Will polycentric cities cause more CO₂ emissions?
A case study of 232 Chinese cities

Wei Sha¹,², Ying Chen¹, Jiansheng Wu¹,²,*, Zhenyu Wang¹

¹Key Laboratory for Urban Habitat Environmental Science and Technology, School of Urban Planning and Design, Peking University, Shenzhen 518055, China
²Laboratory for Earth Surface Processes, Ministry of Education, College of Urban and Environmental Sciences, Peking University, Beijing 100871, China

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A B S T R A C T
From 2000 to 2010 China experienced rapid economic development and urbanization. Many cities in economically developed areas have developed from a single-center status to polycentricity. In this study, we used exploratory spatial data analysis (ESDA) to identify the population centers, which identified 232 cities in China as having urban centers. COMP was used to represent urban agglomeration, and POLYD (representing how far is the city’s sub-centers to the main center), POLYC (representing the number of a city’s centers), and POLYP (representing the population distribution between the main center and the sub-centers) were used to indicate urban polycentricity. Night light data were used to determine the CO₂ emissions from various cities in China. A mixed model was used to study the impact of urban aggregation and polycentric data on the CO₂ emission efficiency in 2000 and 2010. The study found that cities with higher compactness were distributed in coastal areas, and the cities with higher multicity were distributed in the Yangtze River Delta and Shandong Province. The more compact the city was, the less conducive it was to improving CO₂ emission efficiency. Polycentric development of the city was conducive to improving the CO₂ emission efficiency, but the number of urban centers had no significant relationship with the CO₂ emission efficiency. Our research showed that the compactness and multicity of the city had an impact on the CO₂ emission efficiency and provided some planning suggestions for the low carbon development of the city.

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Introduction
There is a consensus among all mankind that climate change has a tremendous impact on human production and life (Cai et al., 2016; Wang et al., 2016a). The CO₂ emissions produced by human activities have reached unprecedented levels (Pearson and Palmer, 2000). Studies confirm that greenhouse gases (GHGs), especially CO₂ emissions, have a serious impact on global warming (Wang et al., 2017a; Zhang et al., 2014). There are some studies on processes to improve CO₂ emission efficiency (Chen et al., 2019; Hafeez et al., 2015; Shahkarami et al., 2015). Although transportation and electricity generation bring a lot of carbon emissions in contemporary society, among these human activities, the emission of CO₂ from fossil energy combustion is the main reason for reaching this situation (Wang et al., 2016b). Researchers studied how population, economic, political indicators and electricity consumption affect CO₂ emissions (Adom et al., 2018; Bello et al., 2018). The developing countries consume a lot of fossil energy to develop their economies because of their

* Corresponding author.
E-mail: wujs@pku.edu.cn (J. Wu).
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backward production modes, and this produces a lot of CO₂ emissions (Jiang et al., 2018; Jiang and Guan, 2016). China is the largest developing country, and its carbon emissions are growing steadily every year (Wang et al., 2014; Wang et al., 2015). For a long time, China’s industrial structure has been based on low-energy manufacturing with high energy consumption, and this leads to a large amount of CO₂ emissions (Wu, 2016), China’s poorer and backward areas implement low-carbon development by changing their industrial structure (Tian et al., 2019). A panel co-integration model is used to study the relationship between CO₂ emissions, economic growth, and energy consumption, and this confirmed the existence of the positive correlation (Liddle and Lung, 2013). One study has shown how the per capita GDP, urbanization rate and other indicators of 14 developed economies affect the peak of CO₂ emissions (Dong et al., 2019b). The relationship between CO₂ emission flows from 28 sectors in China from 1997 to 2015 was studied (Ma et al., 2019). When the sensitivity of CEI (CO₂ emission intensity) changes to various factors from 2000 to 2014 was analyzed, the elasticity coefficient of the secondary industry factor was found to be larger in China (Dong et al., 2019a). In recent studies, the impact of trade barriers within China on CO₂ emissions and CO₂ emissions of metal industries has been researched (Shao et al., 2014; Shao et al., 2019). With the acceleration of urbanization, cities produce over 70% of the global CO₂ emissions. This is due to the direct correlation between urbanization and CO₂ emissions has become the focus of many scholars’ research (Wang et al., 2019a). Studies have shown that urban development patterns have a significant impact on CO₂ emissions in China. and other studies have compared CO₂ emissions and their impact factors in the United States and China (Glaeser and Kahn, 2010; Shi et al., 2019). Different urban forms have different impacts on CO₂, but in academic circles there is no definite conclusion on the relationship between them at present (Behera and Dash, 2017; Wang et al., 2013; Zhang and Lin, 2012; Zhang and Xu, 2017). In this study we will endeavor to shed some light on these contradictory findings.

