



## OPEN Urban density and spatial carbon emission performance of megacities in China

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Increasing urban density promotes a greater social role for cities. The current low-carbon city development goals put forward higher requirements for carbon performance. Based on the viewpoint of minimizing natural resource input and maximizing value acquisition in ecological benefits, the influence of urban density on spatial carbon performance is analyzed by polynomial function relationship, and Beijing and Shanghai with different urban function positioning are taken as examples for comparative analysis. Combined with Point-of-Interest (POI), the classification benchmark of industrial activities was established, and the spatial kernel density of ArcGIS software was used to analyze the industrial agglomeration characteristics of the two cities. The results show that: 1) The “increase-decrease-increase-decrease” trend of urban spatial carbon performance over time fluctuates around the unary linear trend of urban density. 2) Population and building density are too low or too high, which is not conducive to emission reduction. The change of economic density is influenced by the industrial structure. The change of urban density is negatively correlated with the growth rate of spatial carbon performance. In a certain development stage, the increase of urban density will inhibit the growth of spatial carbon performance to some extent. 3) Maintaining the original economic and industrial structure, the increase in economic density brought by the simple expansion of scale is not conducive to emission reduction. The increase of economic density brought by the transformation of economic or industrial structure and the reduction of the proportion of secondary industry is conducive to urban emission reduction.

**Keywords** Megacities, Urban density, Industrial agglomeration, Spatial carbon performance

China's carbon dioxide (CO<sub>2</sub>) emissions have a significant impact on global climate change<sup>1</sup>. In recent years, China's development requirements for carbon peak and carbon neutrality have promoted a balance between urban spatial structure, scale and intensity. Brand Law states that the bigger the city, the more sustainable it is, and the greener the city is. Under the premise of maintaining the quality of urban life, higher density can bring good social utility, which is far more efficient than low density<sup>2</sup>. Promoting the optimal allocation of urban resources can improve urban spatial economic, environmental and social performance. Performance is not only a concept of economics, but also includes the coordination and development of urban economic, social, environmental and spatial levels<sup>3</sup>. It is required to measure the relationship between inputs and outputs in detail, including positive outputs or positive effects, such as welfare or economic output per unit of resource consumption, and negative outputs or negative effects, such as carbon emissions per unit of resource consumption. Spatial carbon performance is based on the perspective of spatial economics and ecogeography, and adds the factor of land size<sup>4</sup>. It is defined as the amount of carbon emissions or environmental load within a certain spatial range. The performance is extended from the positive effect of economic and welfare output per unit of carbon emissions to the negative effect of environmental load per unit space. The relationship between land resource input and environmental impact targets is presented, which not only controls the scale of carbon emissions in a certain space, but also includes the constraints of resource input and emission output intensity targets<sup>5</sup>.

Beijing and Shanghai are megacities in China, with large urban density and high economic level. According to the China Emission Accounts and Datasets (CEADs), which is based on the calculation method of the United Nations Intergovernmental Panel on Climate Change (IPCC), Beijing and Shanghai are ahead of other Chinese cities in achieving the goal of China's low-carbon green transition. This paper proposes a research hypothesis: there is an inevitable and time-changing dynamic correlation between urban density and spatial

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carbon performance. Based on the ecological benefit perspective of ecological economic theory, econometrics method and urban spatial geography analysis tools are used to further verify the hypothesis. However, there are differences between them in the aspects of urban function positioning, regional characteristics and industrial development policies. A comparative analysis of the correlation between urban density and spatial carbon performance in Beijing and Shanghai can better verify whether there is any particularity in the impact of urban density on spatial carbon performance.

## Literature review

In the literature on urban density and performance, carbon emission scale or carbon intensity are more discussed, focusing on the correlation between urban structure and density. For example, Peter Newman first applied the study of spatial structure and spatial intensity (building intensity) to the scale of carbon emissions, and pointed out that urban space use efficiency is negatively correlated with carbon emissions<sup>6</sup>. Later, Jonathan Norman et al. found that the per capita energy consumption and carbon emission intensity of low-density suburbs far from the center were twice that of high-density urban centers<sup>7</sup>. Population density has become an important measurement factor for the change and adjustment of spatial structure, which provides ideas for the study of environmental problems caused by subsequent urban expansion.

Ding C.R. combined urban economics and geography to study the relationship between urban structure and ecological environment in Manhatring, New York, and pointed out that under the high density of cities (capital, buildings, and population density), buildings are interconnected, labor is highly concentrated, land resources are the most efficient, and ecological environment is optimized, so as to expand the study of urban density from a single population and buildings to an economy<sup>8</sup>. At present, the carbon intensity per unit of GDP of some high-density cities in China is only half of that of comparable cities in the United States, indicating that there are differences in economic structures and carbon emissions under the same building density and population density. At the same time, by establishing a model of the relationship between urban building density and traffic energy consumption, it is found that under the same control of socio-demographic variables, the annual vehicle mileage can only be reduced by 5% if the building density increases by 40%<sup>9</sup>. This confirms that the relationship between urban density and carbon emissions is diverse and complex, and that high-density space does not necessarily bring high environmental benefits. It proves that carbon emissions can be controlled through the improvement of physical space or population size in urban development. This suggests that the effect of density on emissions is nonlinear. It is necessary to superimpose other socio-economic factors for analysis to extend single density to multiple densities.

Chokhachian, A. proposed the concept of ecological performance and its relationship with green development from the perspective that economic growth cannot exceed the carrying limit of the ecological environment in the theory of ecological economics<sup>10</sup>. Zhu, D.J. drew on Daly's concept of ecological performance, selected carbon emissions in a certain space as an environmental indicator, defined performance as less carbon emissions to obtain better economic and social welfare, and proposed carbon economic performance in the sense of economic output and carbon welfare performance in the sense of welfare output<sup>11</sup>. Ronchi, S. further refined it into energy utilization, water environment, air environment, soil environment and biodiversity performance, reflecting the ratio of environmental consumption to target output, including environmental cost and environmental benefit, and applied this as an evaluation method to urban planning<sup>12</sup>.

To sum up, the above analysis mainly focuses on the correlation between urban density and the scale or intensity of carbon emissions, and there are few studies on the performance of urban density and the positive and negative effects brought by the supply of spatial resources.

## Data source and methods

### Research area

Beijing is the capital, municipality, national central city and megacity of China. In recent years, Beijing has continued to optimize its energy structure and adjust its industrial structure<sup>13</sup>. According to *Statistical Yearbook of China*, Beijing's economic development has been rapid in the past 20 years. From 1999 to 2020, the GDP increased from ¥217.4 billion to ¥3,610.3 billion. Among them, the proportion of primary industry: secondary industry: tertiary industry in GDP changed from 4:38.7:57.3 to 0.3:15.8:83.9, as shown in Fig. 1.

Shanghai is a municipality directly under the central government, national central city, and megacity in China. It is the first key city to clearly propose to strive to achieve carbon peak before 2025<sup>14</sup>. According to *Statistical Yearbook of China*, Shanghai's economic development has been rapid in the past two decades. The GDP increased from ¥403.5 billion to ¥3870.1 billion. Among them, the proportion of primary industry: secondary industry: tertiary industry in GDP has changed from 2:48.4:49.6 to 0.3:26.6:73.1, as shown in Fig. 2.

