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The Spatial Distribution Characteristics of Carbon Emissions at County Level in the Harbin–Changchun Urban Agglomeration

Yixia Wang

School of Humanities, Shanghai Jiao Tong University, Shanghai 200240, China; coral0526@alumni.sjtu.edu.cn; Tel.: +86-21-5474-2436

Abstract: China has clearly put forward the strategic goals of reaching the "Carbon Emission Peak" by 2030, and achieving "Carbon Neutrality" by 2060. To achieve these goals, it is necessary to precisely understand the spatial distribution characteristics of historical carbon emissions in different regions. This paper has selected a representative national-level urban agglomeration in China, the Harbin–Changchun urban agglomeration, to study the temporal and spatial distribution characteristics of carbon emissions in its counties. This paper has constructed global and local Moran's I indexes for the 103 counties in this urban agglomeration by using the carbon emission values reflected by night light data from 1997 to 2017 to perform global and local autocorrelation analysis on a spatial level. The results show that: (1) the main characteristic of carbon emission clustering in the Harbin–Changchun urban agglomeration is similar clustering; (2) the changes in carbon emissions of the Harbin–Changchun urban agglomeration have a strong correlation with relevant policies. For example, due to the impact of the "Twelfth Five-Year Plan" policies, in 2013, the global county-level Moran's I index of the carbon emissions in the Harbin–Changchun urban agglomeration decreased by 0.0598; (3) the areas where high carbon emission values cluster together ("High–High Cluster") and low carbon emission values cluster together ("Low–Low Cluster") in the Harbin–Changchun urban agglomeration are highly concentrated, and the clusters are closely related to the development level of different regions.

Keywords: carbon emission peak; carbon neutrality; Harbin–Changchun urban agglomeration; carbon emission; spatial agglomeration

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1. Introduction

Since the industrial revolution, the extensive use of fossil fuels by human society has emitted a large amount of carbon dioxide which has posed a serious threat to the ecological environment [1–3]. According to statistics from the International Energy Agency, global energy-related carbon dioxide emissions reached 33 gigatonnes (Gt) in 2019, which has greatly affected the global environment [4].

As a major carbon emitter, China attaches great importance to this issue. Chinese President Xi Jinping has mentioned that China will scale up its Intended Nationally Determined Contributions by adopting more vigorous policies and measures, aiming to reach the "Carbon Emission Peak" by 2030 and achieve "Carbon Neutrality" by 2060 [5]. This is a higher goal set by China regarding the timing of carbon emission peak and long-term carbon neutrality on the basis of the commitments of the Paris Agreement. As the world's largest carbon dioxide emitter, balancing the relationship between economic growth and carbon emissions is a major challenge currently facing China.

In the process of achieving such goals, the issue of carbon emissions by urban agglomerations has attracted increasing attention from the academic circle [6–10]. On the one hand, China's urbanization has been accelerating since the reform and opening up. According to the national plan since 2014, in addition to the three traditional urban agglomerations of the Yangtze River Delta, the Pearl River Delta, and the Bohai Rim (Beijing−Tianjin−Hebei) urban agglomerations, the middle reaches of the Yangtze River, the Central Plains of the Yellow River, the Chengdu−Chongqing city cluster, and the Harbin–Changchun urban agglomeration are also listed as China's national-level urban agglomerations [11,12]. On the other hand, the planning and rapid development of urban agglomerations have made it even more difficult for China to reduce carbon emissions [13–15]. From the definition in Geography, urban agglomeration is an "aggregate" of cities within certain geographic areas [16]. Within an urban agglomeration, the central city is the core aggregation point of its economy, culture, technology, and transportation. When a large amount of resources concentrate in the central city along with the rapid development of the transportation network and application of information technology [17], carbon emissions have also increased day by day, causing larger environmental impact to the urban agglomeration and putting the urban agglomeration under greater pressure of emission reduction [18–20].

Therefore, this paper has selected a representative urban agglomeration among the four new national-level urban agglomerations in China, the Harbin–Changchun urban agglomeration, as the research object. The reasons are: First of all, this urban agglomeration is located in the traditional industrial base of Northeast China. Due to its developed heavy industry, it has historically been one of the main sources of carbon emissions in China [21–24]. Secondly, China attaches great importance to the economic development and urban construction of this region, and has successively issued a number of national-level policies to prioritize the economic construction and development of this urban agglomeration, which has further brought challenges to carbon emission reduction in this region [25–27]. Finally, unlike the Yangtze River Delta and the Pearl River Delta, the overall ecological environment of the Harbin–Changchun urban agglomeration is relatively fragile [28,29]. In recent years, with shrinking areas of forests and wetlands and weaker ability to absorb carbon emissions, it has become more urgent to conduct in-depth research on carbon emissions [30–32].

In recent years, scholars at home and abroad have conducted extensive researches and analysis on the carbon emissions of urban agglomerations. For examples, Chamberlain et al. (2016) monitored methane and carbon dioxide emissions in Ithaca, New York. Their results show that power generation facilities are important sources of urban carbon dioxide there. Although the probability of natural gas pipeline leakage is low, strong winds over the city have an important impact on carbon dioxide emissions [33]. Requia et al. (2017) studied the use of plug-in hybrid electric vehicles (PHEV) in eight Canadian cities to reduce carbon dioxide emissions. The research results show that due to differences in the existing energy consumption structure of those cities, the carbon dioxide emission reduction effects of them show great differences during the PHEV life cycle. In this regard, they believe that the use of PHEV should be combined with the renewable energy power generation policies of different cities to enhance the effect of carbon dioxide emission reduction [34]. Ježek et al. (2018) measured black carbon and nitrogen oxide emissions in Maribor, Slovenia during working days. By comparing the simulated emission concentration with the actual emission concentration, they established an emission inventory and analyzed the emission reduction status under different scenarios. The results show that if the 10% of vehicles with the highest black carbon and nitrogen oxide emissions are banned on the road during working days, it will reduce Maribor's black carbon emissions by 39% and nitrogen oxide emissions by 33% [35]. Zhu et al. (2019) studied the carbon dioxide emissions caused by the use of fossil fuels in Shanghai, China. They believe that large-scale point pollution sources are the main source of carbon dioxide emissions in Shanghai, and that carbon dioxide emissions are also affected by the circular planning and increasing population density of the city. Therefore, they believe that reasonable urban planning will help reduce urban carbon dioxide emissions [36]. Using 2010 as a benchmark, Harris et al. (2020) set up two scenarios to analyze the carbon emissions of ten cities in Europe in 2050. The results show that there is a significant difference between the carbon emissions calculated based on production and consumption. With the growth of the economy, the carbon emissions based on consumption will continue to increase, putting tremendous pressure on emission reduction. Therefore, cities need to take proactive measures against the increase in carbon emissions caused by consumption [37]. Zhao et al. (2020) studied the carbon dioxide emissions of cities in the Yangtze River Delta in China. Through the analysis of satellite data, they found that during 2000–2017, despite the slowdown in the growth rate, the area's carbon dioxide emissions still increased significantly. At the same time, the increase in carbon emissions has led to an obvious increase in the night surface temperature of cities in the region [38]. Falahatkar and Rezaei (2020) studied the relationship between carbon dioxide emissions and sustainable development in 15 Iranian cities during 2001–2015. They argued that there is a positive correlation between urban development and carbon dioxide emissions, but the increase in urban compactness will lead to a reduction in carbon dioxide emissions. For this reason, they suggested that city planners consider increasing the compactness of the city to reduce the carbon dioxide emissions [39]. Zhang et al. (2020) calculated the total factor carbon emission efficiency index of 64 prefecture-level cities in China from 2006 to 2016. The results show that the total factor carbon emission efficiency indexes of these cities have shown upward trend year by year. In order to further reduce carbon emissions and improve the efficiency of total factor carbon emission, they suggested that these cities further optimize their industrial structure and energy consumption structure to improve their carbon emission reduction efficiency [40]. Ahmad et al. (2021) studied the dynamic relationship between the level of economic development, carbon emissions, and health expenditures in China's urban agglomerations. The results show that there is a two-way positive correlation between carbon emissions and urban public health expenditures, while there is a mixed causal relationship between carbon emissions growth and urban GDP growth. Therefore, in order to realize the sustainable development of Chinese cities, policy makers should fully consider the above-mentioned correlations and formulate effective carbon emission reduction policies according to the different development levels of cities [41].

However, the studies above are still insufficient in that: (1) most of the studies were based on the national, provincial, and city level data, and less attention was paid to the county-level carbon emissions; (2) due to data deficiency, the research periods were relatively short and the data were relatively old; (3) the studies ignored the carbon emission problem caused by the resurgence of traditional industrial bases such as the Harbin–Changchun urban agglomeration.

Therefore, this paper has conducted spatial autocorrelation analysis in order to study the spatial distribution characteristics of carbon emissions in the Harbin–Changchun urban agglomeration. The Harbin–Changchun urban agglomeration covers 11 cities, i.e. Harbin, Daqing, Qiqihar, Suihua and Mudanjiang of Heilongjiang Province, and Changchun, Jilin, Siping, Liaoyuan, Songyuan, and Yanbian Korean Autonomous Prefecture of Jilin Province, with 105 counties under their jurisdiction (Please refer to Figure 1).

This paper focuses on the 103 counties in this urban agglomeration (the historical data of the Qianguoerluosi Mongolian Autonomous County in Songyuan City and the Durbert Mongolian Autonomous County in Daqing City are missing), and performs global and local autocorrelation analysis on a spatial level by utilizing the carbon emission values reflected by night light data from 1997 to 2017. This paper has studied the spatial correlation between carbon emissions by different counties in this urban agglomeration by constructing global and local Moran's I indexes; examined and measured the spatial agglomeration and interdependence of carbon emissions in different counties; and obtained the geographical distribution characteristics and patterns of carbon emissions of these counties in order to further determine the spatial correlation and spatial clustering location.

The structure of this paper is as follows: Section 2 establishes a spatial weight matrix to analyze the global and local spatial autocorrelation of the spatial distribution characteristics of carbon emissions of each county in the Harbin–Changchun urban agglomeration. Section 3 studies the spatial correlation and spatial clustering location of carbon emissions of different counties in the Harbin–Changchun urban agglomeration based on the carbon emission values of the counties from 1997 to 2017 and discusses the analysis results. Section 4 concludes this paper and provides relevant policy recommendations for carbon emission reduction and achieving sustainable development based on the calculation and analysis results above.