We believe that reducing CO₂ emissions by changing urban spatial patterns should be a useful method (Liu et al., 2019). The positive correlation between urbanization and CO₂ emissions has also been confirmed (Zhou et al., 2018). Cities have more opportunities and potential for development, so they attract more and more rural people, which leads to the continuous expansion of urban areas and significant changes in the urban structure (Bai et al., 2014; Seto et al., 2011). There are many ways for big cities to develop. Multicenterness (i.e., the agglomeration of sub-central economic activities in major centers) has become a major trend of urban development (Giuliano and Small, 1991). The definition of polycentricity is always unclear. Different authors have different definitions of it at different scales (Meijers, 2008; Rauhut, 2017). In this paper, polycentricity is defined as the uniform and centralized distribution of population in urban areas, while the single-center city is defined as a city with uneven and centralized distribution of population. Compared with the unlimited expansion mode, the polycentric city has become the preferred development direction for many big cities, wherein multiple sub-centers develop that are linked with the main center (Liu and Wang, 2016). Multi-center cities can better coordinate the development of the urban society, economy, and environment, and they also bring more employment opportunities (Burger and Meijers, 2010; Parr, 2004).

The measurement of urban polycentricity is usually different around the world. For example, urban studies in the United States and Europe usually determine urban centers and measure urban multicentricity based on comprehensive employment data (Ewing et al., 2018). A microeconomic model based on the AMM (Agent-based Microeconomic Model) framework is used to study the multi-center structure of cities. This has been proven to be a useful method (Lemoy et al., 2017). Studies have found that multi-center cities can effectively alleviate income segregation (Garcia-López and Moreno-Monroy, 2018). However, due to the unavailability of data in China, many studies are based on the urban multi-center development map in government planning, so there will be a big deviation from the actual situation (Engelriet and Koomen, 2018; Sun et al., 2016), or they simply divide cities into single centers and multiple centers by using the binary variable method (Zhao et al., 2017). With the optimization of geospatial data, more and more studies can identify the city’s multicentricity more accurately (Cai et al., 2017; Liu and Wang, 2016). Other studies have found that there is a negative correlation between urban multi-centralization and traffic congestion in China, whereas there is a positive correlation between urban compactness and traffic congestion (Li et al., 2019). Meaningful research has been done on the multi-centralization of Chinese cities, but they lack a comparison between cities and have not defined the relationship between the urban structure and the economic development level or CO₂ emission efficiency (Liu et al., 2016; Yang, 2005; Yang et al., 2015; Zhang and Wu, 2006). Most of the articles about the relationship between urban form and CO₂ emission only choose the index of urban landscape pattern or urban fragmentation to represent urban form, and there is no analysis on the relationship between the number of urban centers and CO₂ emission (Ou et al., 2019; Wang et al., 2019b; Zuo et al., 2020).

In order to fill this gap, this study used detailed grid population data and CO₂ emission efficiency data to study the compact and polycentric structures of Chinese cities and their relationship with CO₂ emission efficiency. Specifically, we first identified the multi-center degree of urban areas in China and then used DMSP/OLS nighttime light imageries and population and GDP data to calculate the CO₂ emission efficiency of each city. By comparing their relationship with each other, we judged whether the multi-center cities improved the CO₂ emission efficiency. We then discussed the impact of polycentricity, compactness, the socio-economic index, and population distribution on the CO₂ emission efficiency. Finally, the main research results, limitations of the methodology, and direction of further research were summarized.