By comparison, the GDP of Shanghai is higher than that of Beijing. The same is that the proportion of the tertiary industry in the gross domestic product of both is the highest level. The proportion of tertiary industry in Beijing is higher than that in Shanghai. The proportion of secondary industry is lower than that of Shanghai. The proportion of secondary industry in Shanghai is twice that of Beijing.

### Methods

Based on the existing research, the basic hypothesis is that there is an inevitable and time-varying dynamic correlation between urban density and spatial carbon performance. However, this hypothesis needs to be further analyzed and verified. First of all, the theory of ecological economics is used to study methods with the help of econometric methods. This paper explores the specific correlation between urban density and spatial carbon performance, the basic logic of urban density change and how it affects spatial carbon performance. Secondly, based on different types of POI data, etc., methods such as kernel density analysis of ArcGIS software are used.

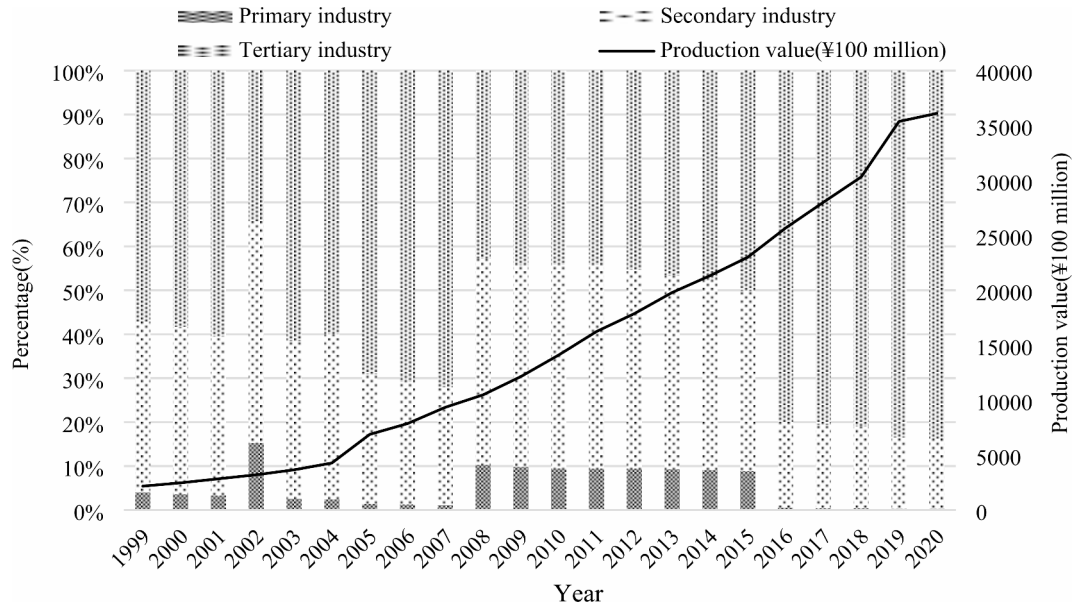


Fig. 1. Beijing's GDP and tertiary production ratio from 1999 to 2020.

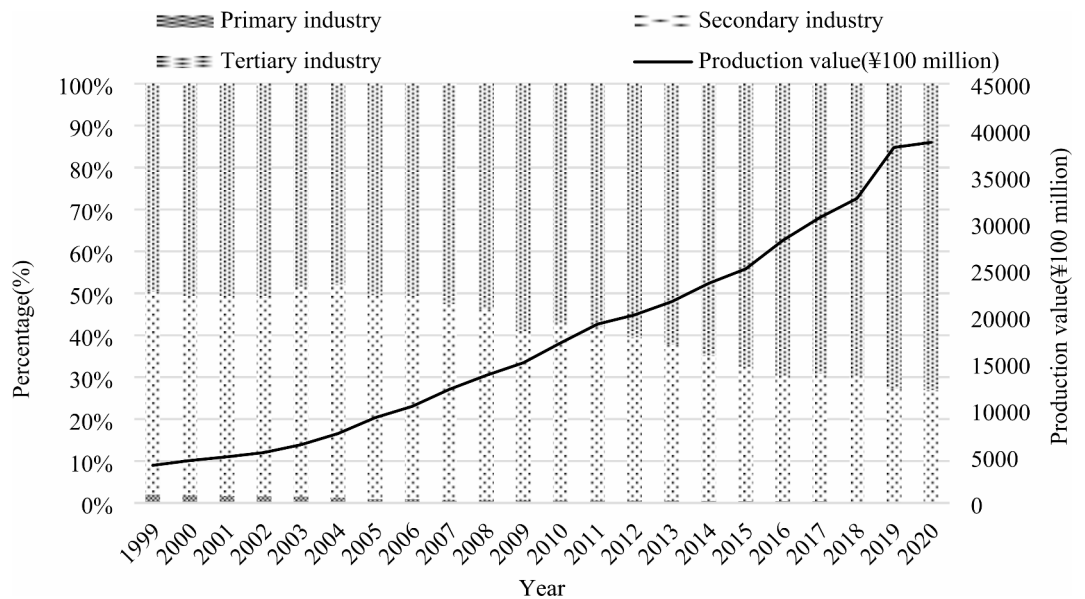


Fig. 2. Shanghai's GDP and tertiary production ratio from 1999 to 2020.

The impact of industrial structure distribution changes on the spatial carbon performance of different megacities was compared and analyzed.

The main research methods include polynomial function relational regression model, comprehensive regression model, Pearson correlation coefficient model and kernel density estimation model. The specific mathematical model is as follows:

(1) Polynomial function relationship regression model.

There are multiple linear possibilities for the correlation between spatial carbon performance and urban density, and the density is included in the regression model as the primary, secondary and tertiary terms of the independent variable, and the curve relationship between the independent variable and the dependent variable is analyzed by using the cubic logarithmic function (Eq. (1))<sup>15</sup>. If the regression results show that the cubic coefficient is not significant, the quadratic polynomial is selected.

$$\ln \frac{CO_2}{L} = a + b_1 \ln D + b_2 \ln D^2 + b_3 \ln D^3 + \varepsilon \tag{1}$$

where  $a$  represents constant;  $b_1$ ,  $b_2$  and  $b_3$  indicate the coefficients of the primary, quadratic and tertiary terms, respectively.  $CO_2/L$  represents spatial carbon performance, Millon tonnes/km<sup>2</sup>;  $D$  represents the urban density index.  $\varepsilon$  is an error term.

(2) Comprehensive regression model.

By establishing a multiple linear regression model of spatial carbon performance and urban density, a time series regression analysis was carried out on the overall spatial carbon performance and urban density change in Beijing<sup>16</sup>. Study the relationship between urban population, economic or building density and spatial carbon performance, the logical and general regularity characteristics of urban density evolution, and analyze the causes. In order to simplify the analysis, the role of technical factors is not considered in the empirical evidence.

$$\ln \frac{CO_2}{L} = \beta_0 + \beta_1 \ln \frac{P}{L} + \beta_2 \ln \frac{G}{L} + \beta_3 \ln \frac{B}{L} + \beta_4 \ln T + \mu \quad (2)$$

where  $CO_2$  represents carbon emissions, Millon tonnes;  $P$  represents population, Millions;  $G$  for economy, ¥100 million;  $B$  represents the floor area, km<sup>2</sup>;  $L$  represents the built-up area, km<sup>2</sup>;  $CO_2/L$  indicates the carbon performance of urban space, Millon tonnes/km<sup>2</sup>;  $\beta_0$  represents a constant;  $\beta_i$  is the regression coefficient of the respective variables;  $\mu$  is the error term.