Figure 1. The Harbin–Changchun urban agglomeration in China.

2. Materials and Methods

This paper draws on the method of Chen et al. (2020) [42], and obtains the carbon emission values of the 103 counties of the Harbin–Changchun urban agglomeration from 1997 to 2017 based on the night light data provided by DMSP/OLS images and NPP/VIIRS images by utilizing the PSO-BP algorithm to downscale the provincial carbon emission data [43–47]. Specifically, the DMSP/OLS and NPP/VIIRS images from 1997 to 2017 are unified based on the PSO-BP algorithm, and the artificial neural network is used to explore the DMSP/OLS and NPP/VIIRS data. Then, based on the night light data, the relationship between provincial carbon emissions and night light data is established, and the PSO-BP algorithm is used to downscale the provincial carbon emissions to calculate the carbon emissions of each county from 1997 to 2017 [42].

Based on that, this paper has further established the global and local Moran's *I* index, and conducted global and local autocorrelation analysis to study the spatial distribution characteristics of carbon emissions in different counties of the Harbin–Changchun urban agglomeration. This paper has identified the geographical distribution characteristics and patterns of carbon emissions on a county level in this urban agglomeration in order to further determine the spatial correlation and spatial clustering location.

2.1. Original Sample Data

This paper takes the county-level carbon emission values of the Harbin–Changchun urban agglomeration from 1997 to 2017 as the research object (Please refer to Appendix A to find the spatial distribution of the carbon emissions in this region). There are 105 counties in this urban agglomeration, with the historical data of two counties missing [42]. For each sample i ($i = 1, 2, \ldots, 103$), the definition of each indicator is shown in Table 1 below:

Table 1. Definition of Each Indicator in the Original Data.

Variable	Definition
x_i	The x-coordinate of the ith county
y_i	The y-coordinate of the ith county

2.2. Global Spatial Autocorrelation Analysis

The global Moran's I index is used to determine whether county-level carbon emissions and different county-level spatial units have special spatial distribution patterns, and to analyze the spatial clustering characteristics of carbon emissions at the county level (Please refer to Appendix B to find the establishment of the spatial weight matrix). The formula of the global Moran's I index is shown as Equation (1) below:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(e_i - \bar{e})(e_j - \bar{e})}{S_0 \sum_{i=1}^{n} (e_i - \bar{e})^2} \tag{1}$$

In Equation (1), I is the global Moran's I index; n represents the total number of counties; e_i stands for the carbon emission value of the ith county; $\bar{e} = \frac{1}{n} \sum\limits_{i=1}^{n} e_i$ represents the average carbon emissions of all counties; $S_0 = \sum\limits_{i=1}^{n} \sum\limits_{j=1}^{n} w_{ij}$ represents the aggregation of all spatial weights; and the range of the global Moran's I index is $[-1, 1]$. Positive Moran's I index indicates positive correlation. The higher the index, the higher the degree of aggregation of carbon emissions between areas due to similarity. Negative Moran's I index indicates negative correlation. The smaller the value, the higher the degree of aggregation of carbon emissions between areas due to dissimilarity. For the global Moran's I index, the standardized statistic Z can be used to test whether there is a significant spatial autocorrelation between counties. The formula of Z is shown as Equation (2) follows:

$$Z = \frac{I - E(I)}{\sqrt{VAR(I)}} \tag{2}$$

In Equation (2), $E(I) = -\frac{1}{n-1}$ is the theoretical expected value; $VAR(I) = E\left(I^2\right) - E(I)^2$ is the theoretical variance; $E\left(I^2\right)$ is the theoretical first-order moment of origin. Their calculation formulas are shown as Equations (3)–(6) below:

$$E\left(I^2\right) = \frac{n\left[\left(n^2 - 3n + 3\right)S_1 - nS_2 + 3{S_0}^2\right] - A\left[\left(n^2 - n\right)S_1 - 2nS_2 + 6{S_0}^2\right]}{(n-1)(n-2)(n-3){S_0}^2} \tag{3}$$

$$A = \frac{\sum_{i=1}^{n} (e_i - \bar{e})^4}{\left(\sum_{i=1}^{n} (e_i - \bar{e})^2\right)^2} \tag{4}$$

$$S_1 = (1/2) \sum_{i=1}^{n} \sum_{j=1}^{n} \left(w_{ij} + w_{ji}\right)^2 \tag{5}$$

$$S_2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{n} w_{ij} + \sum_{j=1}^{n} w_{ji}\right)^2 \tag{6}$$

when the significance level is set to 0.05, when $Z > 1.96$, the locations in the county with high carbon emission values cluster together ("High–High Cluster"), and the locations in the county with low carbon emission values also cluster together ("Low–Low Cluster"), showing the characteristics of spatial clustering. When $Z < 1.96$, the locations in the county with high carbon emission values cluster with locations with low carbon emission values ("High−Low Cluster"), showing the characteristics of spatial anomalies. When $|Z| < 1.96$, the global spatial autocorrelation of carbon emissions in the county is not significant and is distributed randomly.

2.3. Local Spatial Autocorrelation Analysis

Local spatial autocorrelation analysis can indicate whether the observed value of each spatial location is correlated with the observed value of its adjacent location. When there is no global spatial autocorrelation, we could look for the location with hidden local spatial autocorrelation. When there is global spatial autocorrelation, we could analyze whether there is spatial heterogeneity, determine the location of spatial outliers or influential points, and look for the location of the local spatial autocorrelation that is inconsistent with the conclusion of the global spatial autocorrelation analysis. The formula of the local Moran's *I* index constructed for local spatial autocorrelation analysis is shown as Equation (7) follows:

$$I_i = \frac{e_i - \bar{e}}{{M_i}^2} \sum_{j=1, j\neq i}^{n} w_{ij}\left(e_j - \bar{e}\right) \tag{7}$$

In Equation (7), I_i is the local Moran's I index of the ith county; ${M_i}^2$ is the average value of the sum of squared deviations of the carbon emission values of counties apart from the i^{th} county from their mean value, as shown in Equation (8) below:

$${M_i}^2 = \frac{\sum_{j=1, j\neq i}^{n}\left(e_j - \bar{e}\right)^2}{n-1} \tag{8}$$

The standardized statistic Z for the local Moran's I index test is shown in Equation (9) below:

$$Z(I_i) = \frac{I_i - E(I_i)}{\sqrt{VAR(I_i)}} \tag{9}$$

In equation (9), $E(I_i) = -\frac{\sum_{j=1,j\neq i}^{n} w_{ij}}{n-1}$ is the theoretical expected value; $VAR(I_i) = E\left({I_i}^2\right) - E(I_i)^2$ is the theoretical variance; $E\left({I_i}^2\right)$ is the theoretical first-order moment of origin. Their calculation formulas are shown as Equations (10) and (11) below:

$$E\left({I_i}^2\right) = \frac{\left(n - b_{2_i}\right)\sum_{j=1,j\neq i}^{n} {w_{ij}}^2}{n-1} - \frac{\left(2b_{2_i} - n\right)\sum_{k=1,k\neq i}^{n}\sum_{h=1,h\neq i}^{n} w_{ik}w_{ih}}{(n-1)(n-2)} \tag{10}$$

$$b_{2_i} = \frac{\sum_{j=1,j\neq i}^{n}\left(e_j - \bar{e}\right)^4}{\left(\sum_{j=1,j\neq i}^{n}\left(e_j - \bar{e}\right)^2\right)^2} \tag{11}$$

When the local Moran's I index is greater than 0 and passes the test, it indicates that the carbon emissions of the i^{th} county show the characteristics of similar clustering with carbon emissions of adjacent counties, that is, locations with high carbon emission values cluster together ("High–High Cluster"), and locations with low carbon emission values also cluster together ("Low–Low Cluster"). The higher the index value, the greater the radiation effect this county's carbon emissions have on adjacent counties. When the local Moran's I index is less than 0 and passes the test, it indicates that the carbon emissions of the i^{th} county show the characteristics of dissimilar clustering with carbon emissions of adjacent counties, that is, locations with high carbon emission values would cluster with locations with low carbon emission values ("High−Low Cluster").

3. Results and Discussion

This paper takes the county-level carbon emission data of the Harbin–Changchun urban agglomeration from 1997 to 2017 as the research object, and conducts global and local autocorrelation analysis on a spatial level by utilizing the spatial autocorrelation analysis method based on the carbon emission values estimated from the night light data. This paper explores the geographical distribution characteristics and patterns of carbon emissions of these counties in order to further determine the spatial correlation and spatial clustering location.

Figure 2 and Table A1 in the Appendix C shows the global Moran's *I* indexes of the Harbin–Changchun urban agglomeration from 1997 to 2017 based on methods introduced in Section 2.