1. Methods

1.1. Estimation of carbon emissions using DMSP/OLS night lights

Due to the incompleteness of the statistical yearbook records and the absence of data, this study used the DN (digital number) value of the night light to retrieve CO₂ emissions. Using night light data to divide urban and non-urban areas in China has been widely adopted in various studies. (Henderson et al., 2003; Imhoff et al., 1997a; Imhoff et al., 1997b; Milesi et al., 2003). For the extracted construction land, the total DMSP/OLS DN values can be used to calculate the CO₂ emissions of each city separately. These articles used night light data to retrieve CO₂ emissions, and got the inversion formula, but they were not completely consistent with the spatial and temporal scales of this study (Lv et al., 2020; Ou et al., 2019; Shi et al., 2016). So I choose the research results that meet all my conditions (Su et al., 2014). Correlation coefficient between statistical CO₂ emissions and the total DMSP/OLS DN values of the same city was also calculated. Results indicated that there was a significant linear relationship between DMSP/OLS night lights and statistical CO₂ emissions (R = 0.91, p < 0.001). The
The carbon emission intensities include PGCE (Per GDP CO_2 emission) (Antanasijevic et al., 2015; Bhattacharyya and Matsumura, 2010) and PCCE (Per capita CO_2 emission) (Duro and Padilla, 2013; Huang and Meng, 2013) using the total CO_2 emission data and corresponding statistical GDP and human population data for each city in China, which are the two most commonly used. PGCE, which is a ratio-based indicator used to characterize CO_2 emission efficiency, is calculated by dividing total CO_2 emissions by GDP, aiming to minimize CO_2 emissions per unit of GDP. The measure CO_2 emissions per capita averages total CO_2 emissions according to the total population of a region, and is used with the aim of minimizing the CO_2 emissions of each person. The following formulas are used:

\[
\text{PGCE} = \frac{\text{CO}_2}{\text{GDP}}
\]

(2)

\[
\text{PCCE} = \frac{\text{CO}_2}{P}
\]

(3)

where GDP represents the total gross domestic product of each city, and \( P \) represents the total human population of each city.

### 1.3. Recognizing and measuring polycentricity and compactness

In order to measure polycentricity and compactness, we draw on the recent use of LandScan\textsuperscript{TM} high resolution global population dataset in urban spatial structure research (Li et al., 2018B; Liu and Wang, 2016). The dataset used in this study contains grid specific population information for 2000 and 2010. The population center can be identified more precisely, which is the key to the multicentricity and compactness of subsequent measurement. The disadvantage of using this method is that only the data set can be used to identify the population center of the city, not the employment center of the city. Although employment centers are more commonly used in the literature, it is still meaningful to measure polycentricity and compactness based on population centers, especially for the study of Chinese cities. The main reason is that the Chinese government develops polycentric cities mainly to disperse the population.

This study used exploratory spatial data analysis (ESDA) to identify the population centers, which can be treated as city centers too (Arribas-Bel and Sanz-Gracia, 2014; Li and Liu, 2018; Li et al., 2019). The LandScan population grid data was classified into four categories according to the local Moran's index (LISA) for each city. For example, low population density grids that are surrounded by low values (LL), the same reason, other three were (LH), (HL) and (HH). Only the cities with a local population showing an HH trend were selected as city centers. As the centers should not be separated, we then integrated these similar grids into a center if they were not far away from each other under the criterion of root contiguity. The centers with insufficient areas (< 2 km\(^2\)) and small population (< 50,000 inhabitants) were filtered out in order to improve the calculation accuracy.

For each Chinese city, the most populous centers are regarded as the main center, while the other centers (if any) are regarded as the sub-centers. Three indicators were used to represent polycentricity. The primary indicator POLYP, adopted the approach of (Lee and Gordon, 2007), which measured how the population distributed between the main center and the sub-centers. If a city had only one city center, POLYP value would be zero. A higher value of POLYP showed a city with more centers. The other indicator is POLYC, which represented the number of a city's centers, and the last indicator is POLYD, which showed how far is the city's sub-centers to the main center. A lower value of POLYC meant that a city had less or no sub-centers. A higher value of POLYD would also suggest the city's sub-centers were more likely to be self-sufficient when they had a greater distance between the main center and themselves (Li et al., 2019).

COMP represented compactness, which was the proportion of the population in each center to the total population. Compact cities are believed to reduce carbon emissions and the negative impact of urban sprawl (Heinonen et al., 2013; Xu et al., 2018A). This reflected the uneven distribution of a city's population in its central and non-central areas. This approach was used in (Lee and Gordon, 2007; Li et al., 2019) which defined scatter. A compact city represents a high concentration of employed people. By definition, a higher value of COMP signifies a more compact city.