(3) Pearson correlation coefficient model.

Correlation analysis is a statistical analysis method commonly used to study the degree of correlation between different variables<sup>17</sup>. The correlation coefficient can not only indicate the degree of correlation between different variables, but also express the positive and negative correlation between variables. Correlation analysis is suitable for comparative analysis of more significant variables and less significant variables through comparative analysis when there are many variables<sup>18</sup>. The correlation between urban density and spatial carbon performance in Beijing and Shanghai was judged by spatial correlation analysis, mainly based on the Pearson correlation coefficient model. The calculation formula is as follows:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (3)$$

where  $x_i$  and  $y_i$  represent the  $i$ -th observation of the two variables, respectively.  $\bar{x}$  and  $\bar{y}$  represent the mean of the variables  $x$  and  $y$  respectively. The value of the coefficient  $r$  ranges from  $-1.0$  to  $1.0$ . When the  $r$  value is close to  $0$ , it means that the variable has no correlation. When the  $r$  value is close to  $1$  or  $-1$ , it indicates that the variable has a strong correlation.

(4) Kernel density estimation model.

Kernel density estimation is one of the most widely used nonparametric distribution estimation methods<sup>19</sup>. Setting the kernel function at the sample is the main feature of the model, which analyzes the probability density estimate to show the distribution of the sample in the spatial range of the domain. Suppose the samples can be obtained as  $X_1, X_2, X_3, \dots, X_n$ , and the kernel density calculation formula is as follows:

$$D = \frac{1}{r^2} \sum_{i=1}^n \left[ \frac{3}{\pi} \times X_i \left( 1 - \frac{d_i^2}{r^2} \right)^2 \right] \quad (4)$$

where  $D$  represents the predicted density in kernel density analysis;  $d_i$  represents the distance between the estimated point and the sample point;  $r$  represents the search radius (bandwidth), generally  $d_i < r$ ;  $n$  represents the number of observations.

## Data sources

The data used in this study include urban density data, carbon emission data, and POI data. The process of data collection, processing and validation is as follows:

### Urban density data

The building, economic and population size per unit of land is urban density, and the carbon emissions per unit of land are spatial carbon performance. Indicators such as population, GDP, per capita GDP, total energy consumption and construction area are derived from the Beijing Statistical Yearbook and Shanghai Statistical Yearbook respectively, and the built-up area is derived from the China Statistical Yearbook. All of them can be downloaded directly from the national public website.

### Carbon emission data

The carbon emission data in this article comes from the Carbon Emission Accounts and Datasets (CEADs) database. CEADs gathers a group of experts from the UK, USA and China to work on China and other emerging economies' emission accounting methods and applications. Providing accurate and most up-to-date carbon emission and social economic and trade data is the duty of the whole academic field for policy stakeholders and the public. All datasets published by CEADs are the results of current research projects funded by National Natural Science Foundation of China, Ministry of Science and Technology of China, Research Councils UK. All data is free to download for academic usages.

### POI data

POI data can be written by python and Java crawler programs on the AutoNavi Map developer platform. According to the Web service API provided by it, the rectangular area enclosed by the latitude and longitude coordinates is retrieved, and the crawled POI data coordinate system is the WGS84 coordinate system. The data is filtered, deduplicated, and cropped to generate a data file in CSV format. Finally, 314,302 data in 2012 and 881,457 data in 2022 were obtained from Beijing, and 383,668 data in 2012 and 976,425 data in 2022 from Shanghai.

Refer to the POI classification document of AutoNavi Map Developer Platform and the industry standard of the Industrial Classification of the National Economy (GB/T4754-2017) to merge and classify the crawled POI data. Finally, the industry data with a large amount of data and representative carbon dioxide emissions were selected for spatial visualization analysis. The data supply includes eight categories: culture, education and entertainment, transportation, storage and postal services, construction and real estate, residential services, repair and other services, wholesale and retail, manufacturing, accommodation and catering, medical care, education.

## Results

Chen Fei et al. studied the impact of urban density on spatial carbon performance in Shanghai, and concluded that the relationship between spatial carbon performance and population, economic density shows “N” and inverted “N” curve respectively, which was consistent with the research results of Beijing<sup>3</sup>. The relationship between spatial carbon performance and building density is inverted “U”, which is inconsistent with that of Beijing. At the same time, the rate of change of spatial carbon performance is consistent with the conclusion of the correlation analysis of urban density, that is, the annual growth rate of spatial carbon performance decreases with the increase of urban density.

### Temporal evolution of spatial carbon performance

The built-up area of Beijing from 1999 to 2019 was growing. Between 1999 and 2003, the growth rate was faster than the growth rate from 2003 to 2009, and the built-up area decreased from 2009 to 2011, and since 2011, the built-up area has shown a slow growth trend, as shown in Fig. 2. During this period, CO<sub>2</sub> emissions are increasing, but they are increasing first and then decreasing. Since the peak of carbon emissions in 2010, carbon emissions have been declining. Due to the expansion rate of built-up area and changes in carbon dioxide emissions, the spatial carbon performance showed a fluctuating downward trend.

Compared with Beijing, the built-up area of Shanghai has hardly changed from 1999 to 2003. From 2004 to 2017, it increased at a steady rate, and the overall increase trend was increasing in a stepwise manner. The trend of CO<sub>2</sub> emissions is the same as in Beijing, both of which are rising first and then declining. However, the inflection point of Beijing’s total carbon emissions decline occurred in 2010 and in Shanghai in 2013, and the decline in total carbon emissions was later than that of Beijing, and the rate of decline was lower than that of Beijing, as shown in Fig. 3. By 2019, Shanghai’s total carbon emissions had exceeded twice Beijing’s total carbon emissions, Beijing’s spatial carbon performance had dropped to about 6 Million tonnes/km<sup>2</sup>, and Shanghai’s spatial carbon performance had been about 15 Million tonnes/km<sup>2</sup>.

As shown in Fig. 4, whether it is Beijing or Shanghai, the correlation between the scale of land use in built-up areas and carbon emissions is relatively high, and the total carbon emissions in Beijing are synchronized with the increase and decrease rate of built-up area, and Shanghai has significantly expanded in 2014 and 2018. On the whole, the change trend of carbon emissions and built-up area shows a synchronous growth trend.

### Temporal evolution of urban density

Figure 5 shows that the economic density has grown at a relatively rapid rate since 1999. The overall population density did not change much, but showed an “S” pattern fluctuation trend. Population density increased in 1999–2000 as population growth was higher than the expansion of urban built-up areas in two years, which affected changes in population density. Between 2000 and 2003, population density showed a downward trend due to a slowdown in population growth and an increase in the expansion of built-up areas. From 2003 to 2012, population density showed an upward trend, which was due to population growth that was faster than the expansion of built-up areas, which affected the change in population density. Since 2012, population density has shown a downward trend, also due to the slower population growth rate than the growth rate of built-up area.