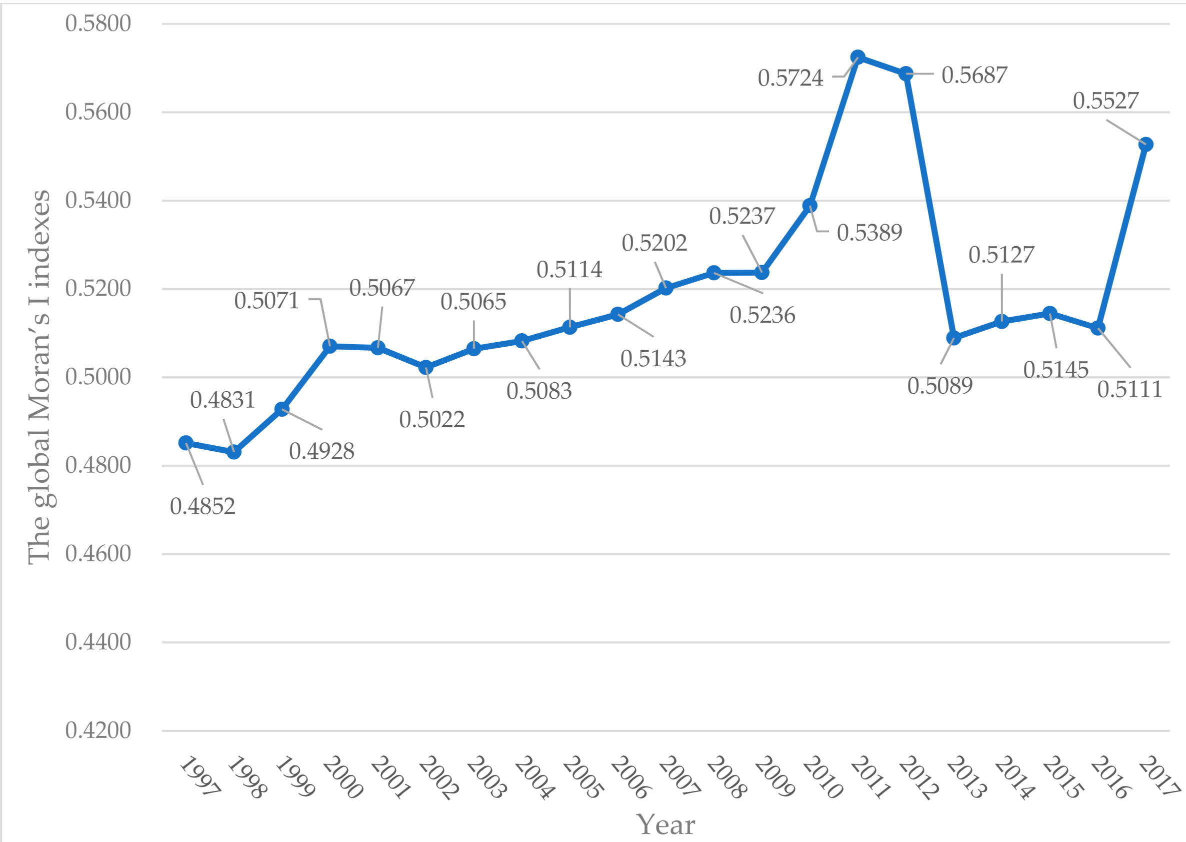
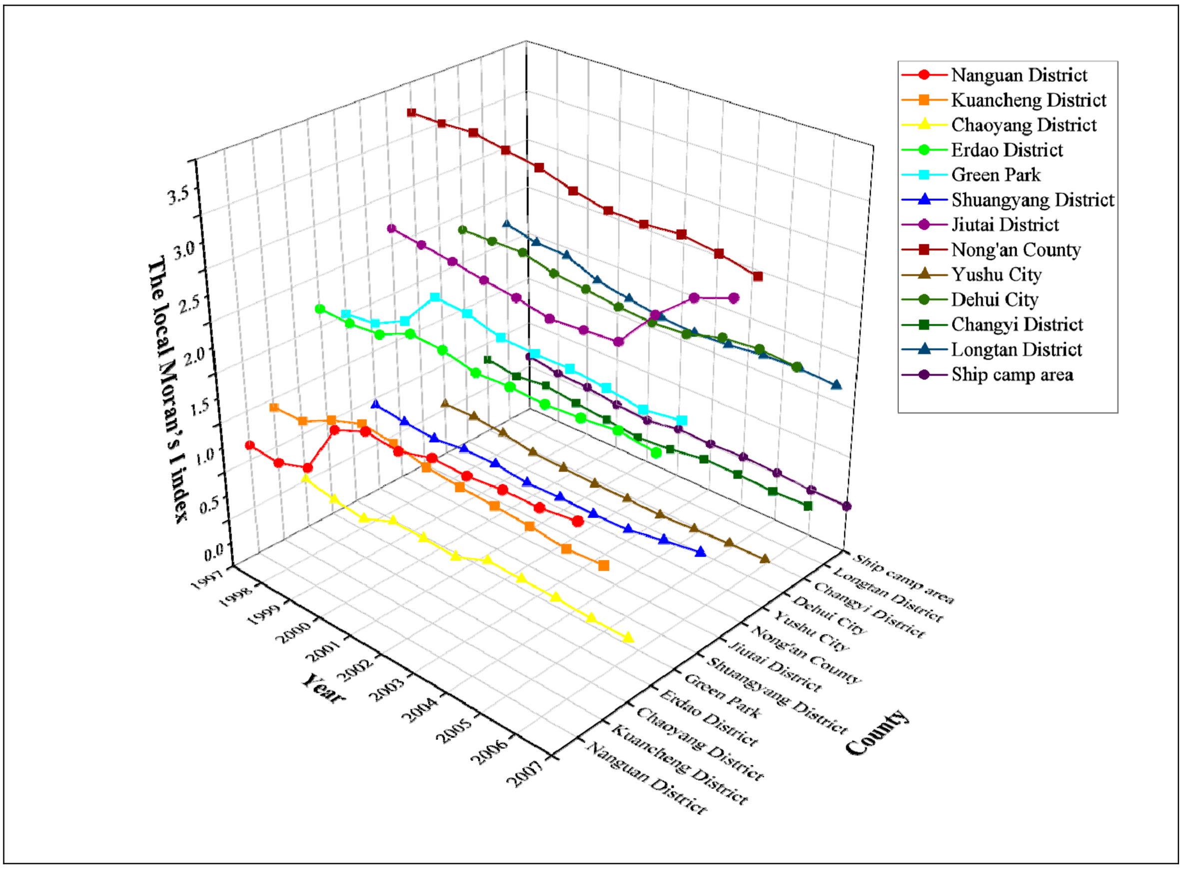
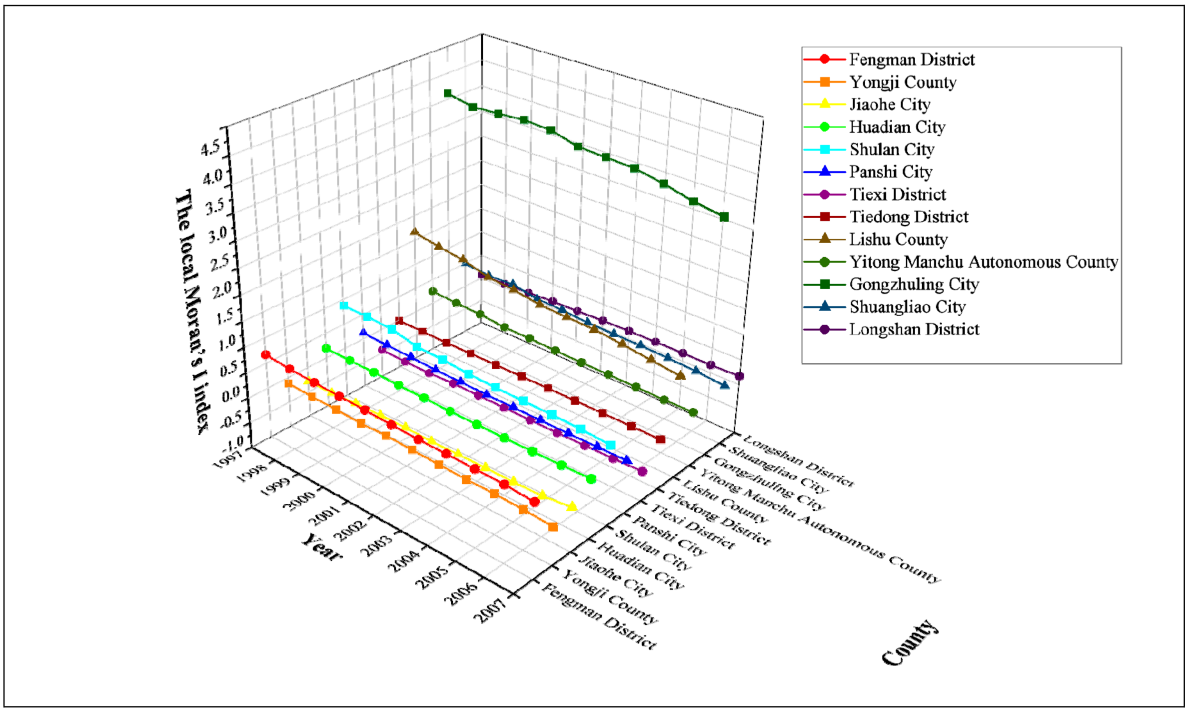


Figure 2. The global Moran's *I* indexes of the Harbin–Changchun urban agglomeration from 1997 to 2017.

Figures 3 and 4, with Tables A2 and A3 in the Appendix C, show the local Moran's *I* indexes of the Harbin–Changchun urban agglomeration from 1997 to 2017.

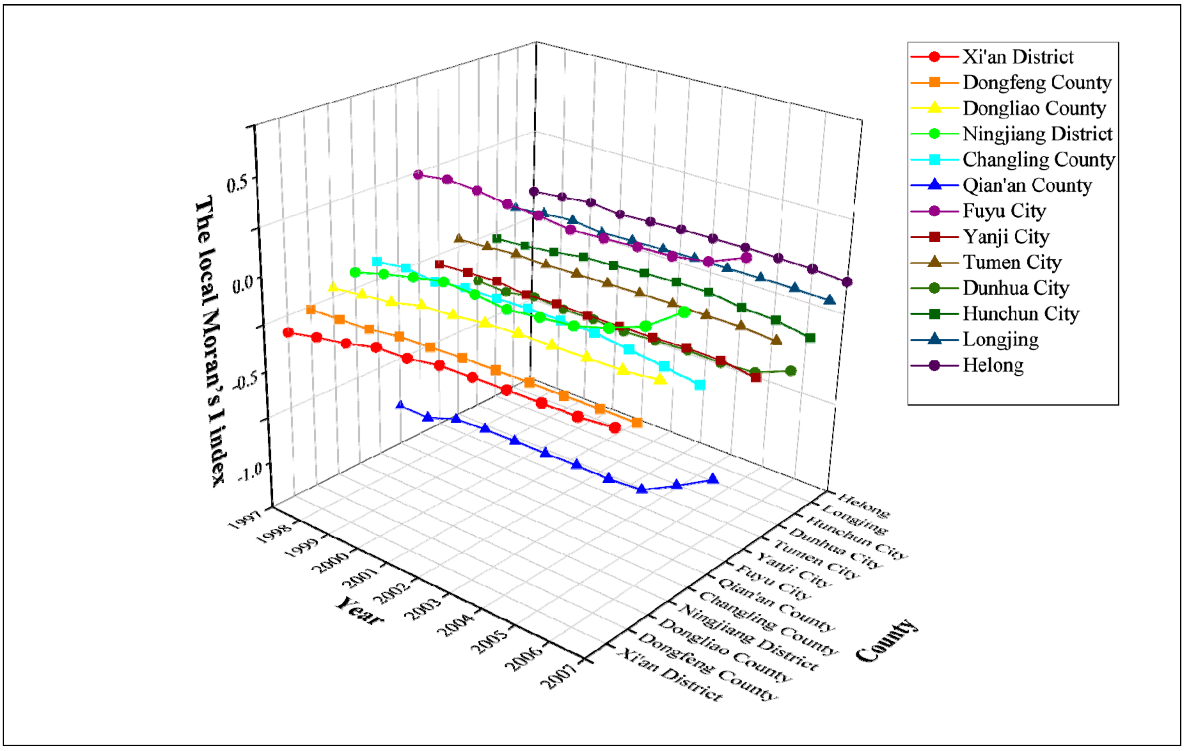


(**a**)

