively. Comparatively speaking, the spatial agglomeration of urban GDP (*GDP*) and secondary industry output (*SSI*) had a relatively low correlation with total carbon emissions and carbon emission intensity. This finding indicates that the spatial agglomeration of service industries is more helpful in terms of reducing the carbon emission level than the spatial agglomeration of production industries. The correlation between the change of urban population agglomeration level (*G-POP*) and the total carbon emission and carbon emission intensity is not significant. However, a significant negative correlation is shown with the per capita carbon emission; the Pearson correlation coefficient is also -0.870. This finding indicates that, although the spatial agglomeration of the urban population does not have a significant impact on the total and intensity of carbon emissions, that agglomeration helps to improve the carbon emission efficiency of industrial activities.

Table 2. Correlation analysis of carbon emission levels and the spatial Gini index of cities and towns in Jilin Province, from 2004 to 2020

Spatial Gini coefficient / Carbon emission targets	*G-POP*	*G-GDP*	*G-SSI*	*G-TSI*	*G-SST*
Total carbon emissions	——	-0.595*	-0.631**	-0.820**	-0.819**
Per capita carbon emissions (tons per capita)	——	-0.545*	-0.583**	-0.779**	-0.817**
Carbon emissions per unit area (megatons per 10,000 square kilometers)	0.473*	-0.595*	-0.631**	-0.820**	-0.819**
Carbon emissions per unit of output (10,000 tons per 100 million yuan)	-0.870**	——	——	——	0.609**

Note: ** indicates a significant correlation at the 0.01 level (two-tailed); *G-POP* represents the spatial Gini coefficient for the population, and so forth.

5. Analysis of the correlation mechanism between urban spatial agglomeration and carbon emissions

5.1 Mechanism analysis of the impact of urban spatial agglomeration on regional carbon emission intensity

The mechanism of the influence of the spatial agglomeration of urban elements on the level of carbon emissions in Jilin Province is now further analyzed. Regression analyses were conducted with the total carbon emissions (Y_{TP}), per capita carbon emissions ($Y_{P\text{-}TP}$), land-averaged carbon emissions ($Y_{A\text{-}TP}$), and production-averaged carbon emissions ($Y_{I\text{-}TP}$) in Jilin Province used as the dependent variables. The spatial Gini coefficients of various types of socioeconomic indicators (X_{POP}, X_{GDP}, X_{SSI}, X_{TSI}, and X_{SST}) were used as the independent variables. The four models that passed the test were further tested (Table 3).

Table 3. Regression modeling and parameters of carbon emission indicators and spatial Gini index of cities and towns in Jilin Province, from 2004 to 2020

Regression model		Adjusted R^2	F-statistic (α=0.05)
Y_{TP}=2001.78-1307.58$X_{G\text{-}GDP}$+1188.93$X_{G\text{-}SSI}$-2177.80$X_{G\text{-}TSI}$-711.49$X_{G\text{-}SST}$	(5)	0.90	36.54
$Y_{P\text{-}TP}$=74.77-57.86$X_{G\text{-}GDP}$+51.90$X_{G\text{-}SSI}$-74.95$X_{G\text{-}TSI}$-31.76$X_{G\text{-}SST}$	(6)	0.88	30.24
$Y_{A\text{-}TP}$=110.02-81.20$X_{G\text{-}GDP}$+72.39$X_{G\text{-}SSI}$-116.89$X_{G\text{-}TSI}$-40.69$X_{G\text{-}SST}$	(7)	0.89	31.87
$Y_{I\text{-}TP}$=43.91-107.70$X_{G\text{-}POP}$+4.74$X_{G\text{-}SSI}$ (8)		0.90	73.65

The spatial Gini coefficients of GDP (X_{GDP}), tertiary sector output (X_{TSI}), and total retail sales of consumer goods (X_{SST}) had a significant negative effect on total carbon emissions (Y_{TP}). Each increase of 1307.58, 2177.80, and 711.48 units in $X_{G\text{-}GDP}$, $X_{G\text{-}SSI}$, and $X_{G\text{-}SST}$, respectively, induced a decrease of one unit in total carbon emissions. In this study, GDP (X_{GDP}) is a composite indicator of the level of development of the local economy as a whole, suggesting that the economic agglomeration of the region as a whole contributes to the reduction of total carbon emissions. The output value of the tertiary industry (X_{SSI}) and the total retail sales of consumer goods (X_{SST}) are the main components of the service industry. This indicates that the spatial agglomeration of the service industry in towns and cities will significantly reduce the total amount of carbon emissions. In addition, the spatial agglomeration of the service industry has an impact on carbon emission reduction in two main aspects. Firstly, the clustering of spatial services in towns and cities means that the region has, to a certain extent, upgraded its industries. The proportion of the tertiary industry in Jilin Province increased from 34.4 percent to 48.0 percent during the period 2004-2020. Furthermore, the service sector is becoming increasingly important in large cities, so the region’s economic development is less dependent on industrial enterprises that emit more carbon, thus causing a reduction in carbon emissions. Secondly, the clustering of the service sector means that the flow of people and logistics is concentrated in large cities. The spatial friction between the matching of supply and demand for economic activities is also reduced. Therefore, large cities will help improve the level of efficiency in the organization of industrial production, logistics and transport, etc., thereby reducing the level of regional carbon emissions.