From the perspective of the change relationship between spatial carbon performance and urban density, the change range of spatial carbon performance from 1999 to 2019 was basically the same as the change range of population density, showing an “M” change trend of first rising and then falling, followed by an identical process. Since 2010, the spatial carbon performance has been declining, which is the result of a combination of factors such as urban growth and transformation, renovation, industrial land replacement and transfer, industrial structure upgrading, technological progress, and national policy adjustment.

Compared with Beijing, Shanghai has a larger urban density as a whole, and the trend of economic density and building density is the same, however, Fig. 5. shows that the trend of population density is declining. The size of built-up areas has increased faster relative to the size of the population, from 1,003 km<sup>2</sup> in 1995 to 1,242 km<sup>2</sup> in 2019, and the population density has continued to decrease. With the growth and transformation of urban development, urban renewal, structural adjustment, replacement of land functions and spatial transfer, the construction volume in 2019 increased by nearly 3 times compared with 2000, while due to industrial structure upgrading and technological progress, the total economic volume increased by nearly 10 times, and the building density and economic density slowly increased.

The policy is implemented with temporal effects. From the data analysis, it can be seen that when the population density and building density change, the carbon emissions change at the same time. However, from

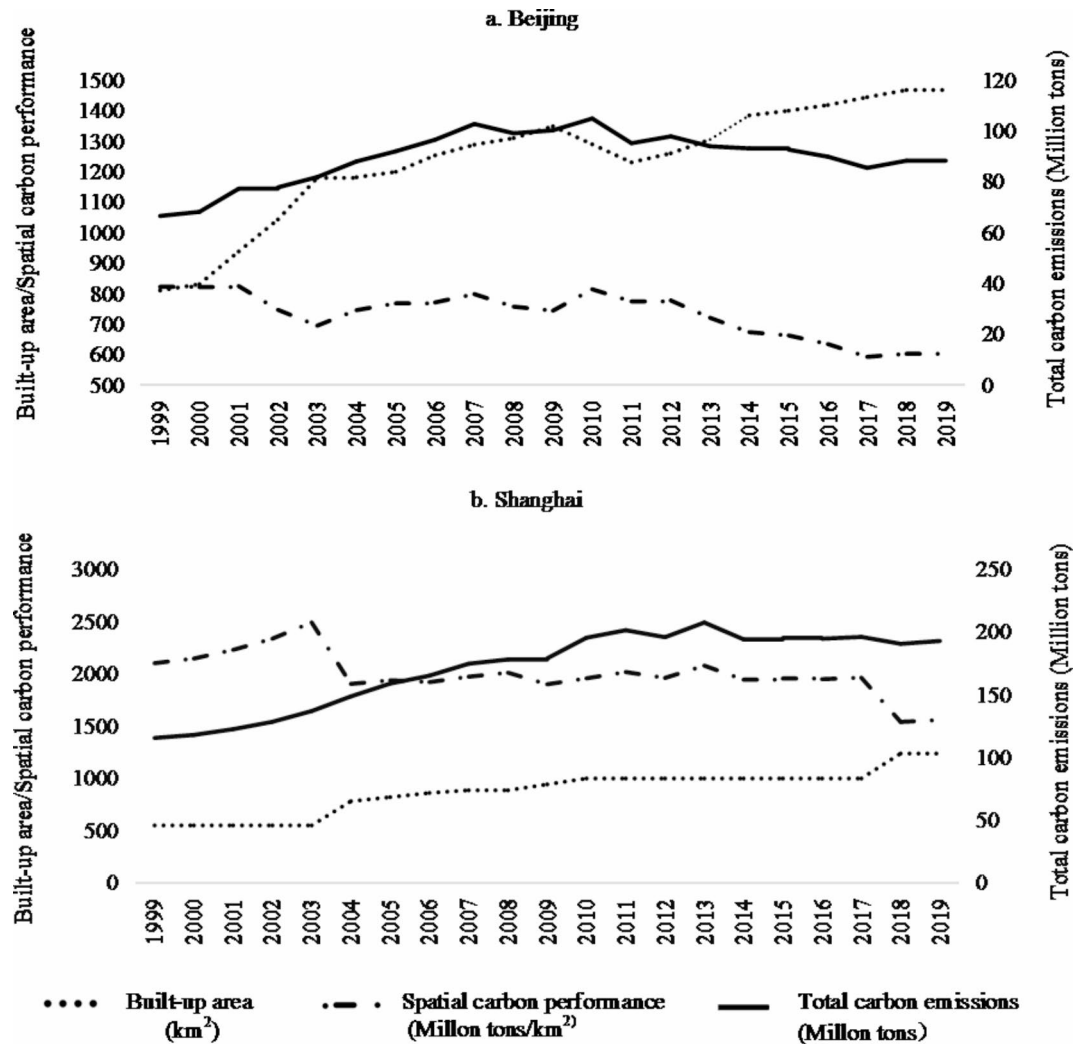


Fig. 3. Spatial carbon performance, total carbon emissions and built-up area change trends during 1999–2019. (a) Beijing, (b) Shanghai.

the perspective of the time series diagram, when the urban density changes over time, the carbon emission performance will not change significantly until nearly ten years. Beijing's carbon emission performance decreased significantly in 2012, and Shanghai's carbon performance decreased significantly in 2017. The differences between the two are closely related to their respective industrial structures.

### Correlation between spatial carbon performance and urban density

By using the polynomial function relationship model, the regression analysis and curve fitting of the spatial carbon performance and population, building and economic density in Beijing from 1999 to 2019 were carried out, and the change logic of each density and spatial carbon performance over time series was explored, and the curve fitting is shown in Fig. 6.

#### Population density and spatial carbon performance

According to the regression Eq. (5), the quadratic function relationship  $R^2$  value is small, and the cubic regression equation model is continued. The  $R^2$  value obtained by the cubic equation model is 0.732, and the fitting effect is good. From the fitting curve, it can be seen that the relationship between population density and spatial carbon performance shows an “N” type cubic curve. Two inflection points occurred around 2004 and 2011, respectively, corresponding to population densities of 12,600 people/km<sup>2</sup> and 16,400 people/km<sup>2</sup> respectively. After the population density did not reach inflection point 1 and exceeded inflection point 2, population density and spatial carbon performance were positively correlated. This means that during a stage where the population density is has fluctuated considerably, spatial carbon performance increases as population density increases, i.e., environmental pressures increase as population density increases. When the density is between inflection point 1 and inflection point 2, population density is negatively correlated with spatial carbon performance. This means that the population density will have a negative effect on the spatial carbon performance in this range. With the