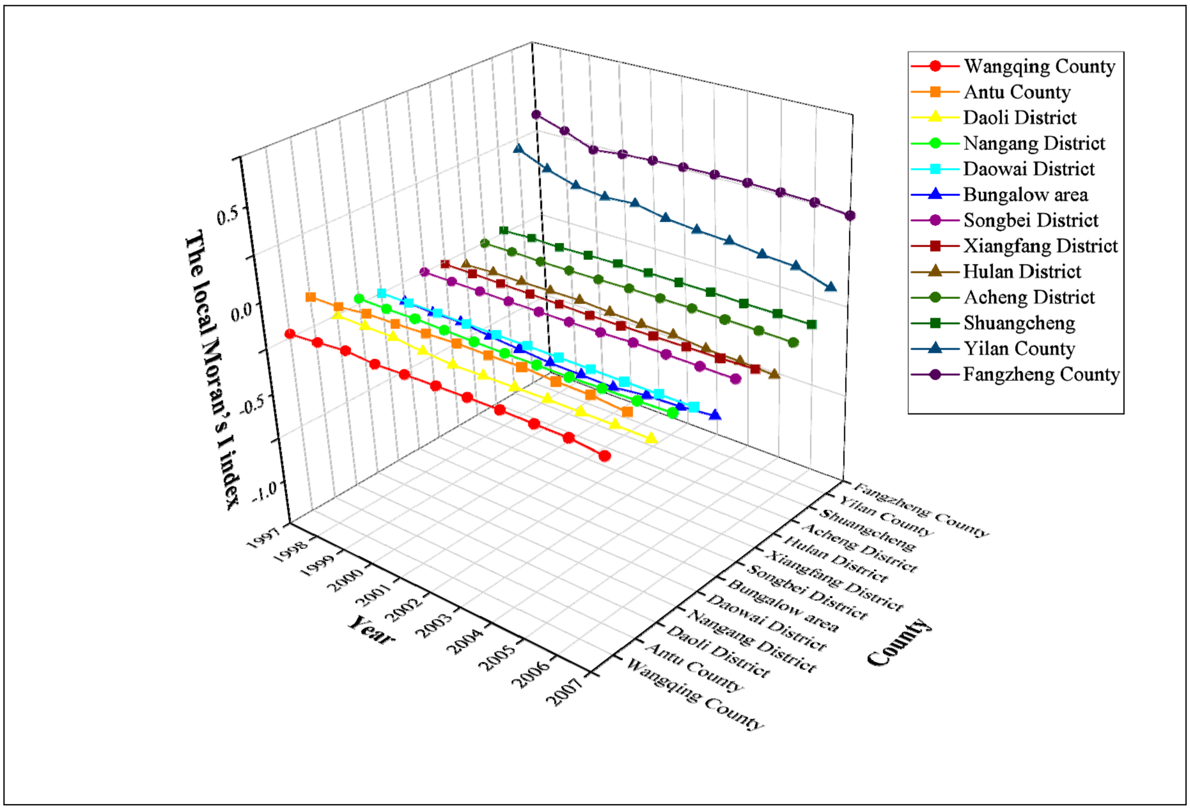


(**b**)

Figure 3. *Cont.*

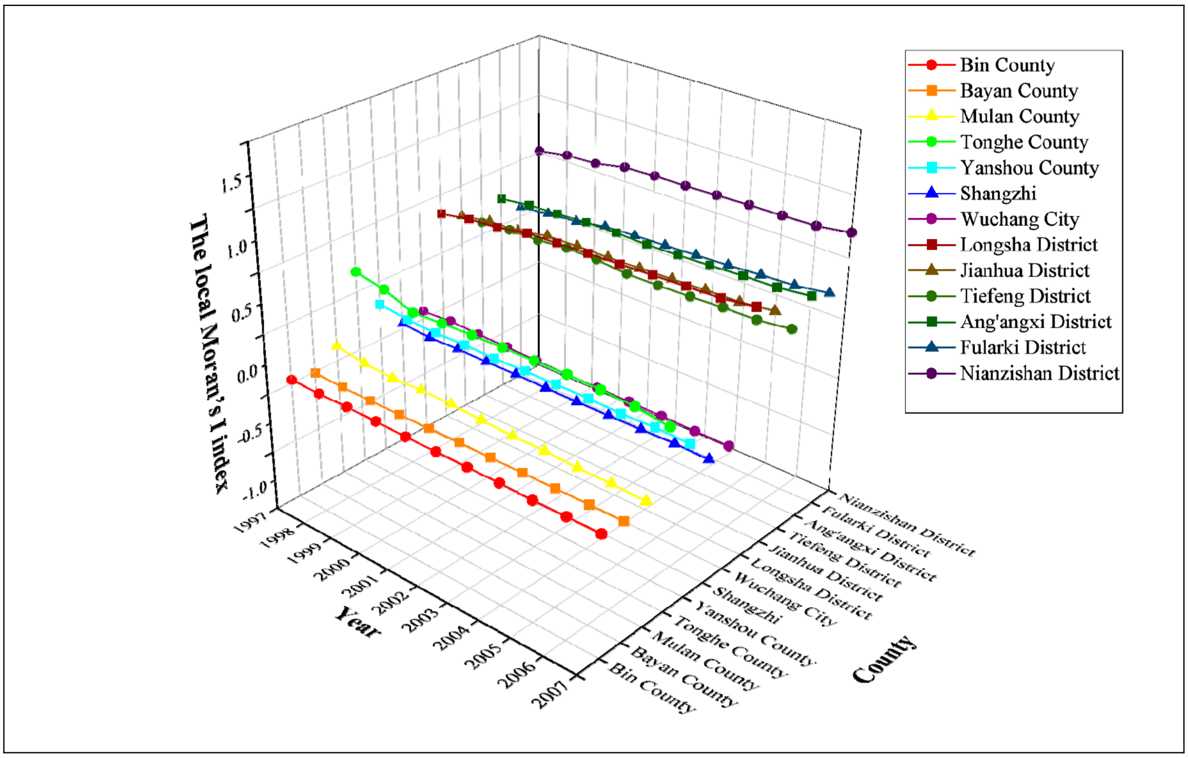


(**c**)

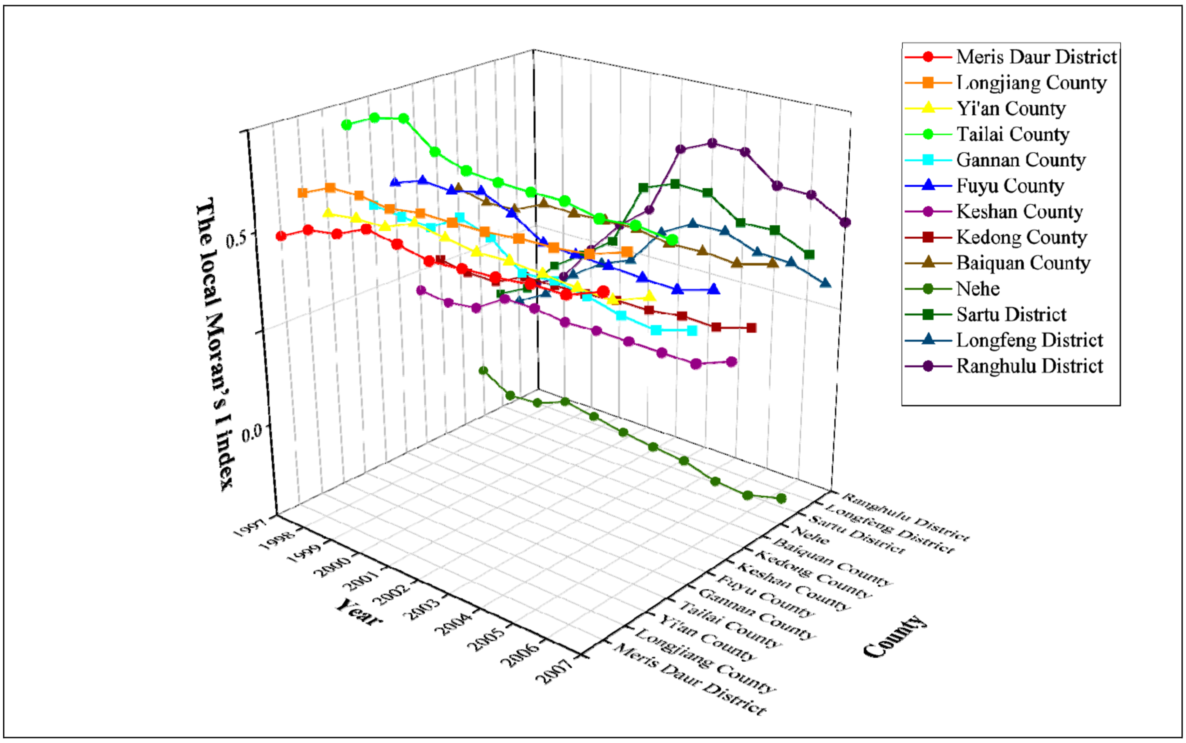


(**d**)