### 1.4. Regression model

Because only two-year data cannot be used to form the time series, a mixed model was used instead of a panel data regression model to estimate the impacts of compactness and polycentricity on carbon emissions.

\[
\ln(\text{PCCE}) = a_0 + a_1\ln(\text{POLYP}) + a_2\ln(\text{POLYD}) + a_3\ln(\text{POLYC}) + \epsilon
\]

(4)

\[
\ln(\text{PGCE}) = a_0 + a_1\ln(\text{POLYP}) + a_2\ln(\text{POLYD}) + a_3\ln(\text{POLYC}) + a_4\ln(\text{POP}) + a_5\ln(\text{GDP}) + \epsilon
\]

(5)

where PGCE refers to CO_2 emissions per GDP, and PCCE refers to CO_2 emissions per capita. COMP, POLYD, POLYC, and POLYP represent polycentricity and compactness, which have been discussed above. POP and GDP represent the population of each city and local GDP of each city, respectively.

All the data used in this study were derived from the China Statistical Yearbook for Regional Economy, the China Energy Statistical Yearbook, the China City Statistical Yearbooks, and the relevant yearbooks of the Chinese cities. All the indicators are listed in Table 1.

### 2. Results and discussion

This paper emphasized the relationship between polycentricity, CO_2 emissions, and compactness. The research used a mixed model, taking the years in 2000 and 2010. The main results are shown below.

### Table 1 - Summary statistics of the variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>Std. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCCE</td>
<td>ton/capital</td>
<td>1.98</td>
<td>193.39</td>
<td>27.87</td>
<td>22.22</td>
</tr>
<tr>
<td>PGCE</td>
<td>ton/yuan</td>
<td>0.63</td>
<td>126.40</td>
<td>14.71</td>
<td>16.45</td>
</tr>
<tr>
<td>COMP</td>
<td>%</td>
<td>0.01</td>
<td>0.86</td>
<td>0.22</td>
<td>0.18</td>
</tr>
<tr>
<td>POLYP</td>
<td>%</td>
<td>0.00</td>
<td>0.75</td>
<td>0.24</td>
<td>0.20</td>
</tr>
<tr>
<td>POLYC</td>
<td>-</td>
<td>1.00</td>
<td>10.00</td>
<td>2.95</td>
<td>1.91</td>
</tr>
<tr>
<td>POLYD</td>
<td>Km</td>
<td>1.00</td>
<td>290.62</td>
<td>37.31</td>
<td>34.44</td>
</tr>
<tr>
<td>POP</td>
<td>Ten thousand</td>
<td>11.96</td>
<td>1542.77</td>
<td>133.95</td>
<td>162.71</td>
</tr>
<tr>
<td>GDP</td>
<td>Ten thousand</td>
<td>40.29</td>
<td>40986400.00</td>
<td>986129.83</td>
<td>2946754.63</td>
</tr>
</tbody>
</table>

The carbon emission intensities include PGCE (Per GDP CO_2 emission) (Antanasijevic et al., 2015; Bhattacharyya and Matsumura, 2010) and PCCE (Per capita CO_2 emission) (Duro and Padilla, 2013; Huang and Meng, 2013) using the total CO_2 emission data and corresponding statistical GDP and human population data for each city in China, which are the two most commonly used. PGCE, which is a ratio-based indicator used to characterize CO_2 emission efficiency, is calculated by dividing total CO_2 emissions by GDP, aiming to minimize CO_2 emissions per unit of GDP. The measure CO_2 emissions per capita averages total CO_2 emissions according to the total population of a region, and is used with the aim of minimizing the CO_2 emissions of each person. The following formulas are used:

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(2)

\[
\text{PCCE} = \frac{\text{CO}_2}{P}
\]

(3)

where GDP represents the total gross domestic product of each city, and \( P \) represents the total human population of each city.
2.1. Spatial distribution of CO₂ emission efficiency at cite with centers in China

After reviewing the urban centers of 293 prefecture-level cities in China, it was found that the urban centers could be identified in only 232 cities. The urban centers in the other cities could not be identified because of their large area or small population (see Fig. 1).