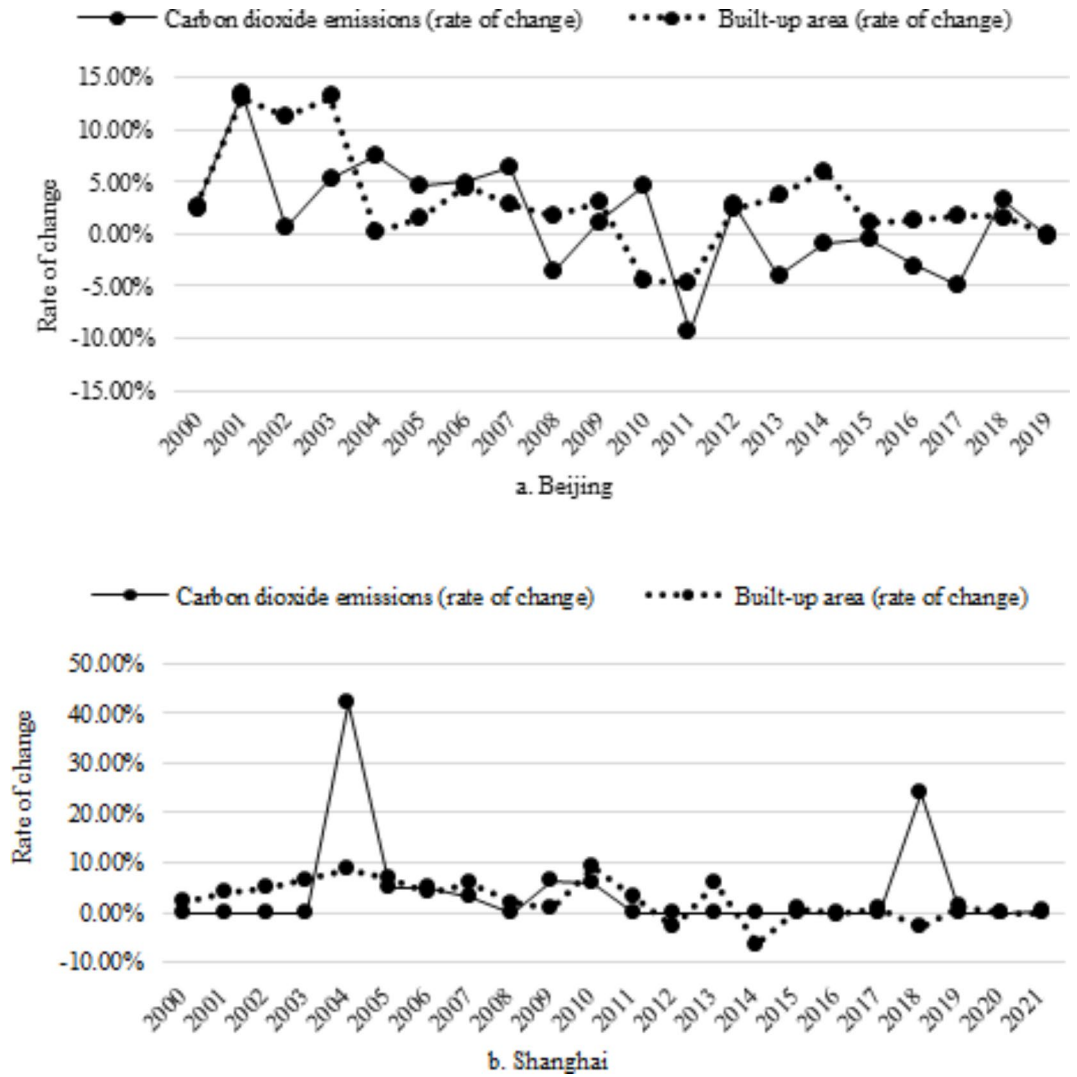


Fig. 4. Trends of carbon emissions and urban built-up area from 1999 to 2019 (a) Beijing, (b) Shanghai.

increase of population density, the spatial carbon performance decreases, which means that it is conducive to achieving the purpose of energy conservation and emission reduction at this stage.

$$\ln \frac{CO_2}{L} = -5.685 + 29.2 \ln \frac{P}{L} - 88.055 \ln \left( \frac{P}{L} \right)^2 + 84.256 \ln \left( \frac{P}{L} \right)^3 \quad (5)$$

*Building density and spatial carbon performance*

Through the fitting curve and regression equation of building density and spatial carbon performance from 2001 to 2019, the R<sup>2</sup> obtained after the quadratic equation is established is 0.778, and the quadratic regression equation model is continued, and the R<sup>2</sup> obtained by the cubic equation model is 0.779, which has a good fitting effect. From the fitting curve, it can be seen that the building density and spatial carbon performance show an “M” curve relationship. From 2001 to 2007, building density and spatial carbon performance are positively correlated, during this period, China’s construction industry has made rapid development, building density continues to increase, spatial carbon performance also continues to increase. From 2007 to around 2009, building density and spatial carbon performance in Beijing showed a negative correlation trend, and after 2010, building area and spatial carbon performance showed a negative correlation. From 2004 to 2019, the building density in Beijing remained basically stable, the spatial carbon performance continued to decline, and the pressure on the environment gradually decreased.

$$\ln \frac{CO_2}{L} = 0.647 - 5.480 \ln \frac{B}{L} - 5.732 \ln \left( \frac{B}{L} \right)^2 - 0.898 \ln \left( \frac{B}{L} \right)^3 \quad R^2 = 0.779 \quad (6)$$

