Spatiotemporal variations and driving forces of per capita carbon emissions from energy consumption in China

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\textbf{ABSTRACT}

The carbon emissions vary over space and time in China, as well as driving forces. It is particularly important to analyze the spatiotemporal variations and driving factors of China’s per capita carbon emissions. This study adopted global Moran’s I and local indicators of spatial association to analyze the spatial autocorrelation of per capita carbon emissions in China during 2004–2019 and discussed the driving factors of per capita carbon emissions by geographically and temporally weighted regression model. The results demonstrated a positive spatial correlation between interprovincial per capita carbon emissions, but this correlation has gradually decreased since 2008. The High-High clusters were concentrated in the Bohai Economic Rim and the Low-Low clusters were mainly located in the south. Driving factors of per capita carbon emission at the provincial level have spatiotemporal heterogeneity. From 2004 to 2019, per capita GDP, urbanization rate, and energy intensity are the main contributors to per capita carbon emissions, and the role of per capita GDP is weakening, while urbanization rate and energy intensity change in the opposite direction. Foreign direct investment is the main disincentive in most regions. These findings provided a reference for emission reduction policies implemented in different regions.

\textbf{1. Introduction}

According to estimates by the Netherlands Environmental Assessment Agency, China topped the list of carbon dioxide ($\text{CO}_2$) emitters for the first time in 2006 with emissions about 8% higher than those of the United States (Gregg et al. 2008). At the United Nations Climate Change Conference in Copenhagen in 2009, China pledged that its $\text{CO}_2$ emissions per unit of gross domestic product (GDP) (i.e. $\text{CO}_2$ emissions intensity) in 2020 will be 40–45% lower than that in 2005 (Cheng et al. 2014). China achieved this goal ahead of schedule in 2017, with a 46% reduction in $\text{CO}_2$ emissions intensity compared to 2005 (Zhou et al. 2020). In 2020, China aimed to peak $\text{CO}_2$ emissions intensity.
emissions before 2030 and achieve carbon neutrality before 2060 at the General Debate of the 75th session of the United Nations General Assembly (Chen et al. 2021). In view of the large area in China and the dramatic changes in its carbon emissions, achieving these goals requires a more in-depth study of carbon emissions from a spatiotemporal perspective to aid policy formulation (Zheng et al. 2020).

The spatiotemporal variations of per capita carbon emissions have been analyzed at different scales, such as country, province, and city. At the country level, Rios and Gianmoena (2018) investigated the variation of per capita CO2 emissions in 141 countries between 1970 and 2014, demonstrating the spatiotemporal dependence and convergence in CO2 emissions among countries. At the provincial level, Wang et al. (2016) pointed out that conspicuous regional disparity of per capita CO2 emissions existed between 1995 and 2011, but it decreased gradually as well as spatial agglomeration. Cui et al. (2021) proved that significant regional differences existed in the per capita CO2 emissions of the planting industry from 1997 to 2017 and provinces with higher agricultural per capita CO2 emissions are mostly northeast and individual central provinces. At the city level, Wang and Liu (2017) identified the increasingly evident spatial agglomeration of per capita CO2 emissions in China between 1992 and 2013, and higher per capita CO2 emissions emerged in northern and western regions and some developed coastal regions. Similarly, Meng et al. (2014) analyzed per capita CO2 emissions in 1995 and 2010 and found that cities with the highest emission level were located in western China. Cui et al. (2019) revealed a clustered spatial pattern of per capita carbon emissions in Guangdong province and suggested that high carbon emission sources were concentrated in the Pearl River Delta. Considering the availability of energy consumption data and the heterogeneity of the research subjects, the spatiotemporal variations of per capita carbon emissions were studied at the provincial level in this study. In addition, several studies in the field of carbon emissions (Cheng et al. 2014; Wang et al. 2016; Meng et al. 2017; Cai et al. 2018; Tang et al. 2019) analyzed spatiotemporal variations over more than a decade, suggesting that a sufficiently long period is necessary for a comprehensive spatiotemporal analysis.