The spatial Gini coefficients of GDP (X_{GDP}), tertiary sector output (X_{TSI}), and total retail sales of consumer goods (X_{SST}) had a significant negative effect on per capita carbon emissions (Y_{P-TP}). Each increase of 57.86, 74.95, and 31.76 units in XG-GDP , XG-TSI , and XG-SST , respectively, caused a decrease of one unit in per capita carbon emissions. A comparison of the regression coefficients clearly shows that the spatial Gini coefficients of GDP (X_{GDP}), tertiary industry output (X_{TSI}), and total retail sales of social consumer goods (X_{SST}) have a significantly stronger impact on per capita carbon emissions than on total carbon emissions. This finding suggests that promoting spatial service industry agglomeration in towns and cities will help to reduce the intensity of per capita carbon emissions. The spatial agglomeration of the service industry will inevitably lead to the spatial agglomeration of the population, and the external scale effect will lead to the reduction of per capita resource consumption. This, in turn, will reduce the level of per capita carbon emissions.

The spatial Gini coefficients of GDP (X_{GDP}), tertiary sector output (X_{TSI}), and total retail sales of consumer goods (X_{SST}) also had a significant negative effect on land-averaged capita carbon emissions ($Y_{A\text{-}TP}$). Every increase of 81.20, 116.89, and 40.69 units in $X_{G\text{-}GDP}$, $X_{G\text{-}TSI}$, and $X_{G\text{-}SST}$, respectively, causes a decrease of one unit in land-averaged carbon emissions. This likewise indicates that the spatial clustering of services in towns and cities will significantly reduce the intensity of carbon emissions.

The spatial Gini coefficient of population (X_{POP}) had a significant negative effect on the average carbon emissions per unit of production ($Y_{I\text{-}TP}$). Every increase of 107.70 units in X_{POP} caused a decrease of one unit in average carbon emissions per unit of production. This indicates that the external scale effect brought about by population agglomeration helps to improve the efficiency of industrial production and carbon emissions.

All four of the tested models showed the positive effect of the spatial Gini coefficient of secondary sector output ($X_{G\text{-}SSI}$) on the level of carbon emissions. Every increase of 1188.93, 51.90, 72.39, and 4.74 units in $X_{G\text{-}SSI}$, respectively, caused an increase of one unit in total carbon emissions (Y_{TP}), per capita carbon emissions ($Y_{P\text{-}TP}$), land-averaged capita carbon emissions ($Y_{A\text{-}TP}$), and production-averaged capita carbon emissions ($Y_{I\text{-}TP}$). This finding suggests that the spatial concentration of real industries (represented by the secondary industry) causes an increase in the level of carbon emissions, to some extent. The spatial agglomeration of real industries is often accompanied by a significant increase in the investment scale of industrial enterprises, which in turn leads to an increase in the level of carbon emissions.

In summary, the spatial agglomeration of urban population and economic factors has a significant negative impact on both total carbon emissions and carbon emission intensity. The spatial agglomeration of urban services (represented by the output value of tertiary industry (X_{TSI}) and the total retail sales of consumer goods (X_{SST}) will significantly reduce the total carbon emissions and carbon emission intensity. In addition, the spatial agglomeration of the population will reduce production-averaged carbon emissions. In other words, the spatial agglomeration of the population contributes to the improvement of the efficiency of carbon emissions. Comparatively speaking, the spatial agglomeration of the total value of secondary industry (X_{SSI}) had a certain positive effect on the impact of total carbon emissions and carbon emission intensity. This, to a certain extent, indicates that the spatial agglomeration of real industry may increase the regional carbon emission level.

6. Conclusion and discussion

6.1 Conclusion

This paper takes Jilin Province as an example to explore the correlation mechanism between urban spatial agglomeration and regional carbon emission. The objective is to provide a scientific basis for the planning and management of urban territorial space under the background of China's "low-carbon" target constraints.

The Herfindahl index, spatial Gini coefficient and urban primacy degree are respectively used to measure the spatial agglomeration characteristics of 47 spatial units in Jilin Province. The results show that, during the period from 2004 to 2020, the spatial agglomeration degrees of GDP, the output value of the secondary industry, the output value of the tertiary industry, and the total retail sales of consumer goods in Jilin Province all demonstrated a trend of initial decrease, followed by an increase. However, overall, there was an upward trajectory during this period. In addition, the overall level of urban spatial agglomeration reflected by the population index also slightly improved. During the study period, the total carbon emissions in Jilin Province exhibited an overall trend of initial increase, followed by a decrease, but again with a slight overall rise. Similarly, carbon emission intensities (per capita carbon emissions and carbon emissions per unit area) demonstrated a trend of initial increase, followed by a decrease. In contrast, emission efficiency (carbon emissions per unit of output) showed a consistent trend of decrease. The spatial agglomeration trend of urban elements and the overall level of carbon emissions exhibited changes in opposite directions.