Figure 3. *Cont.*

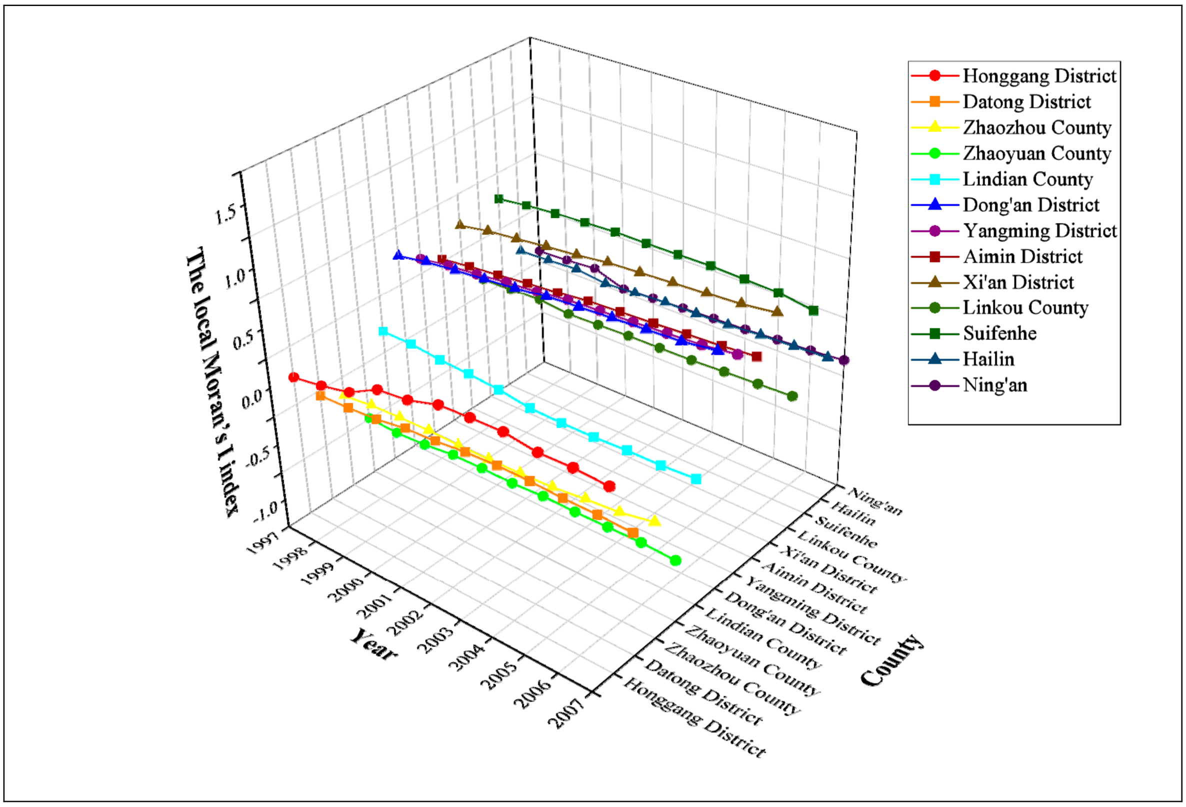


(**e**)

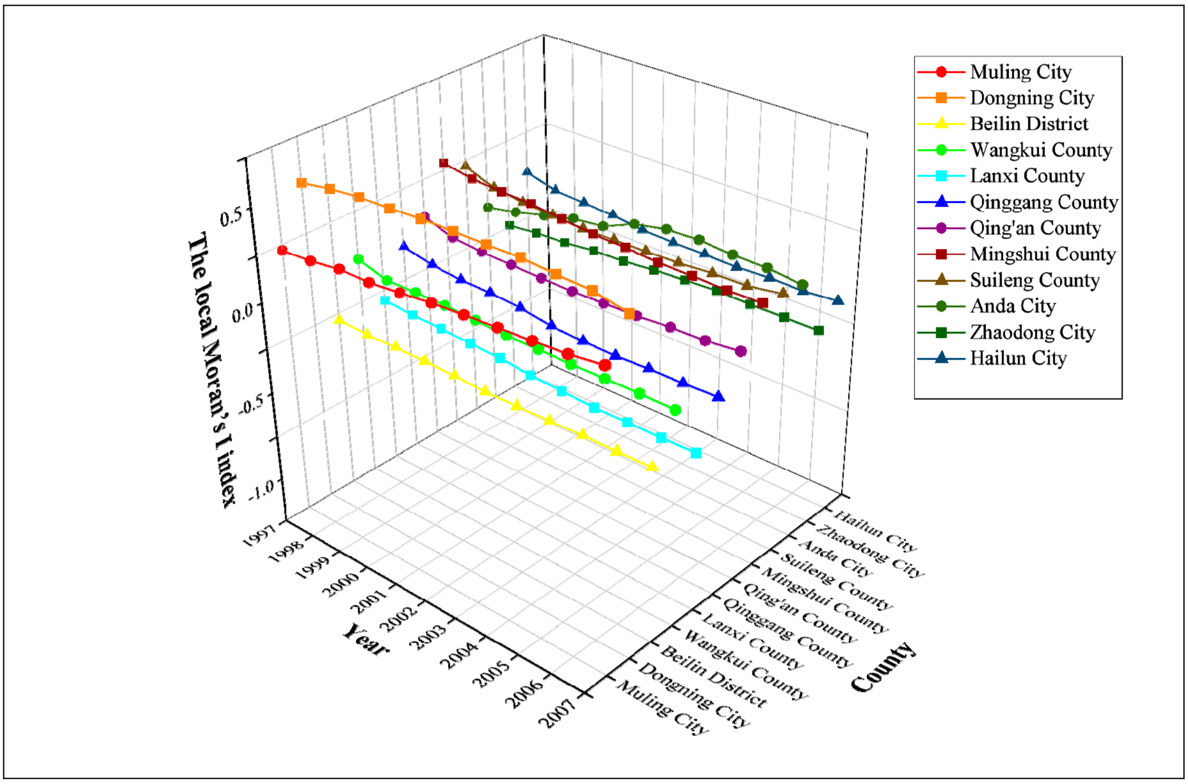


(**f**)

Figure 3. *Cont.*

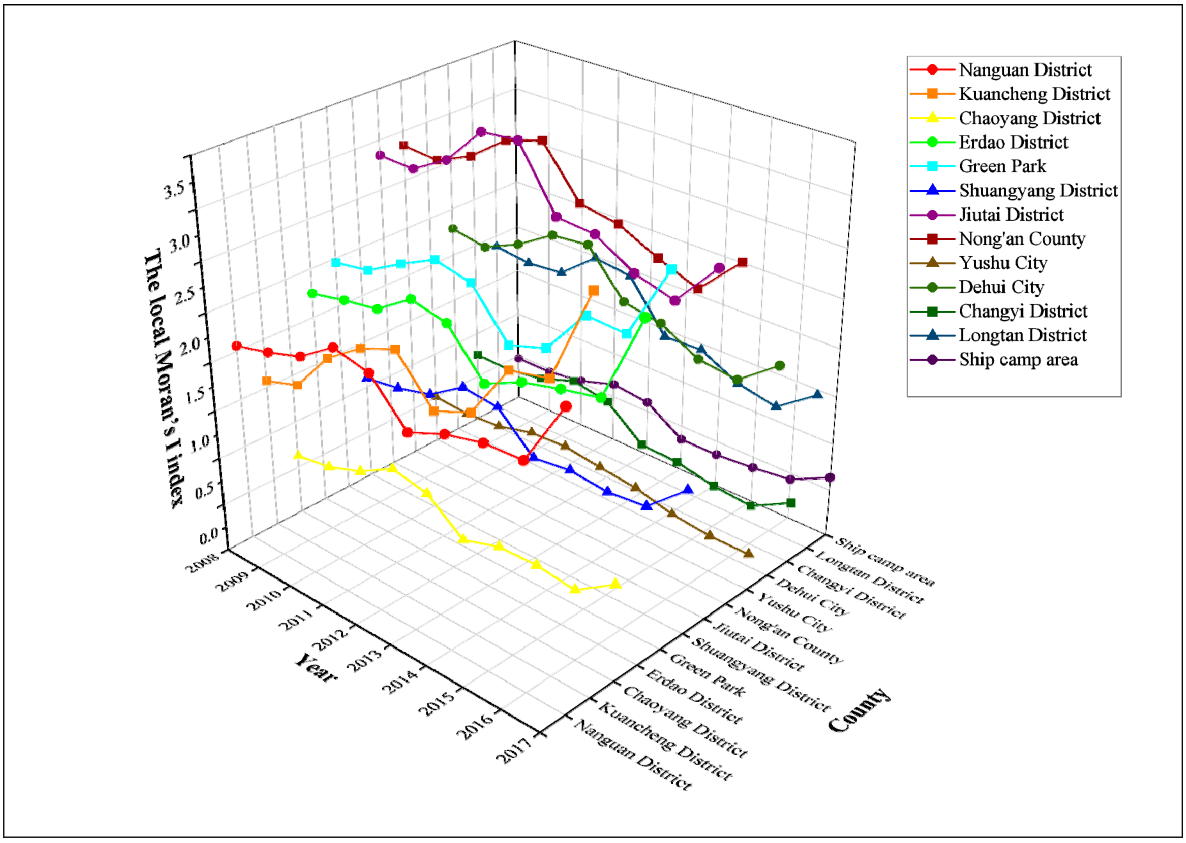


(g)