Regarding the methods to study the driving factors of carbon emissions, existing studies mostly used traditional global regression models such as logarithmic mean Divisia index (LMDI) (Ang 2004), Kaya identity (C Wu et al. 2019; Ma et al. 2019; Wang et al. 2020), Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) (York et al. 2003; Wang et al. 2012), and IPAT (Dietz and Rosa 1997). These global models assume that the effects of independent variables on dependent variables do not differ by region. According to Tobler’s first law of geography, everything is correlated to each other, but there is a higher correlation between near things (Tobler 1970). Therefore, the assumption that parameters are constant over the study area is generally unrealistic, and the prevalence of spatial non-stationarity among environmental variables in spatial data cannot be neglected. The geographically weighted regression (GWR) model could analyze different relationships that exist at different points in space (Brunsdon et al. 1996), and it has been adopted to investigate the influencing factors of carbon emissions (Qin et al. 2019; S Wang et al. 2019). Further, Huang et al. (2010) introduced temporal effects into the GWR model and extended it to the geographically and temporally weighted regression
(GTWR) model, which was initially used to deal with both spatial and temporal non-stationarity in real estate data, and the GTWR model had smaller absolute errors than the GWR model. Liu et al. (2017) applied the GTWR model to the analysis of the influencing factors of CO₂ emissions in China, however, the data they used during the short period 2006 to 2010 could not bring out the advantages of GTWR over GWR very well. Space and time are two fundamental dimensions pertaining to social activities and environmental processes (Fotheringham et al. 2015); therefore, taking into account both spatial and temporal dimensions to study the driving forces of per capita carbon emissions in China is a more scientific and reasonable approach.

Due to strict emission reduction measures, there have been remarkable changes in per capita carbon emissions over the past dozen years in China, while few studies analyzed the spatiotemporal variations of long-time series per capita carbon emission data and its driving forces. This study aims to fill the research gap, and a series of targeted policy recommendations are drawn to support future local practices for achieving carbon peaking and carbon neutrality goals. Here we propose two hypotheses. The first hypothesis is that there is a significant spatial autocorrelation of per capita carbon emissions in China. The second one is that per capita carbon emissions and driving factors are spatially and temporally heterogeneous. To verify these assumptions, this study adopts Global Moran’s I, local indicators of spatial association (LISA), and the GTWR model to explore the spatiotemporal characteristics and driving factors of per capita carbon emissions in China from 2004 to 2019, taking into account both spatial and temporal non-stationarity.

2. Data and methods

2.1. Data sources

The energy consumption data was used to calculate carbon emissions caused by traditional energy resources, including 17 items of fossil energy consumption data such as raw coal, cleaned coal, other washed coal, briquettes, coke, coke oven gas, other gas, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, refinery gas, natural gas, other petroleum products, and other coking products. The terminal energy consumption data was got from the energy balance sheets of each provincial-level administrative division in the China Energy Statistical Yearbook (2005–2020). The socio-economic data such as population, and per capita GDP was obtained from the National Bureau of Statistics (http://www.stats.gov.cn/). Due to the unavailability of data, Tibet Autonomous Region, Taiwan, Hong Kong, and Macau were not considered in the analysis.

2.2. Carbon emissions from energy consumption

The calculation of carbon emissions is mainly based on the Intergovernmental Panel on Climate Change (IPCC) method (IPCC, 2006). The low heating value (also known as net calorific value) and carbon emission factors of the various fossil energy sources are used during the calculation. In addition, besides CO₂, this study took into account methane (CH₄), the world’s second-largest greenhouse gas after CO₂ with great global
warming potential (Bridgham et al. 2013; Saunois et al. 2020), to calculate the carbon emissions of fossil energy.