From 2000 to 2010, the PCCE in every city generally showed an upward trend, but the increase was not large; it was basically between 0 and 30 ton/capita. The main reason was that the PCCE was inversely proportional to the population. In recent years, due to the implementation of the family planning policy and the improvement of the national economic level, the upward trend of the population in China slowed down gradually, while the CO₂ emissions were driven by the economic and social development.

As a result, the PCCE in all cities in the country has increased each year. The Beijing-Tianjin-Hebei region, Pearl River Delta region, and Yangtze River Delta region are the three high PCCE regions in China. From 2000 to 2010, the PCCE in the Beijing-Tianjin-Hebei region and Pearl River Delta region continued to rise, whereas the Yangtze River Delta region remained relatively stable. The main reason may be that the economic development model of the Beijing-Tianjin-Hebei and Pearl River Delta regions was still dominated by their secondary industry, which would make the PCCE continue to grow, whereas the Yangtze River Delta region was mainly in the tertiary industry, which was declining year by year. The PCCE in Northeast China has also steadily increased in the past decade, whereas the PCCE in Central and Southern China has always been at a low level (see Fig. 2).

From 2000 to 2010, the PGCE of each city generally showed a decreasing trend, with a reduction range of from 0 to 90 ton/yuan. The main reason was that the PGCE was inversely proportional to the GDP. In recent years there has been sustained development of China’s economy and there has been a transformation of many cities from primarily secondary industry to tertiary industry as a result of the Chinese government calling for sustainable development and intensive development.

Accordingly, the consumption of resources has gradually decreased, so the PGCE has decreased each year. Beijing-Tianjin-Hebei and Northeast China are the two high-PGCE regions. However, from 2000 to 2010 the PGCE of these two regions decreased significantly, while that of other regions was generally low. During the past decade, the PGCE of most cities in China has also declined steadily, which indicates that most cities have developed steadily and are transforming into energy-saving, energy-intensive, and sustainable and societies. The economic growth of most cities in China has been larger than that of their CO₂ emissions. With the rationalization and increased emphasis on science in the economic growth mode, the PGCE should continue to decrease. (see Fig. 3).

2.2. Spatial distribution of polycentricity and compactness at cities with centers in China

China’s urbanization continues to develop at a high speed, and capital continues to flow into the real estate market (Zhao et al., 2014). This has led to the emergence of a multi-center pattern in some cities, and most of the studies are focused on the urban multi-center traffic congestion (Engelfriet and Koomen, 2018; Schwanen et al., 2003; Sun et al., 2016). Fig. 4 shows the distribution of four indicators, COMP, POLYP, POLYC, and POLYD, which characterized the aggregation and multicentricity of cities in China.

The COMP value did not change much from 2000 to 2010. The coastal areas, such as Liaoning Province, the Yangtze River Delta, and Fujian and Guangdong Province have higher values. These areas have also become compact in the past ten years. However, the cities in some economically backward areas in the north and south showed a downward trend of compactness, which indicated that the urban residents were no longer concentrated in a specific area; in many cities they were scattered. It is a common phenomenon in China for people to move to other economically developed cities.
During the past decade, the POLYP value has increased significantly in the economically developed areas such as Shandong, Jiangsu, Guangdong, and Fujian. Because of the rapid economic development in these areas, a large number of new workers are needed to participate in the construction and development of the cities. A large number of these people have gathered in the cities’ sub-centers, which is driving the trend of development in the direction of the multi-centers. The POLYC value has changed slightly in the past 10 years. Only in Northeast China and Shaanxi have cities changed from multi-center to single-center. This may be due to the agglomeration of cities, where previously dispersed inhabitants have linked together to form a large urban centre. Most single-center cities are still single-center. In Chongqing, Shandong, the Yangtze River Delta, and Pearl River Delta, some cities have developed more urban centers. This indirectly showed that there was serious spatial inequality in the development of Chinese cities. The development speed of developed areas is increasingly fast, whereas that of undeveloped areas is slow. Because of the Matthew effect, the gap between the economically developed areas and economically backward areas has become wider and wider.

During the past decade, the POLYD value has shown two obvious development modes. The first was where the distance between the main and the sub-centers of some cities was getting farther apart. In this scenario the sub-centers develop independently to form an independent individual sub-centre. This has occurred in some cities in the three eastern provinces, Hubei, and the Yangtze River Delta. The second development mode was where the distance between the main and the sub-centers of cities was getting closer and closer. These cities are becoming increasingly concentrated; the scattered populations in the cities are gathering together, which can effectively improve the utilization of public transport and infrastructure. Such cities are generally smaller cities with smaller populations.