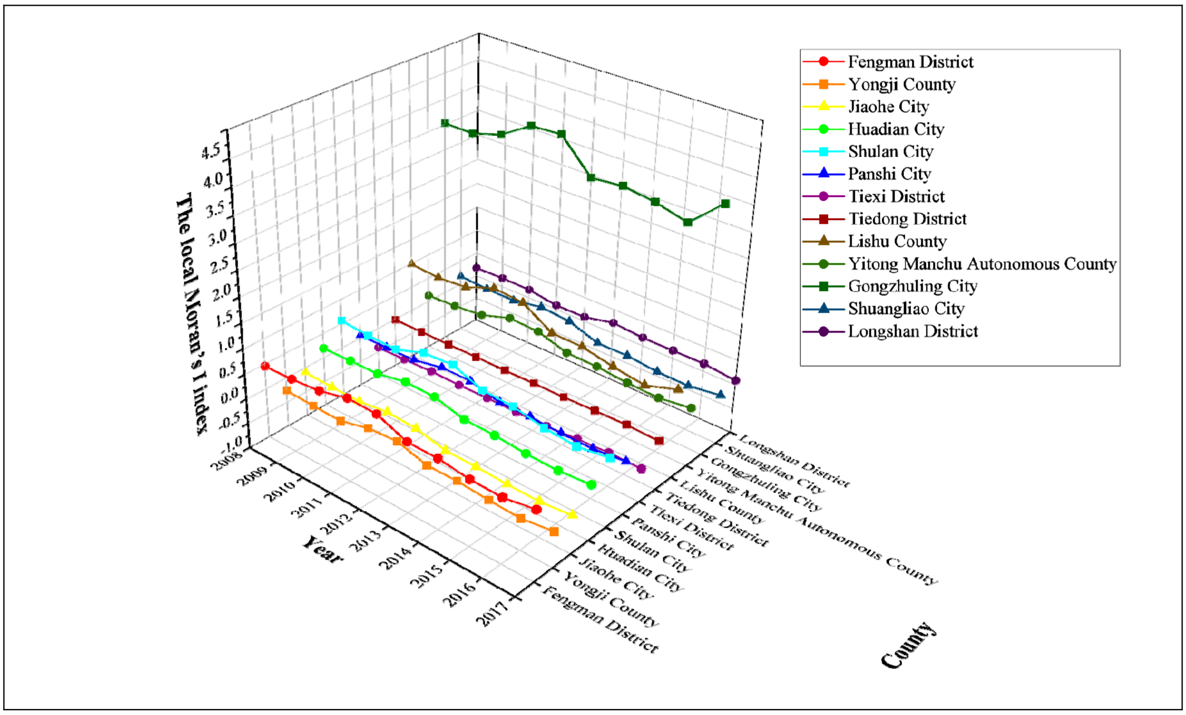


(h)

Figure 3. The local Moran's *I* index of the Harbin–Changchun urban agglomeration from 1997 to 2007 (Panel (**a**–**h**) include the 103 counties).

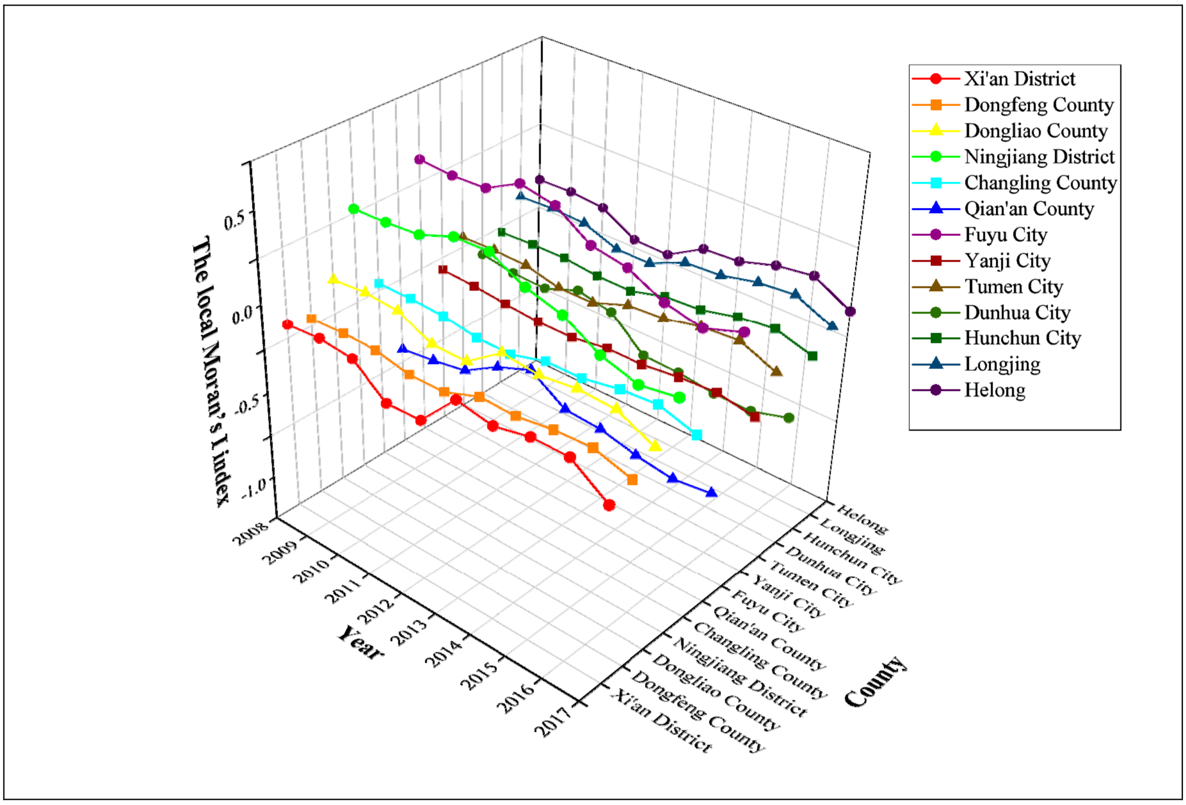


(a)

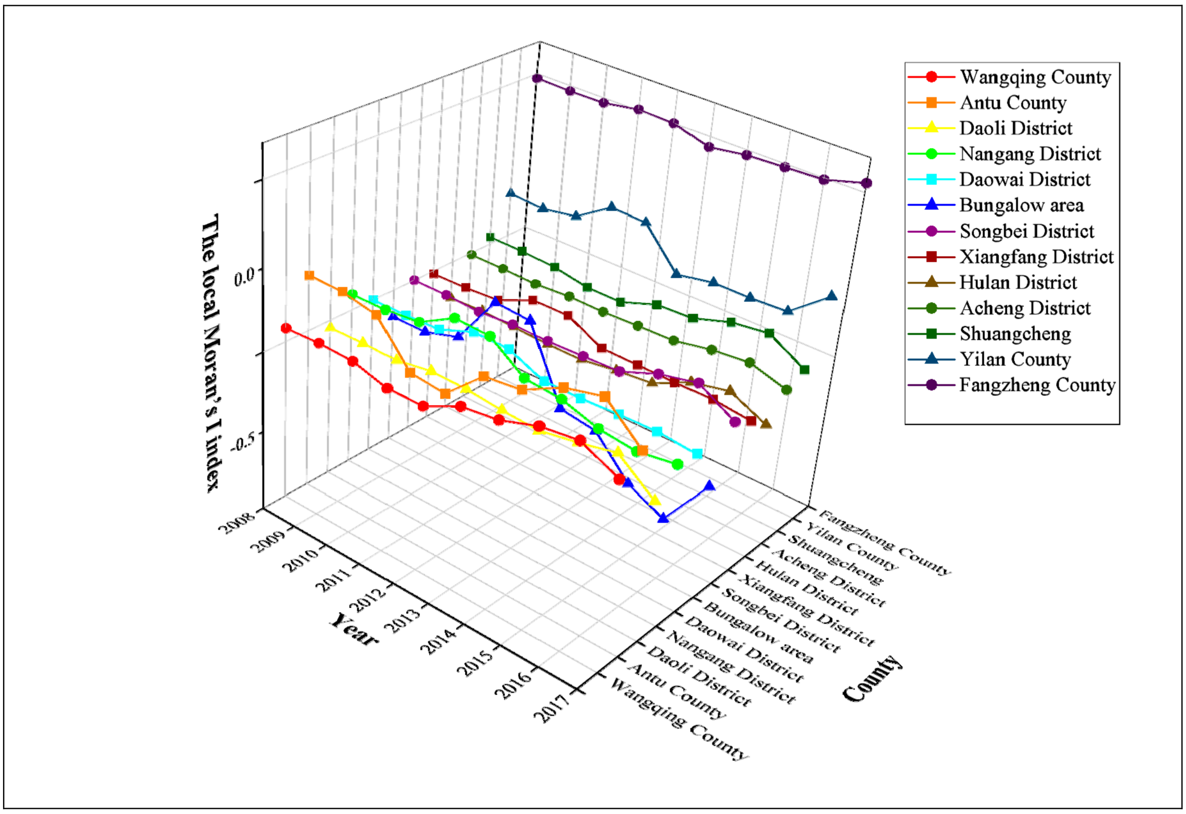


(b)

Figure 4. *Cont.*

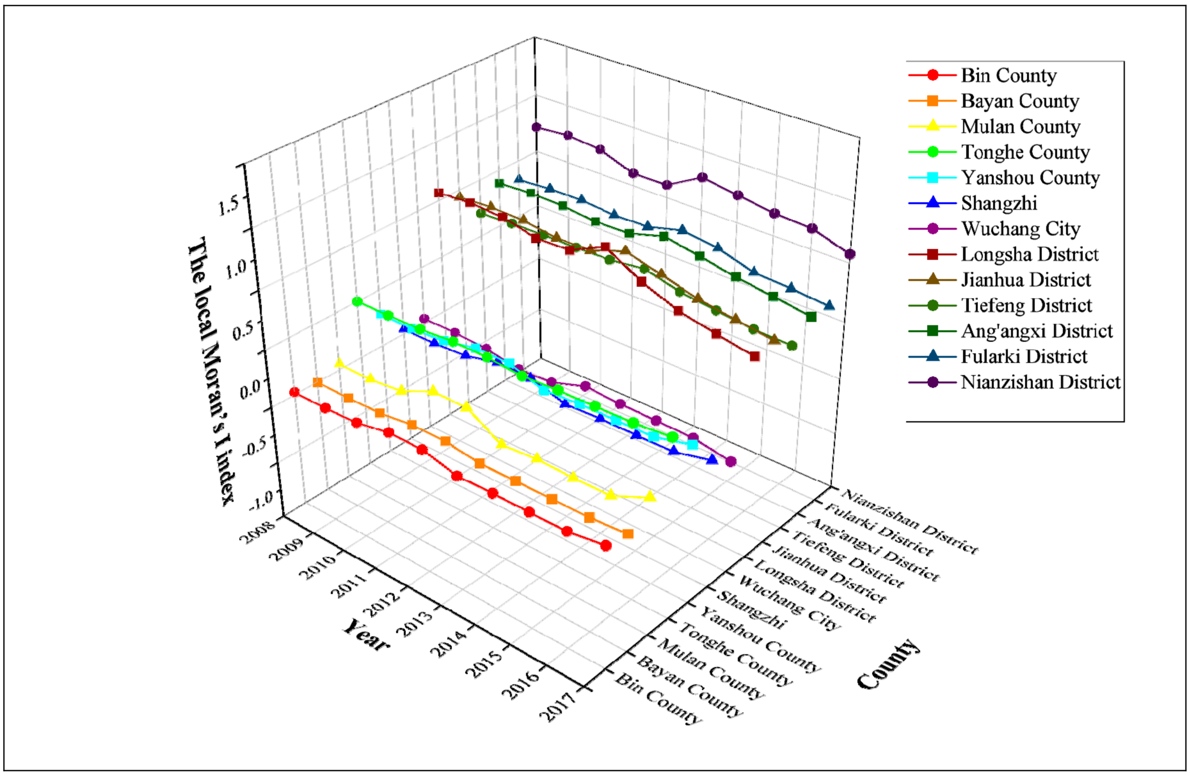


(**c**)