In the China Energy Statistical Yearbook, the consumption of each energy source has a fixed physical unit, such as coal in tons and natural gas in cubic meters. Therefore, calorific value needs to be introduced, and the consumption of each energy source is converted into the corresponding calorific value data units, such as joules (J). In each provincial-level administrative division, through multiplying the consumption of each energy source by its corresponding average low calorific value, the calorific value data of each energy source is obtained. The carbon emission of each energy source can be estimated by multiplying its calorific value data by corresponding carbon emission factors. The carbon emissions from energy consumption can be obtained by summing up all energy sources. The formula is as follows:

$$CE = \sum_{i=1}^{17} Qp_i \times u \times NCV_i \times (C_f i \times V_{CO_2} + M_f i \times V_{CH_4})$$

(1)

where $CE$ depicts the total carbon emission caused by fossil energy consumption, in $10^4$ tons. $i = 1, 2, \ldots, 17$, representing 17 kinds of energy sources. $Qp_i$ denotes the terminal consumption of the energy source represented by $i$, in $10^4$ tons or 100 million m$^3$. $u$ is the unit conversion coefficient, converting $10^4$ tons or 100 million m$^3$ into Gg or m$^3$. $NCV_i$ refers to the net calorific value of energy, in T/100 Gg or T/100 m$^3$. $C_f i$ refers to the default CO$_2$ emission coefficient, in t/TJ. $M_f i$ refers to the default CH$_4$ emission coefficient, in t/TJ. $V_{CO_2}$ is the amount of carbon contained in CO$_2$, with the value of 12/44. $V_{CH_4}$ is the amount of carbon contained in CH$_4$, with the value of 12/16 (Zhao et al. 2011).

### 2.3. Spatial autocorrelation

Spatial autocorrelation is an exploratory spatial data analysis method. It is used to estimate and analyze spatial dependence and spatial heterogeneity among observational units (Wang et al. 2016), including global spatial autocorrelation and local spatial autocorrelation. Global Moran’s $I$ provides a global measure of spatial autocorrelation, with a value between $-1$ and 1. If Moran’s $I$ is positive, it indicates the existence of a positive spatial correlation. Conversely, it indicates the existence of a negative spatial correlation.

The local indicators of spatial association (LISA) is used to measure local spatial autocorrelation and non-stationarity by decomposing the global indicators into the contribution of each spatial unit and comparing the values in each specific spatial unit with values in neighboring units (Anselin 1995). Accordingly, this indicator classifies the pattern of spatial association into four types, namely High-High, Low-High, Low-Low, and High-Low, corresponding to the four quadrants of the Moran scatter plot (Messner et al. 1999).

A spatial weight matrix needs to be constructed before performing the Moran test. In this study, the spatial weight matrix of the queen contiguity criterion is constructed to achieve a spatial autocorrelation analysis of per capita carbon emissions.
The spatial weight matrix of the queen contiguity criterion reflects the neighbors of each spatial unit according to its contiguity (sharing a common border or vertex) (Anselin et al. 2007).

2.4. Geographically and temporally weighted regression model

The traditional GWR model does not deal well with problems involving data that are both spatially and temporally non-stationary, causing the limited sample size of cross-sectional data. Due to the incorporation of temporal data, the GTWR model has higher goodness of fit. The results of the GTWR model will generate $N \times T \times V$ coefficients, where $N$ is the number of all provincial-level administrative divisions, $T$ is the number of all years, and $V$ is the number of explanatory variables. In the supposed three-dimensional space-time coordinate system, the weight matrix is constructed based on spatiotemporal distances (obtained by integrating spatial distance and temporal distance in a specific function) between individual points and other observed data points (Huang et al. 2010). The GTWR model can be expressed as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \quad (2)$$

where $Y_i$ is the observation of the dependent variable at point $i$, $(u_i, v_i, t_i)$ represents the coordinates of the point $i$ in the space-time coordinates system, $\beta_0(u_i, v_i, t_i)$ denotes the intercept value, $\beta_k(u_i, v_i, t_i)$ depicts a set of values of parameters at point $i$, $X_{ik}$ is the value of the independent variable $X_k$ at point $i$, $k = 1, 2, 3, \ldots, 7$, and $\varepsilon_i$ means random error term.

The estimation of parameters can be given by this equation:

$$\hat{\beta}(u_i, v_i, t_i)u_i = [X^TW(u_i, v_i, t_i)X]^{-1}X^TW(u_i, v_i, t_i)Y \quad (3)$$

where $W(u_i, v_i, t_i)$ is an $n$-order diagonal matrix and $n$ is the number of observed data points. The diagonal elements represent the geographical weights of the observed point $i$.