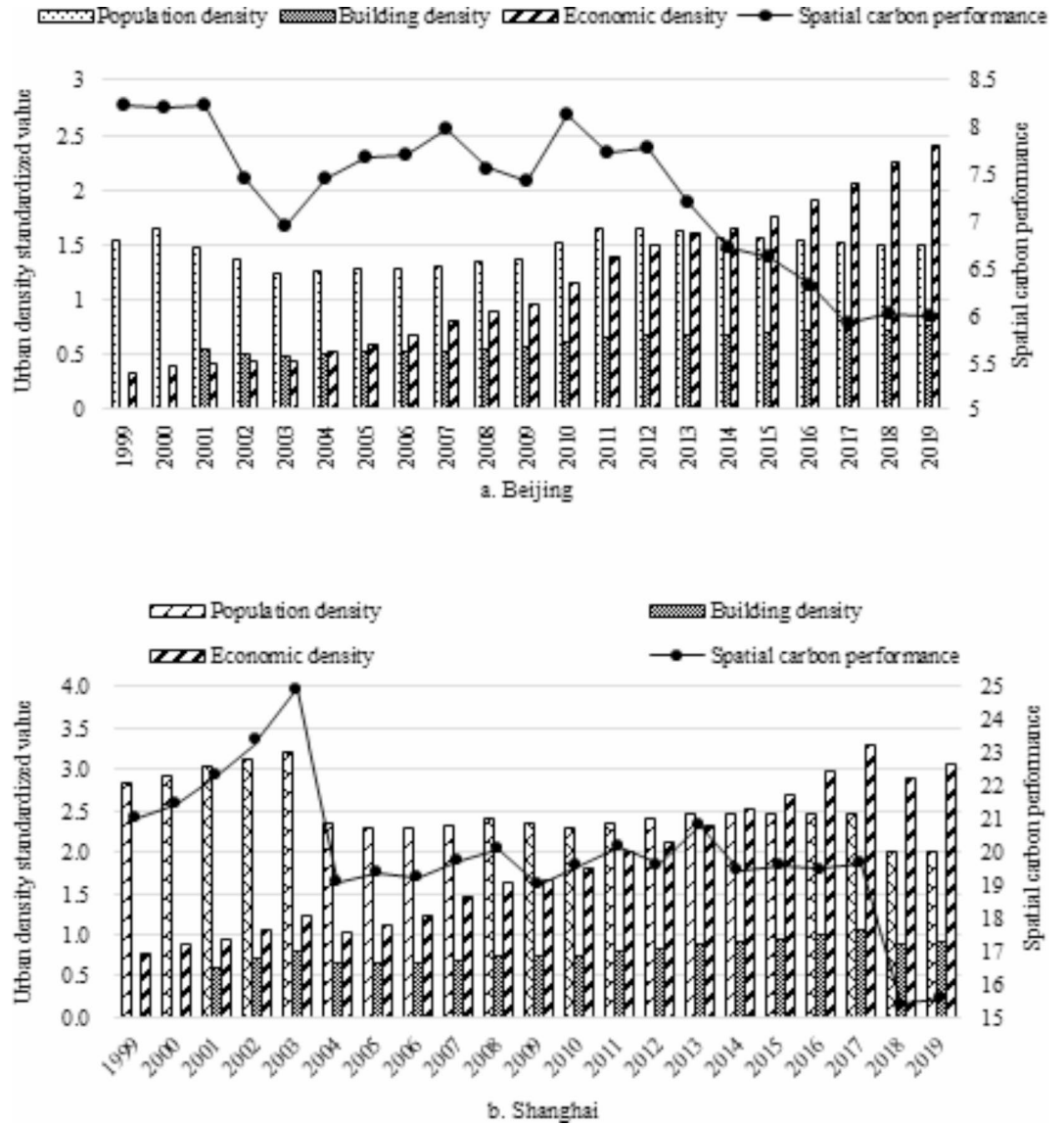


Fig. 5. Spatial carbon performance and urban density trends from 1999 to 2019 (a) Beijing, (b) Shanghai.

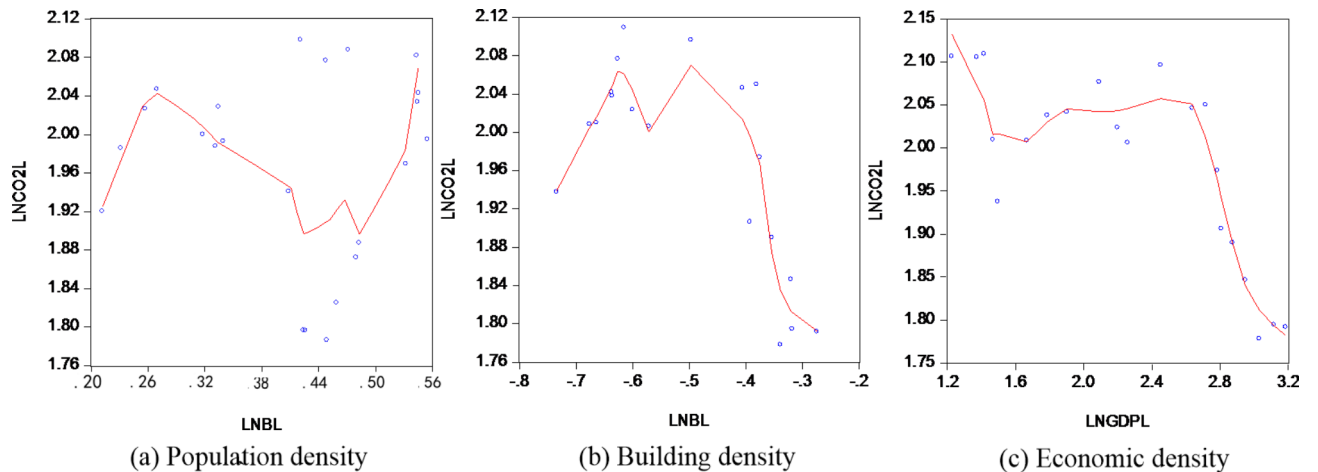


Fig. 6. Curve fitting between urban density and spatial carbon performance.

### Economic density and spatial carbon performance

From the fitting curve of economic density and spatial carbon performance from 1999 to 2019 and the regression equation, the  $R^2$  of the quadratic regression is 0.698, which cannot pass the significance test. Therefore, the quadratic regression equation model is established, and the  $R^2$  obtained is 0.810, which has a good fitting effect. From the fitting curve, it can be seen that from 1999 to 2004, economic density and spatial carbon performance showed a negative correlation. From 2004 to around 2011, the rapid development of China's economy has led to an increase in the scale of the industry and an increase in carbon dioxide emissions. Economic density and spatial carbon performance showed a positive correlation. After 2011, China paid more and more attention to environmental protection issues, continuously improved and optimized existing technologies, and the economic density was increasing, but the spatial carbon performance began to decline significantly.

$$\ln \frac{CO_2}{L} = -0.854 - 2.671 \ln \frac{G}{L} + 1.358 \ln \left( \frac{G}{L} \right)^2 - 0.226 \ln \left( \frac{G}{L} \right)^3 \quad R^2 = 0.810 \quad (7)$$

### Correlation between the rate of change in spatial carbon performance and urban density

Through theoretical and empirical analysis, it is concluded that the increase of urban density has a certain negative impact on spatial carbon performance, which is conducive to low-carbon development in the region. In order to further verify this conclusion, the regression analysis of the growth rate of urban density and spatial carbon performance was carried out to provide a basis for urban spatial structure planning, industrial structure adjustment and relevant policy formulation. The spatial carbon performance growth rate and urban density regression curve are shown in Fig. 7.

Figure 7 shows the regression relationship between population density, economic density, building density, and spatial carbon performance growth is shown. Affected by natural factors and social factors, the fitting effect of the regression equation of urban density and spatial carbon performance growth rate is not too obvious. The results showed that: (1) There was a negative correlation between population density and the growth rate of spatial carbon performance. As population density increases, the annual growth rate of spatial carbon performance decreases. (2) There is a negative correlation between economic density and the growth rate of spatial carbon performance. As the economic density increases, the annual growth rate of spatial carbon performance decreases. (3) There is a negative correlation between building density and the growth rate of spatial carbon performance. As building density increases, the annual growth rate of spatial carbon performance decreases. It can be seen that with the increase of urban density, the growth of carbon emissions will be effectively inhibited.

### Discussion

To a considerable extent, the impact of human economic and energy activities on regional  $CO_2$  emissions is achieved by changing the spatial layout of industries, and changes in industrial spatial layout and regional differences will change the pattern of energy consumption and further affect the rate of regional carbon emissions. Carbon dioxide emissions are significantly affected by energy consumption patterns, which in turn are affected by social production patterns, which in turn are affected by industrial structure. From the perspective of the three industries, the rules of different production sectors are different, and they also have differences in resource utilization, pollutant production and emissions, so the impact on the environment is also significantly different. Among them, some industries with high energy consumption, such as transportation, warehousing, catering, etc., have a relatively large impact on the environment. Some service industries in the product redistribution link, such as finance, electronics, and communications, consume fewer resources and have a relatively small impact on the environment.