2.3. Impact of polycentricity and compactness on CO\textsubscript{2} emission efficiency

In a mixed regression model, multicollinearity is a serious situation in which linear correlation is showed between the explanatory variables (Wang et al., 2013). Multicollinearity testing is necessary before data processing. As indicated in Table 2, there is no serious multicollinearity among the four factors. Therefore, parameter estimations of the mixed models are possible. Five regression models were estimated; the estimation results are listed in Tables 3 and 4 with respect to the different dependent variables PCCE and PGCE according to Eqs. (4) and (5). The advantage of this approach was that it allowed us to estimate the robustness of the models by comparing the coefficients of each model and identifying the most appropriate
model. Furthermore, the impacts of polycentricity and compactness on the CO₂ emission efficiency could be identified.

Table 3 shows the results of the mixed regression estimation of the PCCE dependent variable for each of the models. Model I, which included only the control variables “population” and “GDP” was used to test the EKC hypothesis. From Table 3, the population of each city was found to have exerted significant influence in relation to the PCCE in China. As the PCCE is a direct population-related indicator of the CO₂ emission intensity, the larger the population, the lower the PCCE value. With the increase of the urbanization rate, the increase in the population will increase the CO₂ emissions (Zhang et al., 2018), but the per capita CO₂ emissions will decrease. However, the GDP of each city was not found to have significant impact on relation to the PCCE in China, because the GDP of each city has no significant relationship with the population of each city but has a significant relationship with the economic development of the region and industrial structure. Our conclusions were different from (Shi et al., 2018), who showed that the urban GDP and urban population exerted a positive influence in urban CO₂ emissions. The difference may be because we focused on the CO₂ emission efficiency not only the CO₂ emissions.

Models II - V expanded the basic hypothesis of Model I by bringing in the focal variables. Model II extended the basic form of Model I by adding the variable “COMP,” which is measured as the compactness of each city. In general, dense cities can agglomerate the population and consume too much resources and energy. Although they can improve the efficiency of the utilities, population agglomeration will, to a certain extent, have a negative effect, which is not conducive to reducing carbon emissions per capita. Therefore, compact cities are not necessarily the best form of cities to reduce the CO₂ emissions intensity (Tamura et al., 2018), because there are many factors that affect the efficiency of CO₂ emissions such as the consumption level of the residents, the total population size, the degree of urbanization, and the proportion of the aging population (Wang et al., 2017b).

Model III added the variable “POLYC,” which was measured as the centers of each city. However, POLYC and PCCE were not

![Fig. 3 - Spatiotemporal distribution of PGCE at cities with centers]
Fig. 4 – Spatiotemporal distribution of COMP, POLYP, POLYC and POLYD at cities with centers in China

significantly correlated; that is, the number of centers in a city was not significantly correlated with the per capita CO₂ emissions. This was because the number of urban centers could only represent the number of population centers. It could not be explained that people living in different urban centers separately, thereby reducing the CO₂ generated by transportation.

Model IV added the variable "POLYP," which measured how disproportionately the population was distributed among a city’s main centers and sub-centers. The percentage of the population of all sub-centers in the total urban population had a significant impact on the PCCE, because if the sub-centers have a large number of people, they can effectively share the population pressure of the city, and a dispersed population can improve the travel efficiency and reduce the transportation costs, thereby reducing the per capita CO₂ emissions. Model V included all the variables and particularly "POLYD," which measured the average distance between a city’s sub-centers and its main center. There was a significant negative correlation between POLYD and PCCE; that is, the farther the distance from all the sub-centers to the main center, the more conducive it is to reducing the per capita CO₂ emissions. A city with many centers and a long distance from each center will reduce the daily travel of residents to some extent, and the residents living in each center can make full use of the re-
sources of each center, such as medical care, education, public transport, and other infrastructure. In the course of their daily lives, the residents of each center can stay in their respective areas, and their travel distance is shorter, so most of them choose to travel by walking or public transport.