With the linear combination of the spatial distance and the temporal distance, the spatiotemporal distance between two observed points can be expressed by:

$$(D_{ij}^{ST})^2 = \rho[(u_i - u_j)^2 + (v_i - v_j)^2] + \mu(t_i - t_j)^2 \quad (4)$$

where $t_i$ and $t_j$ are observed times at observed points $i$ and $j$ respectively. $\rho$ and $\mu$ are scale factors to balance the different impacts to measure the spatial and temporal distance in the three-dimensional space-time coordinate system.

In this way, the distances between point $i$ and all observations can be calculated to build up a weight function (Shi et al. 2018). The diagonal elements of the spatiotemporal weight matrix can be calculated according to this weight function:
\[ w_{ij} = \exp \left[ - \left( \frac{D_{ij}}{h_{ST}} \right)^2 \right] \]  

(5)

where \( h_{ST} \) denotes the fixed parameter of the spatiotemporal bandwidth. In this study, the optimal bandwidth is chosen through a corrected Akaike information criterion (AICc) methodology.

### 2.5. Factors influencing per capita carbon emissions

Ehrlich and Holdren (1971) proposed that the forces of the population (\( P \)), affluence (\( A \)), and technology (\( T \)) contribute to the environmental impact (\( I \)), which was named the IPAT framework. IPAT incorporates key features of human dimensions of environmental change (Dietz and Rosa 1997), and is effective to estimate the impact of human activities on environmental change (Li et al. 2015). This study adopted the \( I = P \cdot A \cdot T \) framework and referred to previous literature to select 7 driving factors of per capita carbon emissions, and they are total population, per capita GDP, urbanization rate, foreign direct investment, the share of second industry, energy intensity, and energy consumption structure. In terms of the \( P \), the total population can reflect the concentration of human capital in a region and positively influence per capita carbon emissions (Wang and Liu 2017). As for the \( A \), it is usually proxied by per capita GDP (Poumanyvong and Kaneko 2010; Li et al. 2012; Wang and Zhao 2015; Y Wu et al. 2019; Zhang et al. 2019) because per capita GDP can measure the economic wealth of a country’s population (Cheng et al. 2019). A long-run causal relationship between per capita GDP and per capita carbon emissions has been proved by previous studies (Dong et al. 2018; Liu and Bae 2018). Growth in per capita GDP can drive increases in individual income, which in turn stimulates greater demand for energy products (Shuai et al. 2018), and enhance the increment in the per capita carbon emissions (Wang and Liu 2017; Liu and Bae 2018; Cheng et al. 2019). Apart from per capita GDP, urbanization rate is also a key influencing factor to per capita carbon emissions in China (Wang et al. 2014; Du et al. 2019) that reflects economic development. In addition, foreign direct investment reflects trade openness (S Wang et al. 2019), and it has been found to produce inhibitory effects on per capita carbon emissions (Hao and Liu 2015; Wang and Liu 2017; Cheng et al. 2019). Energy intensity means energy consumption per GDP, which is a widely recognized proxy for the technical level (Li et al. 2012; Wang and Zhao 2015; Wang and Lin 2017; Y Wu et al. 2019) and poses an important impact on per capita carbon emissions (Liu and Bae 2018; Li et al. 2021). Two other proxies for the technical level are industrial structure i.e. the share of the second industry and energy consumption structure i.e. the share of coal consumption (Zheng et al. 2016), both of which are strongly related to per capita carbon emissions (Du et al. 2012; Liu and Bae 2018; Du et al. 2019). The multicollinearity diagnosis was made for the 7 explanatory variables and the result showed that variance inflation factors (VIF) are all within 5, indicating no significant effect of multicollinearity.
3. Results and discussion

3.1. Temporal variation of per capita carbon emissions

Figure 1 shows the per capita carbon emissions from 2004 to 2019 in China. The per capita carbon emissions increased from 0.630 tons/person in 2004 to 1.046 tons/person in 2019, an increase of 66%, but the growth rate gradually decreased and started to show negative growth from 2013, which demonstrated that per capita carbon emissions were being controlled.