The correlation characteristics between urban spatial agglomeration and carbon emissions are analyzed. The findings show that, during the period from 2004 to 2020, a relatively significant negative correlation existed between the spatial Gini coefficient of various urban spatial elements in Jilin Province and both total carbon emissions and carbon emission intensity. Notably, the spatial agglomeration degree of the service industry (represented by the total output value of the tertiary industry and total retail sales of consumer goods) exhibited a significant negative correlation with the level of carbon emissions.

Further establishing a regression model to study the impact of urban spatial agglomeration on carbon emissions in Jilin Province shows the following: The spatial agglomeration of service industries (represented by the output value of the tertiary industry and total retail sales of consumer goods) had a significant negative impact on both total carbon emissions and carbon emission intensity during the studied years. This indicates that the spatial agglomeration of service industries within urban spaces contributes to reducing regional carbon emission levels. The spatial agglomeration of physical industries (reflected by the total output value of the secondary industry) exhibits a certain positive effect on both total carbon emissions and carbon emission levels. To a certain extent, this finding suggests that the spatial agglomeration of physical industries is detrimental to the reduction of regional carbon emission levels. The spatial agglomeration of the urban population plays an obvious role in improving carbon emissions efficiency.

6.2 Discussion

Firstly, the direct carbon emission effect of the service industry's operation was not significant during the sampled years. However, the spatial agglomeration of the service industry facilitates the realization of regional economies of scale and positive externalities, thereby promoting the efficient organization and operation of the region's overall production and life. Spatial agglomeration of the service industry helps reduce the region’s total carbon emissions and carbon emission intensity. As the marginal benefits of carbon reduction in industry and agriculture decline to lower levels, exploring the impact of the spatial evolution of the service industry on carbon emissions holds significant practical value. Guiding the orderly agglomeration of service industries in urban spaces will be an important component of urban land-use planning under the constraint of China’s low-carbon goals.

Secondly, the migration of population towards densely populated urban areas – especially large and medium-sized cities – represents an important geographical feature of the urbanization process. While having an insignificant impact on the total amount and intensity of regional carbon emissions, the spatial agglomeration of the population significantly influences carbon emission efficiency. As the main factor in regional scientific and technological innovation, economic development and carbon emissions, the spatial agglomeration of the population will effectively reduce the carbon emissions per unit of GDP output. Reasonably guiding the agglomeration of the urban population in regions will also be an important aspect of urban land-use planning in the context of China’s "low carbon" (carbon peaking and carbon neutrality) targets. According research from Jilin Province, the urban population space and the spatial agglomeration of various economic factors were found to have obvious incoordination. The degree of population agglomeration is also significantly lower than the economic indicators. The incoherence of the spatial agglomeration of such urban elements will lead to at least two consequences. First, the spatial agglomeration of economic factors will accelerate the poverty level in the non-agglomeration target area. This is clearly not conducive to the balanced development of the regional economy. Second, the incoordination of the spatial agglomeration of population and economic factors will also lead to the spatial deviation of the supply and demand of economic activities. This will obviously generate long-distance traffic demand, resulting in additional carbon emissions, which is not conducive to the reduction of the overall regional carbon emission level. Therefore, guiding the spatial coordination and agglomeration of population and economic elements is also an issue that needs to be paid close attention in future urban space governance strategies.

Third, the spatial agglomeration of real industries represented by the secondary industry plays a certain positive role in promoting the carbon emission level. The balanced layout of the real industry is not only conducive to the balanced development of the regional economy but can also effectively avoid the excessive agglomeration of real industries in densely populated areas. This is important, this excessive agglomeration in populated areas has a negative impact on the living environment.

By studying the characteristics and mechanisms of the association between spatial agglomeration of cities and towns and carbon emissions in Jilin Province, China. We find that the spatial agglomeration of cities and towns has a significant intrinsic correlation with carbon emissions. The orderly agglomeration of economic and demographic factors in urban space helps to realize a reduction in total carbon emissions and an increase in carbon emission efficiency. This finding provides an important reference for urbanization planning in China and developing countries around the world, as well as evidence that spatial agglomeration in the urbanization process can achieve carbon emissions from human activities. At the same time, this study also enriches the cases of research on spatial agglomeration and carbon emissions in towns and cities, and provides new ideas for the study of resource and environmental effects in the process of urbanization.

Finally, constrained by data limitations, this study only discusses Jilin Province’s urban spatial agglomeration level and carbon emissions-associated characteristics during the years 2004-2020, and failed to conduct an investigation over a longer period of time. Meanwhile, the selection of elements for urban spatial agglomeration is also rather limited, which leads to the fact that the research on the correlative mechanism between urban spatial agglomeration and carbon emissions is still not thorough and comprehensive enough. These issues will be the future research direction.

Acknowledgment

This research was funded by project of National Social Science Foundation of China (23BJL133), by Humanities and Social Sciences Research Project of the Education Department of Jilin Province JJKH20240172SK, by Jilin University of Finance and Economics school-level project (2024LH007).

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