Among the five models, Model V had the strongest explanatory power, because it contained more effective dependent variables. The four indicators indicated that the number of urban multi-centers were significantly related to the PGCE, which indicated that whether a city was a single center or a multi-center had a certain impact on the per capita CO₂ emissions. Table 4 shows the results of the mixed regression estimation of the PGCE dependent variable for each of the models. Model I only included the control variables "population" and "GDP," which were used to test the EKC hypothesis too. As we can see, the GDP of each city had a negative influence on the PGCE. Given that energy consumption grows as the economy grows, this will inevitably lead to an increase in CO₂ emissions. Thus, there is a significant EKC correlation between environmental pollution and economic growth (Du et al., 2012). Our estimation results were also consistent with those of some scholars (Jalil and Mahmud, 2009; Liddle, 2015; Policardo, 2016; Scruggs, 1998; Wolde-Rufael and Idowu, 2017) who also confirmed the correctness of an EKC between the per capita GDP and CO₂ emissions.

Models II - V expanded the basic assumption of Model I by adding the focal variables like those shown in Table 3. In Model II, Model III, and Model IV, all the COMP indexes had a significant positive influence on the PGCE; that is, the greater
the level of urban agglomeration, the higher the PGCE value, which meant the agglomerative cities were not conducive to improving the CO₂ emission efficiency, but because the value of the regression factor was smaller, the impact on the CO₂ emission efficiency was also smaller. In Model III, Model IV, and Model V, all the POLYC variables had no significant influence on the PGCE. Because there was no significant correlation between the number of centers in a city and its economic development level, there was no significant correlation between the number of centers and the intensity of the CO₂ emissions.

For Model IV and Model V, all the POLYP indexes exerted no significant influence on the PGCE. The ratio of the population size of a city’s sub-center to that of the main center had nothing to do with the PGCE of a city, although when the population distribution became dispersed, the PGCE related to the level of economic development did not change significantly. At the same time, the degree of population dispersion could reflect the degree of economic development, nor will it have a significant impact on the CO₂ emissions efficiency.

Model V contained all the independent variables. However, only the POLYD and GDP were significantly negatively correlated with the PGCE; the farther the average distance from all the sub-centers to the main center, the lower the GDP value of the CO₂ emissions per unit, and the more conducive it was to improving the CO₂ emission efficiency. Urban sub-centers far from the main center could effectively promote local economic development. Many urban centers represented a number of commercial centers with multiple population gathering areas. Each center had its own functions and could reflect each other, and they could play a common role in promoting common development, thereby improving the efficiency of the CO₂ emissions.

The fitting effect of the Table 4 model was worse than the Table 3 model, which indicated that the impact of city multicentricity on the PGCE was greater than that on the PGCE. Because the multi-center index selected in this study was based on the population aggregation area, it will have a significant impact on the PGCE, which was closely related to the population. Although the cities with a large population generally had strong economic strength, the impact of the two types of cities (i.e., the concentration of population in one center versus the dispersion in several centers) on the CO₂ emission efficiency was relatively small. Only a few studies have discussed the relationship between the urban landscape pattern and CO₂ emission efficiency (Li et al., 2018a), and the relationship between urban multicentricity and traffic congestion (Li et al., 2019). Although the goodness of fit of the model was not significantly improved by adding the four factors of urban multicentricity, they affected the CO₂ emission efficiency to a certain extent.

3. Conclusions and implications

Due to the rapid industrialization process and rapid economic development in recent decades, China has produced a large amount of CO₂ emissions (Han et al., 2018). Urbanization will bring about a lot of CO₂ emissions, so it is necessary to study the impact of all aspects of cities on global warming and carbon emissions (Ameli et al., 2014; Xu et al., 2018b). First, the degrees of polycentricity and compactness were measured through fine-grained identification of population centers based on the LandScan population dataset, then we made a map of the CO₂ emission efficiency and polycentricity and compactness variables. Last, we showed the results of the relationship between the CO₂ emission efficiency and polycentricity and compactness.