Global Moran’s I can provide a holistic trend of the spatial agglomeration of per capita carbon emissions by taking spatial effects into account (Wang and Liu 2017). The Global Moran’s I from 2004 to 2009 were all significant at the 95% confidence level, indicating that there was pronounced positive spatial autocorrelation in each year. The line with data markers in Figure 1 demonstrates that Global Moran’s I shows a fluctuating downward trend, which indicates that the spatial agglomeration of per capita carbon emissions is diminishing gradually. The value increased from 0.252 to 0.354 during 2004–2007 and began to decline after that. Although the value rebounded in 2010 and 2011 but soon resumed its downward trend. From 2012 to 2015, the value first increased a little and declined immediately, coming to 0.238 in 2015. CO2 emissions intensity had been a constraint index included in the Twelfth Five-Year Plan for National Economic and Social Development of the People’s Republic of China (2011–2015) for the first time, and the growth of per capita carbon emissions was controlled successfully in this phase (Hao et al. 2015). To facilitate the subsequent analysis of per capita carbon emissions at the provincial level, the 16-year-long study period was divided into four phases based on the evolution characteristics of Global Moran’s I. In addition to the first year (i.e. 2004) and the last year (i.e. 2019), the typical years 2007, 2011, and 2015 were used as the time cross-sections for the division.

3.2. Spatial variation of per capita carbon emissions

Based on the cross-sectional data of typical years selected in the previous section (i.e. 2004, 2007, 2011, 2015, and 2019), the per capita carbon emissions of the 30
Provincial-level administrative divisions were calculated and their spatial distribution was visualized in Figure 2, indicating that almost all regions show an increasing trend in per capita carbon emissions before 2011. In 2007, 2011, and 2015, the regions with high per capita carbon emissions were concentrated in patches in the north and west. This characteristic might be dominated by the implementation of the Grand Western Development Program that boosted the economic development of these regions (Cai et al. 2018), and per capita GDP and the urbanization process are closely associated with the growth of carbon emissions (Xu and Lin 2017; S Wang et al. 2019). The high emitting provinces in the north, such as Hebei and Liaoning, consumed a high proportion of fossil energy and have high carbon emission industries (Chang et al. 2020). These regions will be confronted with more severe pressure to carbon reductions than other regions. The eastern and southern regions have been home to large population inflow since 2004 (Liu et al. 2015; Wu et al. 2018), which can explain their low per capita carbon emissions to some extent. In addition, per capita carbon emissions fell to low levels mainly in the southern and eastern China after 2015, which was due to the phasing out of high-emitting industries and improvements in the energy consumption structure as a result of tougher energy conservation and emission reduction policies (Liu et al. 2022). Unlike other northern regions, the capital of China, Beijing city, showed a significant downward trend in per capita carbon emissions after 2007, as it has begun to decentralize its non-capital functions since 2015 (Li et al. 2019), which can promote the synergistic development of the Beijing-Tianjin-Hebei urban agglomeration, but at the same time will increase carbon emissions in its neighboring provinces (Song et al. 2020).