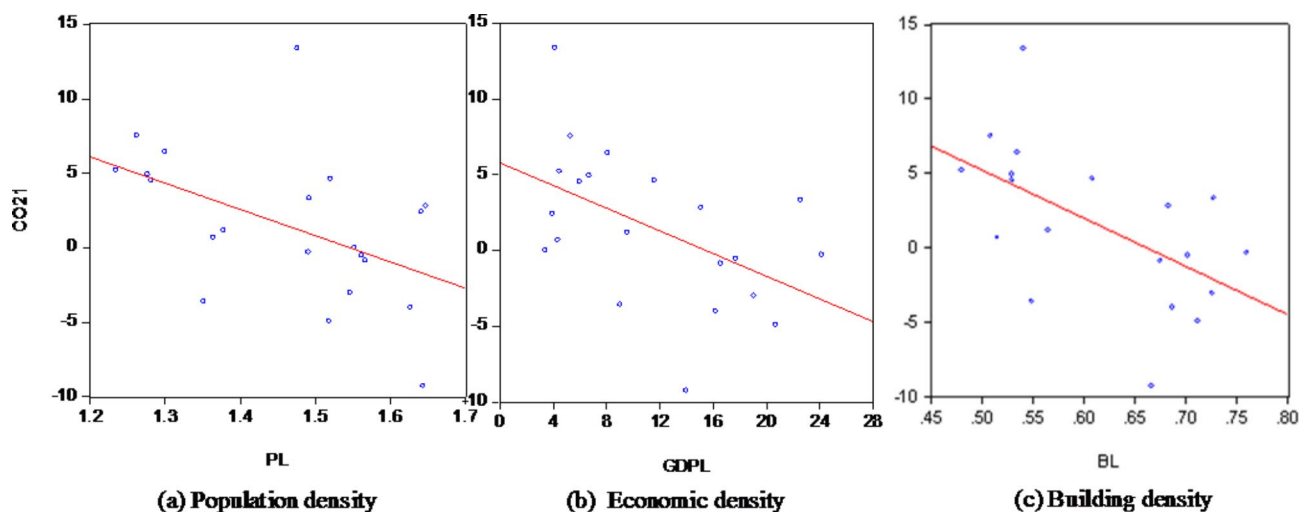


Fig. 7. Scatter plot of the relationship between spatial carbon performance growth rate and urban density.

## Evolution of the spatial distribution of POI

### *The evolution of industrial spatial distribution characteristics*

It is known that from 2000 to the present, Beijing's industrial structure has undergone a process of transformation from traditional manufacturing and infrastructure construction to modern service and high-tech industries<sup>20</sup>. As a result of this change in industrial structure, Beijing's carbon emissions are concentrated in the consumer sector rather than in the overall industry. Since 2010, Beijing has accelerated the development of green economy, gradually strengthened the implementation of environmental protection measures such as energy conservation and emission reduction, and enhanced Beijing's spatial carbon performance<sup>21</sup>. In Beijing's new industrial policy in 2019, some high-emission and inefficient industries were required to withdraw, including heavy industries such as steel and cement and traditional polluting industries, indicating that Beijing's spatial carbon performance will be further improved in the future<sup>22</sup>.

Compared with 2012, Beijing's culture, sports and entertainment industries will gradually develop from being mainly distributed in the city center to the surrounding urban areas, and the development of the south will be faster than that in the north. The transportation, warehousing and postal services industry gradually increased from basically covering the whole urban area to increasing in density, accounting for 8.4–9.1%; At the same time, residential services, repair and other services, wholesale and retail trade also increased, from 10.6% and 20.5–14.7% and 23.6% respectively. The proportion of construction, real estate and manufacturing all declined, from 9% and 10.2–3.8% and 8.7% respectively. The proportions of accommodation and catering, medical care and education remained largely unchanged, at about 14% and 6% respectively. On the whole, Beijing's industries have developed rapidly, mainly in the southeast direction, affected by natural conditions, and the development of northern and western regions is mainly concentrated in urban centers.

Compared with 2012, Shanghai's industries have developed rapidly in 2022, and the data points of other industries have also increased significantly from the original large-scale coverage of manufacturing POI points to mainly the culture, sports and entertainment industries, as well as transportation, warehousing and postal industries. On the whole, the development of all urban areas is relatively balanced. Consistent with the analysis of urban density evolution characteristics above, Shanghai has high space utilization efficiency and greater urban density than Beijing.

### *Evolution of overall kernel density characteristics of POI*

The industrial spatial distribution kernel density map directly reflects the difference of industrial development between Beijing and Shanghai. As Fig. 8. shows, in the past ten years, Shanghai has developed more widely than Beijing. Compared with Beijing, Shanghai has a relatively wide industrial distribution and high density. Both cities show a downward trend in total carbon emissions, however, Shanghai has a smaller built-up area than Beijing, but covers more POI data points than Beijing. The top three are all wholesale and retail trade, accommodation and catering, resident services, repair and other services, but their proportions are slightly higher than Beijing's. Shanghai's manufacturing industry is about 3% higher than Beijing's, and agriculture's is about 0.2% lower than Beijing's. From the analysis of industry carbon emission attributes, it is verified that the total emission decline rate is slower than that of Beijing, and the carbon emission per unit area of Shanghai is higher than that of Beijing.

## The dynamic relationship between urban density and carbon emission performance

### *1. Urban density has a positive impact on carbon emission performance.*

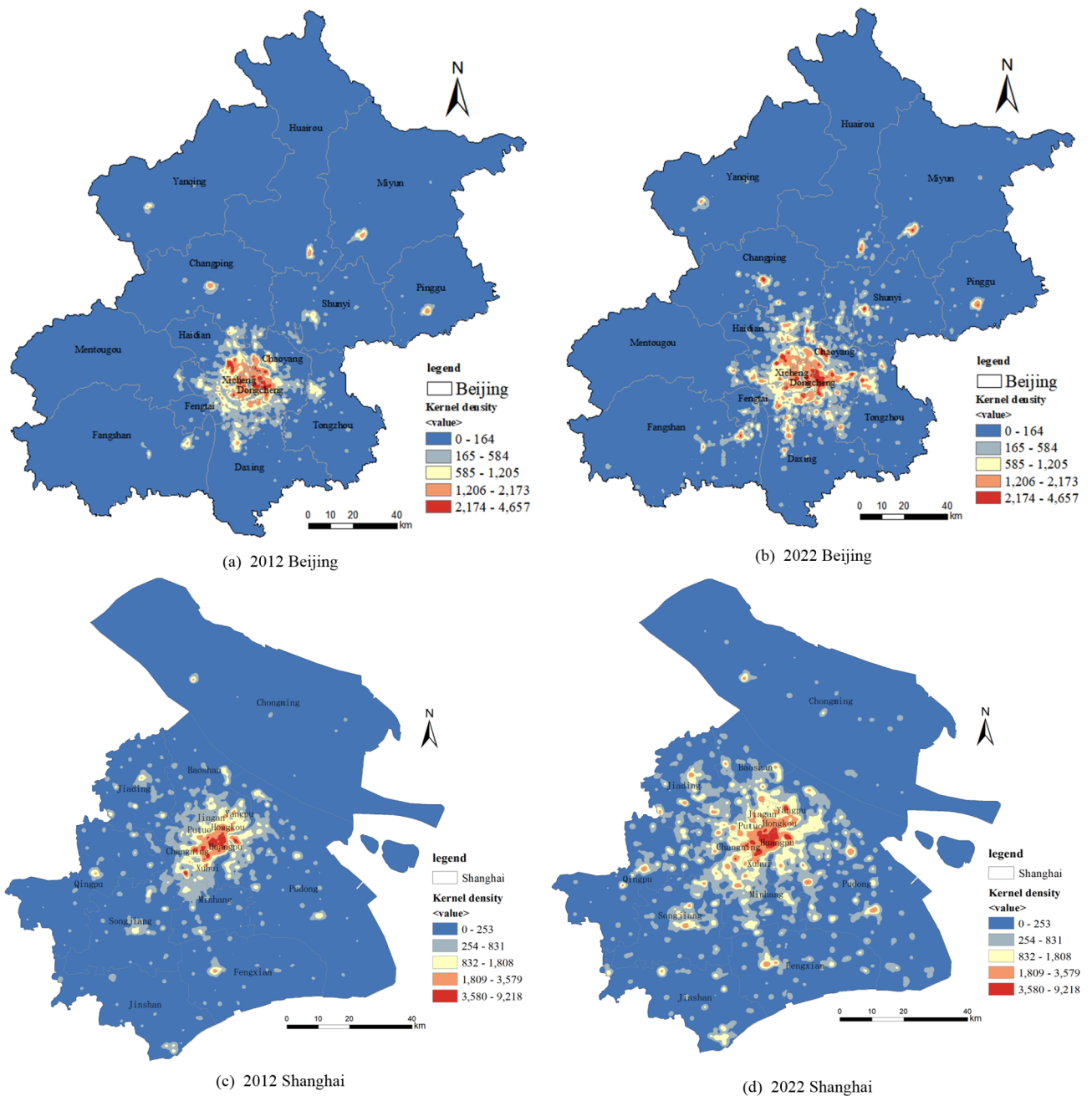
Due to the compact building, the average building space and exterior wall surface are smaller, the indoor and outdoor heat exchange is less, and the heat and cooling storage efficiency is higher. As a result, the energy consumption of buildings is low, which directly leads to an increase in carbon performance. Increased urban density can effectively reduce per capita car usage, fuel consumption and greenhouse gas emissions. High-density urban land use is more compact, reducing the waste of land resources and reducing carbon emissions from long-distance commuting. This helps to maximize the use of land resources and improve the overall carbon performance of the city.