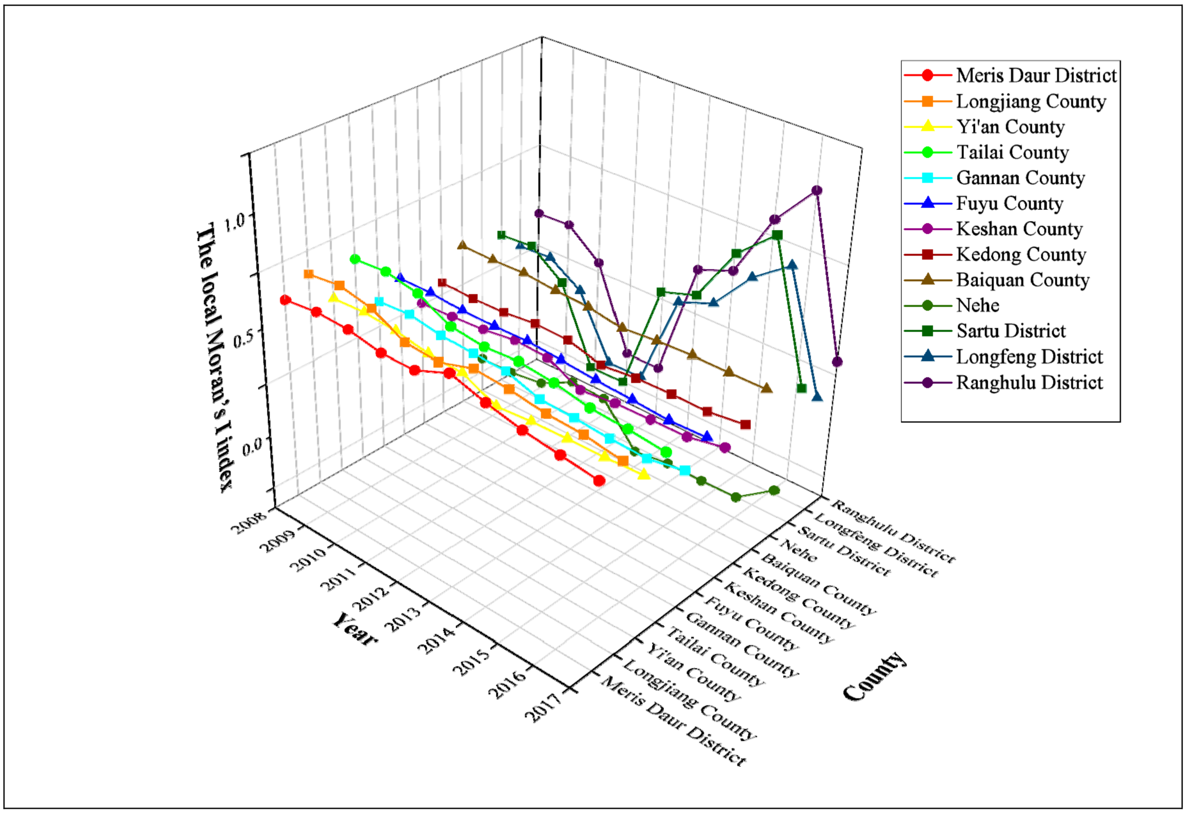


(**d**)

Figure 4. *Cont.*

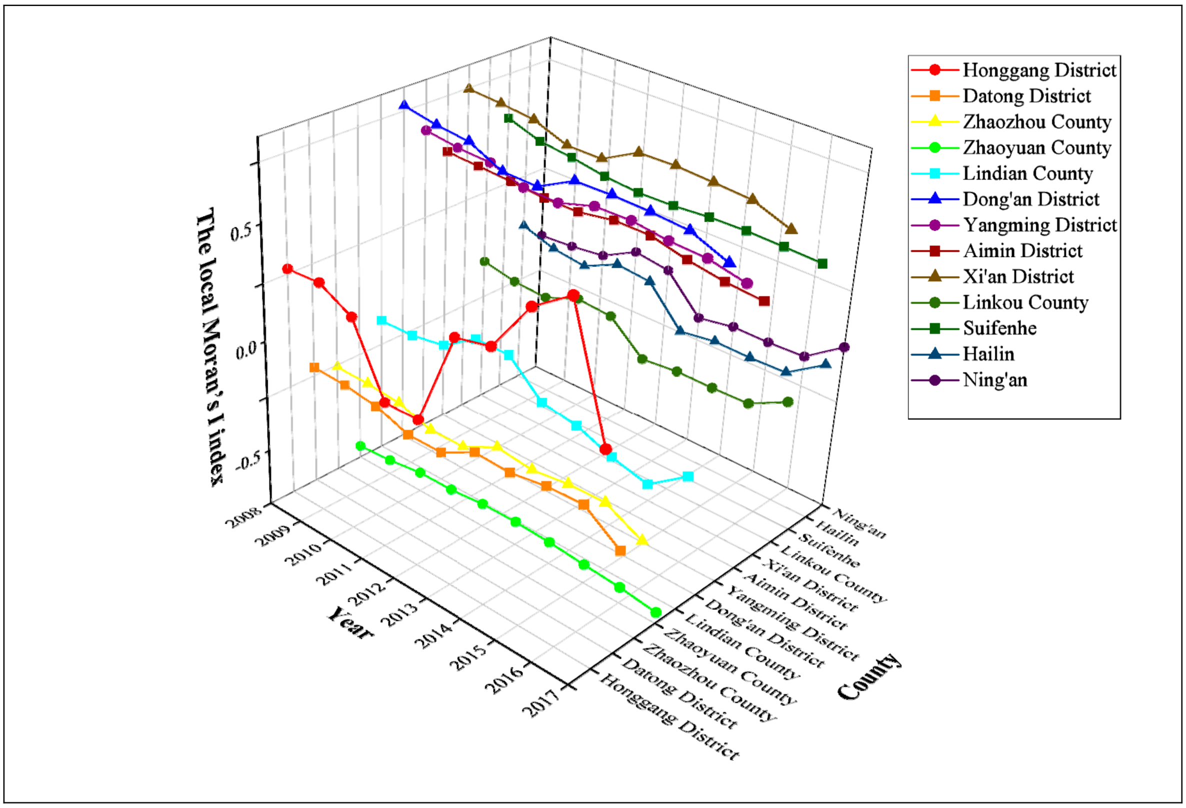


(**e**)

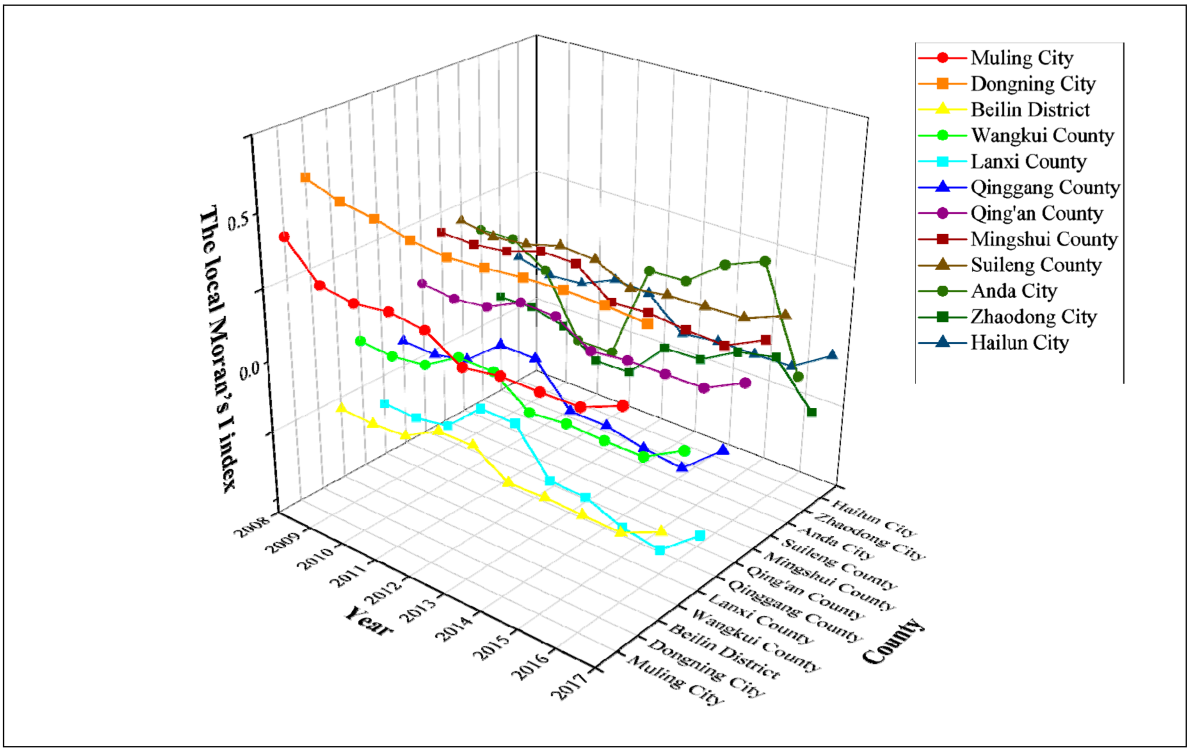


(**f**)

Figure 4. *Cont.*



(**g**)



(**h**)

Figure 4. The local Moran's *I* index of the Harbin–Changchun urban agglomeration from 2008 to 2017 (Panel (**a**–**h**) include the 103 counties).