The results of local spatial autocorrelation are shown in Figure 3. High-High clusters were concentrated in the north, especially in the Bohai Economic Rim (BER, including Beijing, Tianjin, Hebei, Shandong, Shanxi, Inner Mongolia Autonomous Region (Inner Mongolia for short in the text below), and Liaoning that surround the Bohai Sea), presenting a positive spatial correlation and significant spatial agglomeration. Hebei, Inner Mongolia, and Liaoning were the most stable High-High clusters, while Tianjin and Beijing only briefly exhibited spatial patterns of High-High clusters.
in 2007, as did Jilin and Shanxi in 2011. In 2004, Hebei and Inner Mongolia Autonomous Region were classified as high-high clusters, accounting for 29% of the number of provincial-level administrative divisions in the BER. In 2007, the spatial agglomeration between Inner Mongolia and its neighboring provinces became insignificant, while the spatial agglomeration between Beijing, Tianjin, and Liaoning and their neighboring provinces shifted from insignificant to High-High clusters, and the proportion of High-High clusters in the BER increased to 57%. This figure did not drop to 43% until 2015. As one of the three major economic circles in China, the BER has contributed to China’s rapid economic development but also aggravated environmental problems, as the industrial structure of most regions is based on traditional heavy industry. Beijing was a High-High cluster only in 2007 and its energy use efficiency is the highest in the BER, but this comes at the expense of its neighboring regions (Chang et al. 2020). In addition, Hebei, Liaoning, Inner Mongolia, and Shanxi have major energy bases, including steel production bases, coal production bases, etc. (Song et al. 2020). Accordingly, these regions attract heavy industrial plants using energy sources as raw materials, thus explaining their spatial patterns of High-High clusters. The BER should pay attention to regional coordination in the implementation of energy conservation and emission reduction as it strives to achieve synergistic economic development.

Low-Low clusters were mainly located in the south, especially in the southwest from 2004 to 2007. In 2004, Low-Low clusters were spatially concentrated in the southern regions, including Sichuan, Yunnan, Guizhou, Hubei, and Guangdong. Due to the relatively limited opportunities for economic development (Sun et al. 2020) or massive population (Liu et al. 2015), per capita carbon emissions were at a low level in these regions. In 2007, the spatial association between Guizhou, and Hubei and their neighboring provinces turned to be insignificant. After that, Sichuan also dropped out of Low-Low clusters, while Yunnan and Guangdong remained the spatial characteristic of Low-Low clusters until 2019. As technology improves, economic growth in Guangdong has been no longer dependent on large amounts of investment and energy consumption, gradually leading to healthy economic growth (Pei et al. 2020).
The Low-High cluster indicates that the low per capita carbon emissions of a province are associated with the high per capita carbon emissions of its neighboring provinces, and this spatial pattern exists in Gansu, Shaanxi, Jilin, and Heilongjiang, most of which were neighboring provinces to the BER. Gansu exhibited a stable spatial pattern of Low-High clusters during 2011–2019. Economic output plays the most prominent role in the growth of carbon emissions in Gansu, whose economic development is still at a low-level stage, and correspondingly emissions are lower than in neighboring provinces (Xin et al. 2021).

### 3.3. Driving factors of per capita carbon emissions in China

After normalizing variables for the consistency of magnitudes, this study adopted the GTWR model to analyze the regression coefficients of the driving factors. To confirm that the GTWR model has a higher goodness-of-fit, the GWR model and the ordinary least squares (OLS) model are used to make a comparison. Table 1 shows the model evaluation metrics for the GTWR model, the GWR model, and the OLS model respectively. AICc is useful for comparing different models with the same explained variable. If the difference between the AICc values for the two models is greater than 3, the model with the lower AICc value is considered to be the better one (Zeng et al. 2016). $R^2$ is a measure of goodness-of-fit with a value between 0 and 1, the higher the value the better. Therefore, the GTWR model with the lowest AICc value (−196.19) and the highest $R^2$ value (0.977) was proved to be the best model for the sample data used in this paper.

Using the per capita carbon emissions of 30 provincial-level administrative divisions in China during 2004–2019 as the dependent variable, the GTWR model was applied to conduct regression analysis for the 7 driving factors of per capita carbon emissions in different years in each region. The regression results assigned 480 coefficients to each driving factor, and the descriptive statistics in Table 2 implied that the coefficients of the total population, per capita GDP, urbanization rate, foreign direct investment, and energy intensity have large variation (standard deviation > 0.4), further indicating that impacts of each driving factor on the per capita carbon emissions of 30 provincial-level administrative divisions are non-stationary in time and space. In terms of mean value, the main driving factors of per capita carbon emissions are per capita GDP, urbanization rate and energy intensity, which is consistent with other studies (Wang et al. 2014; Wang and Liu 2017; Liu and Bae 2018; Cheng et al. 2019; Du et al. 2019; Li et al. 2021).