### *2. Urban density has a negative impact on carbon emission performance.*

If urban planning is not reasonable, high density can lead to traffic congestion and wasted energy. For example, in high-density cities, inadequate road planning or inadequate public transport systems can lead to an increase in the use of private cars, which in turn increases carbon emissions. As urban density increases, so does the pressure on infrastructure systems such as water, electricity, and gas. If these systems are not properly managed and maintained, they can lead to wasted energy and increased carbon emissions.

### *3. The relationship between urban density and carbon emission performance is not a simple linear relationship.*

The results show that there are different functional relationships between spatial carbon performance and urban density. It is in the declining stage with the population density and building density in the “N” and “M” curves, respectively, and is in the declining stage, and is in the upward stage with the economic density. This suggests that an increase in urban density does not necessarily lead to an increase in carbon performance, and that a suitable balance needs to be found. The adjustment of the social and economic development structure is the key to achieving overall carbon emission reduction. With the development of the economy and the optimization of the industrial structure, the impact of urban density on carbon emission performance will also change. For example, with the development of high-tech and services, urban density is likely to increase further, but carbon performance is likely to increase accordingly.



(Map generated using ArcGIS 10.8.0. For more information, visit: <https://www.esri.com>)

**Fig. 8.** Kernel density of POI data in Beijing and Shanghai.

*4. It has reference value for the formulation of urban sustainable development policies.*

Urban planning should fully consider the relationship between urban density and carbon emission performance. Through reasonable spatial layout and transportation planning, the rational utilization of land resources and the optimization of transportation system are realized. Strengthen the construction and maintenance of infrastructure, improve energy efficiency, and reduce energy waste and carbon emissions. By promoting the optimization and upgrading of the industrial structure, we will reduce the proportion of industries with high energy consumption and high emissions, increase the proportion of low-carbon industries, and achieve the coordinated development of the economy and the environment.

**Comparative analysis of Beijing and Shanghai**

According to spatial visual analysis, there are differences in the characteristics of economic development and carbon dioxide emissions between Beijing and Shanghai. With the acceleration of economic development and urbanization, Beijing and Shanghai have achieved certain results in promoting energy conservation and

emission reduction, adjusting industrial structure and urban planning and construction, and further promoting the improvement of spatial carbon performance. For example, the construction of rail transit networks has also been promoted, gradually alleviating congestion problems, while reducing emissions and carbon emission density. In addition, Beijing has also played an active role in promoting the greening and intelligence of office buildings, further improving the city's spatial carbon performance.

## Conclusion

In this paper, the spatial evolution of urban density and spatial carbon performance, as well as the spatial structure distribution of industries, compares and analyzes the two megacities of Beijing and Shanghai. Taking panel data from 1999 to 2019 as samples, polynomial function regression was used to analyze the correlation between urban density and carbon performance. The comprehensive regression method was used to study the influence of urban density on the dynamic change of carbon performance. Finally, based on POI big data, the industrial spatial structure is visually analyzed, and the carbon emission characteristics of the two cities are supplemented. The specific conclusions and recommendations of the study are as follows:

The common part of the research results verifies the hypothesis of strong correlation between spatial carbon performance and urban density. The following findings apply to the same type of megacities around the world.

(1) The “increase-decrease-increase-decrease” trend of urban spatial carbon performance over time fluctuates around the unary linear trend of urban density.

(2) Population and building density are too low or too high, which is not conducive to emission reduction. The change of economic density is influenced by the industrial structure. The change of urban density is negatively correlated with the growth rate of spatial carbon performance. In a certain development stage, the increase of urban density will inhibit the growth of spatial carbon performance to some extent. Therefore, from the overall planning to the detailed planning stage, the urban spatial structure should be optimized through the setting of urban density and the importance ranking of population density, economic density and building density<sup>23</sup>.

(3) The correlation between economic density and spatial carbon performance is closely related to the adjustment of urban industrial spatial structure. Maintaining the original economic and industrial structure, the increase in economic density brought by the simple expansion of scale is not conducive to emission reduction. The increase of economic density brought by the transformation of economic or industrial structure and the reduction of the proportion of secondary industry is conducive to urban emission reduction<sup>24</sup>.

It should be emphasized that the correlation between economic density and spatial carbon performance in this paper is influenced by China's urban development policies. Both the Beijing and Shanghai governments, especially in Beijing, the government made several rounds of efforts to push high-emitting and high-polluting manufacturing industries out of urban districts to suburban counties or to adjacent regions outside the municipal boundaries. There is no further study on the effect of relevant policies in this paper. Therefore, the research conclusion of this paper should consider the policy impact according to the urban positioning, and comprehensively implement the countermeasures to ensure the sustainable development of the city in other reference applications of urban development. At the same time, There are some limitations to this study. In terms of research data, there may be some inaccuracies in using the built-up area to measure building density. Due to the lack of finer granularity data, the relationship between urban density and spatial carbon performance from the perspective of urban areas has not been further demonstrated.

## Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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## Author contributions

Yang, Yang and Zhang, Jianmin contributed to the study conception and design. And the first draft of the manuscript was written by them. They contributed equally to this work and should be considered co-first authors. Material preparation, data collection and analysis were performed by Huang, Jingyuan., Zhao, Yongchao and Zhao, Qian. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

## Declarations

## Competing interests

The authors declare no competing interests.

## Additional information

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