Our empirical results confirmed that the areas with high PGCE were concentrated in Northeast China, Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta. Northeast China’s economy is backward, but the PGCE value is high, mainly because the economic development model of Northeast China is primarily secondary industry, and heavy industry produces a large amount of carbon emissions. The areas with high PGCE were mainly in the Beijing-Tianjin-Hebei region and the Northeast region, the development speed of the Beijing-Tianjin-Hebei region was faster, and the economic development model has not been completely transformed. Although the Northeast region has a heavy industrial base, its economy is relatively backward. Therefore, the PGCE values of these two regions were higher, while those of the other two more developed regions were lower, because tertiary industry was the main factor in these two regions. These economies were very developed, so even if the CO₂ emissions were large, the CO₂ emission efficiency was still very high. In general, cities that had not been identified as urban centers were mostly concentrated in the northwest, central, and southwestern parts of China, which were sparsely populated and economically backward areas. In the cities identified as urban centers, the vast majority were single-center cities while multi-center cities accounted for a relatively low proportion. This was also in line with China’s basic national conditions; that is, the extremely unbalanced development of the regions. Because of the high degree of economic development and modernization in these regions, a large number of urban and rural people from surrounding or even remote areas were attracted to live and work in these big cities, so Beijing and Tianjin were in line with the basic national conditions of China. The number of multi-center cities in the Yangtze River Delta and Pearl River Delta was obviously more than that in other areas.

This paper directly proves that there is a significant correlation between multicentricity, compactness and CO₂ emission efficiency. Our results showed that the level of per capita CO₂ emissions was positively correlated with compactness and negatively correlated with the three factors characterizing multicentricity. Per capita GDP CO₂ emission was positively correlated with compactness and negatively correlated with POLYD. In other words, living in cities with a more concentrated population was not conducive to improving per capita CO₂ emissions and per GDP CO₂ emissions, whereas multi-center cities, cities with sub-centers that were more distant from the main center, and cities with a higher population of sub-centers were conducive to improving the CO₂ emission efficiency.

Our empirical results also provided some policy recommendations for the Chinese government in planning cities in the future. For example, although agglomerative cities will increase the use of infrastructure and public transport, they will also bring about congestion and decrease the overall collaborative efficiency. Therefore, in the future cities should develop in the direction of multi-centers. The cooperative development of each center can alleviate traffic pressure and improve the CO₂ emission efficiency. At the same time, the Chinese government should also adhere to the policy of “first getting rich, then getting rich,” so that cities with higher urbanization and multi-centers can take the lead and provide suggestions and references for other cities.

In China, the cities with large population are more suitable for the development of multi center cities, while the cities with small scale and sparse population should first develop economy and concentrate the population to improve production and living efficiency. When developing a multi center city, the Chinese government should improve the infrastructure of each center, vigorously develop public transport, and ensure that residents of each center can meet their daily needs in
each center, so as to avoid unnecessary travel and reduce carbon emissions.

As we can see, the Chinese government has paid more attention to improving the CO₂ emission efficiency, and without doubt some achievements have been made. In recent years Beijin has acted as a pioneer in meeting the peaking target of emissions during the in-depth socio-economic transition period (Wang et al., 2018). Growing cities, such as cities in the Yangtze River Delta and Pearl River Delta, can achieve emission mitigation with economic growth (Xiao et al., 2019). In these cities we found that rapid economic development obviously improved the CO₂ emission efficiency. In addition, the transfer of the first and second industries to the third industry in the city has also greatly reduced CO₂ emissions. In many economically developed urban areas, there is no first industry in the urban area, and many factories have moved to the outside or suburbs. The improvement of the production efficiency of the plant also effectively improves the CO₂ emission efficiency.

Some of the data and methods used in this study had limitations and need further study. First, we used population centers instead of employment centers to calculate the urban spatial structure. Focusing on employment centers could provide a clearer understanding of the role of the workplace and housing location in respect of carbon emissions, and this was not taken into account in our study. Second, because only the data for 2000 and 2010 were used to analyze the change of CO₂ emission efficiency, it was impossible to form a long time series and to visualize the interannual change of the CO₂ emission efficiency. Future research can focus on long time series data and then use panel data analysis to accurately analyze the data. Third, this study only focused on cities that could be identified as urban centers in China, as we were not able to obtain travel and industrial emission data that are closely related to carbon emissions. Obtaining this data would enable us to enhance our understanding of urban carbon emissions. At last, the retrieval of CO₂ emissions from nighttime lighting data will reduce the accuracy of the data and affect the experimental results to some extent, but we have selected the most reliable inversion formula to ensure the reliability of the experimental results.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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