The spatiotemporal heterogeneity analysis is complicated due to a large number of coefficients. The study period was divided into four phases as stated before, namely 2004–2007, 2008–2011, 2012–2015, and 2016–2019. The average value of each phase was taken as its representative value.

| AICc    | GTWR  | GWR  | OLS  |
|---------|-------|------|------|
| −196.19 | 257.40| 927.75|
| 0.977   | 0.922 | 0.608|
Figure 4 shows the regression coefficients of total population for each phase. The impact of the total population on per capita carbon emissions in most regions is not crucial in the first two phases, while its trends showed spatial differences in the last two phases. The coefficient of the total population increased in the north and the west, decreased in the south, and stayed at −0.08 to 0.19 in the east and central regions. This indicates that the impact of the total population on per capita carbon emissions is becoming more spatially heterogeneous. The regions where total population contributed to per capita carbon emissions reduction were mainly distributed in the central north and south during 2004–2007 and 2008–2011, but those negative regions changed to Xinjiang Uygur Autonomous Region (Xinjiang for short in the text below) and south during 2012–2015 and 2016–2020. The results suggest that population impact is temporally heterogeneous, contrary to the finding of Liu et al. (2017).

Figure 5 shows the regression coefficients of per capita GDP for each phase. The impacts of per capita GDP on per capita carbon emissions are positive and generally diminishing in all regions except Xinjiang. The positive impact of per capita GDP
demonstrates that economic development is still based on the secondary industry, and a reduction in carbon emissions will be achieved as the focus of economic structure shifts more towards the tertiary industry in the future (Cheng et al. 2019). The growth of per capita GDP had the greatest driving effect on the per capita carbon emissions in the western regions, especially during the first two phases. This characteristic could be attributed to the fact that the Grand Western Development Program brought a large amount of investment (Cai et al. 2018), leading to a rapid rise in the economic level, and consequently driving per capita carbon emissions. For the eastern regions and southern coastal regions, the driving effect was generally at a lower level than in other regions, consistent with the finding of S Wang et al. (2019), and it significantly reduced in the south and northeast from 2008 to 2015.

Figure 6 shows the regression coefficients of urbanization rate for each phase. During 2004–2019, the impact of the urbanization rate on per capita carbon emissions had been increasingly positive across regions during 2004–2015, indicating that rapid economic development and urbanization were not conducive to carbon reduction (Ma et al. 2019). This result is consistent with some previous studies (Wang et al. 2012, 2016, 2018). To avoid environmental degradation from urban expansion while increasing economic growth, policymakers should encourage green and sustainable urbanization (Liu and Bae 2018). In the field of spatial distribution, the growth of per capita carbon emissions caused by the increase in urbanization rate in the eastern and northern regions is generally more pronounced than that in the southwestern regions during 2008–2015. In addition, this positive effect shows a trend of spreading from the three northeastern provinces (Heilongjiang, Jilin, and Liaoning) and the Yangtze River Delta to the BER during the study period. These regions should pay
extra attention to environmental protection and carbon emission reduction in the process of urban construction and expansion, especially the BER where 57% of the number of provincial-level administrative divisions are High-High clusters in 2011.

Figure 7 shows the regression coefficients of foreign direct investment for each phase. Foreign direct investment had a slight dampening impact on per capita carbon emissions in most regions, but a very strong boost in Xinjiang in the first three phases (9.80, 14.97, and 7.37 respectively), which proved that large investments were an important driver of Xinjiang’s per capita carbon emissions. The coefficient of foreign direct investment was getting closer to zero in most regions in the last two phases, indicating a weakening trend in the impact on per capita carbon emissions. However, the change of this coefficient in Liaoning, Jilin, and Heilongjiang was contrary to this overall trend, and the inhibitory effect of foreign direct investment on per capita carbon emissions in these three provinces in Northeast China was getting stronger. Thus, increasing the introduction of foreign direct investment and supporting advanced production technology and management experience of foreign enterprises to play a demonstration role are effective ways to reduce per capita carbon emissions in these regions (Zhang et al. 2020).

The share of secondary industry exhibited a large contribution to the per capita carbon emissions in the BER, explaining its spatial pattern of High-High clusters with high agglomeration. Although the BER contributed to China’s economic development, it still relied mainly on traditional industries and its carbon emissions account for about 35% of the total carbon emissions in China during 2004–2019. After 2011, as the industrial structure was gradually optimized, the contributing effect started to diminish and a slight suppression effect began to appear in the central regions. This
implies that industrial structure adjustment policies are crucial to carbon emission reduction (Li et al. 2017; Wang et al. 2018). In addition, a constant and negative inhibitory effect of the share of secondary industry existed in the southwest during the period studied.

Figure 8 shows the regression coefficients of energy intensity for each phase. Energy intensity reflected how the technical level affects carbon emissions (Zhang et al. 2014). In this study, energy intensity did not play a role in reducing per capita carbon emissions in all regions, which implies that the enhancement of technical level could reduce carbon emissions effectively (Zhang and Da 2013; Y Wang et al. 2019) and the government still needs to enhance the efficiency of non-renewable energy use (Liu and Bae 2018). The energy intensity impact coefficient showed an overall trend of gradually increasing during the last two phases, and this feature was more obvious in the western regions than that in the eastern regions. Also, energy intensity played an increasingly positive role in contributing to per capita carbon emissions in the BER after 2011. While Beijing was committed to optimizing its industrial structure and improving energy use efficiency, other regions in the BER still had higher energy intensity and renewable energy use technologies need to be further improved.

The high energy consumption structure contributed to the rise in per capita carbon emissions during the study period, and the influence increased slightly overall, especially after 2011. The coefficient of energy consumption structure increased significantly in Heilongjiang, Jilin, Ningxia Hui Autonomous Region, Qinghai, Gansu, and the BER during the first two phases. These regions were either heavy industrial bases or had more coal availability and demand, leading to a higher impact on energy consumption structure (Xu and Lin 2017). After 2015, the effect of energy
consumption structure to per capita carbon emissions in these regions began to drop, but still at a higher level than southwestern regions. These northern regions should further optimize their energy consumption structure and augment the use of clean energy when implementing energy conservation and emission reduction.

4. Conclusions

This study analyzed the spatial autocorrelation of per capita carbon emissions in 30 provincial-level administrative divisions in China from 2004 to 2019. From three dimensions of population, affluence, and technology, 7 driving factors of per capita carbon emissions were selected, and the influences of these factors in each provincial-level administrative division and each phase were discussed based on the GTWR model. The results of global spatial autocorrelation suggested that there was a positive spatial autocorrelation of per capita carbon emissions in China during 2004–2019, but this performance has gradually weakened since 2008. Regions with the spatial pattern of High-High clusters were concentrated in the north, especially in the BER. Low-Low clusters were mainly concentrated in the south, especially in the southwest during 2004–2007. The BER should pay attention to the synergy of energy conservation and emission reduction while promoting coordinated economic development. Then, the results of the GTWR model demonstrated that the impacts of driving factors on per capita carbon emissions varied greatly over space and time. The impact of foreign direct investment on per capita carbon emissions was negative in general, total population and the share of second industry posed bidirectional effects on per capita emissions, while the other four factors mainly played a role in increasing per
capita carbon emissions. In terms of spatial heterogeneity, the positive impact of per capita GDP was greatest in the west, while the urbanization rate contributed to more per capita carbon emissions in the north and east than in other regions. The process of urban construction and expansion should control energy consumption and minimize carbon emissions. The positive impact of energy intensity in the north was more pronounced than that in the southwest. Furthermore, the impact of driving factors on per capita carbon emissions was also found to be temporally heterogeneous, mainly in that the change of influencing coefficients starts to be significant after 2011. The results of this study confirmed that the spatial and temporal heterogeneity of per capita carbon emissions are nonnegligible, and therefore the implementation of energy conservation and emission reduction measures should be tailored to local conditions.

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**Data availability statement**

The data that support the findings of this study are available from the corresponding author, Sheng Zheng, upon reasonable request.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

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