It can be seen from the data that there are clear patterns in the spatial distribution of carbon emissions in the Harbin–Changchun urban agglomeration. Spatial differences and geographic proximity are important factors that determine the characteristics of carbon emissions in this region. However, at the same time, the carbon emissions in the Harbin–Changchun urban agglomeration also show a certain degree of spatial randomness. Although the overall structure and distribution are relatively stable, the carbon emissions also show fluctuations over time. The details are illustrated as below.

3.1. The Overall Distribution Characteristics and Patterns of County-Level Carbon Emissions in the Harbin–Changchun Urban Agglomeration

It can be seen from the global Moran's *I* index that the Harbin–Changchun urban agglomeration experienced a period of carbon emission aggregation increase between 1997 and 2012 due to similar clustering among the counties. Although there were fluctuations during this period, overall, it has shown a trend of similar clustering. Especially, the number of aggregation areas where locations with low carbon emission values cluster together ("Low–Low Cluster") has increased significantly. During the 2013–2017 period, although the global Moran's *I* index of carbon emissions in Harbin–Changchun urban agglomeration counties remained within the positive correlation range, the calculation results have significantly decreased compared with those before 2013, and the degree of carbon emission aggregation due to similar clustering among the counties has declined.

As shown in the calculation results of the global Moran's *I* index for county-level carbon emissions of the Harbin–Changchun urban agglomeration, the indexes for year 1997−2012 are: 0.4852, 0.4831, 0.4928, 0.5071, 0.5067, 0.5022, 0.5065, 0.5083, 0.5114, 0.5143, 0.5202, 0.5236, 0.5237, 0.5389, 0.5724, and 0.5687, respectively. Although the characteristics of county-level carbon emissions of the Harbin–Changchun urban agglomeration vary across the years, the above calculation results show that the carbon emissions are not randomly distributed and have shown relatively strong characteristics of aggregated distribution. In addition, the global Moran's *I* indexes during this period indicate that the main characteristic of carbon emission clustering in the Harbin–Changchun urban agglomeration is similar clustering. During this period, except for the slight fluctuations and declines in the global Moran's *I* index in 1998, 2001 and 2002, this index has shown an upward trend in the rest of the years. Overall, there is a significant upward trend in this index. The global Moran's *I* index for county-level carbon emissions of the Harbin–Changchun urban agglomeration increased from 0.4852 in 1997 to 0.5687 in 2012. The significant increase of this index has further confirmed that during this period, there is a significant spatial positive correlation in the distribution of carbon emissions in this region, and the degree of similar clustering has increased significantly. This evolution of data also coincides with the development stage of the Harbin–Changchun urban agglomeration during that period. During this period, the polarization of development in this region has become more and more prominent. The areas that developed faster had stronger radiation effect on neighboring areas, while those less developed areas suffered from industry withering and population outflow. These changes have significant impacts on the carbon emissions of the Harbin–Changchun urban agglomeration.

On the contrary, the county-level carbon emission clustering in the Harbin–Changchun urban agglomeration has shown a downward trend after 2013. This change is closely related to the relevant policies issued during that period. The calculation results of the global Moran's *I* index for county-level carbon emissions of the Harbin–Changchun urban agglomeration for year 2013−2017 are: 0.5089, 0.5127, 0.5145, 0.5111, and 0.5527, respectively. Compared with the global Moran's *I* index of 2012 (0.5687), the index of 2013 is 0.5089, showing a decrease of 0.0598. Despite the fluctuations of the global Moran's *I* index between 2013 and 2017, overall, the values of the index are relatively lower compared with those in 2013 and before and have remained stable in general. This result shows that 2012 is an important turning point in the spatial distribution of carbon emissions in the Harbin–Changchun urban agglomeration. Such change is also related to the fact that the "Twelfth Five-Year Plan" of China has included carbon emission indicators into consideration [48]. Since the implementation of the "Twelfth Five-Year Plan", energy conservation and emission reduction have become binding targets in the development of various regions. On 6 August 2012, the State Council issued the "Twelfth Five-Year Plan for Energy Conservation and Emission Reduction" (the "Plan"), namely the Guofa (2012) No. 40 [49]. The "Plan" is divided into 6 sections: the current situation; guidelines, basic principles and main objectives; main tasks; key energy-saving and emission-reduction projects; supporting measures; planning and implementation. Its purpose is to ensure the achievement of energy conservation and emission reduction targets of the "Twelfth Five-Year Plan", ease the pressure on resources and the environment, respond to global climate change, promote the transformation of current economic development model, build a resource-saving and environment-friendly society, and enhance the ability of sustainable development. The formulation and implementation of the "Plan" have greatly urged and guaranteed the energy saving and emission reduction actions of various regions, which is reflected by the fact that the global Moran's *I* index for county-level carbon emissions of the Harbin–Changchun urban agglomeration showed a significant downward trend after 2012, further confirming the strong impact of energy-saving and emission-reduction policies on carbon emissions in this region.

In addition to the impact of relevant policies and their requirement on green development, the changes in the global Moran's *I* index are also closely related to the slowdown of economic growth in the Northeast region and transformation of the regional industrial structure there in recent years [50–52]. Not only has the global Moran's *I* index, which represents the spatial clustering of carbon emissions in the Harbin–Changchun urban agglomeration, declined, but the carbon emissions have also dropped. The global Moran's *I* indexes have different development trends across the years during this period, but overall, there has been no significant decline, and the spatial aggregation of locations where high carbon emission values cluster together ("High–High Cluster") and low carbon emission values cluster together ("Low–Low Cluster") has also shown a trend of regional dispersion. The number of aggregation areas where locations with high carbon emission values cluster together ("High–High Cluster") has experienced significant fluctuations during this period.

3.2. The Local Distribution Characteristics and Patterns of County-Level Carbon Emissions in the Harbin–Changchun Urban Agglomeration

Based on the analysis of carbon emissions in Harbin–Changchun urban agglomerations, it can be seen that there is certain spatial correlation in the carbon emissions of this region from 1997 to 2017. The distribution characteristics and patterns of local carbon emissions can be identified by analyzing the local Moran's *I* indexes. The carbon emissions of different counties in the Harbin–Changchun urban agglomeration can be analyzed from two dimensions: time and space:

(1) Time Dimension

On the time dimension, there are obvious changes in the distribution of carbon emissions across the years at the county level of the Harbin–Changchun urban agglomeration. Take the "High–High Clusters" as an example, based on the changes in the number of locations where high carbon emission values cluster together ("High–High Clusters"), the period between 1997 and 2017 could be divided into two time periods with different characteristics, i.e., a time period between 1997 and 2010 and a time period between 2011 and 2017. During the period from 1997 to 2010, the numbers of "High–High Clusters" of carbon emissions in the Harbin–Changchun urban agglomeration are 15, 14, 13, 13, 13, 14, 15, 15, 14, 14, 13, 12, 13, and 13, respectively. Within this time period, the changes in the numbers and geographic locations of "High–High Clusters" are relatively small, and the distribution of the numbers is also quite balanced, with the number of "High–High Clusters" ranging from 12 to 15. It can be seen that the distribution of "High–High Clusters" is relatively stable during this period.

During the period from 2011 to 2017, the numbers of "High–High Clusters" of carbon emissions in the Harbin–Changchun urban agglomeration are 17, 17, 12, 14, 15, 15, and 14, respectively. It can be seen that the numbers and distribution of "High–High Clusters" have experienced large fluctuations. Although the clustering type in the core area has been relatively stable and the changes in the local Moran's *I* index are relatively small, there are still some increases and changes in the geographical locations of "High–High Clusters" of carbon emissions, which are mainly concentrated in Daqing City, Heilongjiang Province. According to statistics released by the Heilongjiang Provincial Bureau of Statistics, in 2014, despite the adverse domestic and international environment as well as downward pressure on the economy, Heilongjiang Province maintained a steady economic growth; the number of rural migrant labor force reached 5.51 million, and its petrochemical industry, one of the four pillar industries, achieved a growth of 5.2 % [53], which could explain the increase in the number of locations of "High–High Clusters" of carbon emissions and the formation of larger carbon emission clustering in Daqing City, Heilongjiang Province in 2014. However, the existence of the "High–High Clusters" of carbon emissions is relatively short, and the scale and scope of the "High–High Clusters" of carbon emissions are also relatively small compared with those in Changchun City. It can be seen that economic development and the structure and scale of related industries have a significant impact on the carbon emission level of the Harbin–Changchun Urban Agglomeration.

On the other hand, if taking the locations where low carbon emission values cluster together ("Low–Low Clusters") as an example, based on the changes in the number of "Low–Low Clusters", the period between 1997 and 2017 could be divided into two time periods with different characteristics, i.e., a time period between 1997 and 2006 and a time period between 2007 and 2017. During the period from 1997 to 2006, the numbers of "Low–Low Clusters" of carbon emissions in the Harbin–Changchun urban agglomeration are 8, 8, 9, 11, 10, 10, 10, 10, 11, and 11, respectively. In this period, there is a significant upward trend in the number of "Low–Low Clusters" of carbon emissions. Based on the analysis above, it can be concluded that this trend is mainly related to the relatively less developed industries [54,55], population loss due to labor outflow [55], and relatively lagging economic development in this region [56,57], which have eventually resulted in the characteristics of "Low–Low Clustering" of carbon emissions.

During the period from 2007 to 2017, the numbers of "Low–Low Clusters" of carbon emissions in the Harbin–Changchun urban agglomeration are 12, 12, 12, 12, 12, 12, 12, 11, 10, 10, and 9, respectively. It can be seen that since 2004, the number and geographical distribution of local "Low–Low Clusters" in the spatial distribution of carbon emissions in the Harbin–Changchun urban agglomeration have remained relatively stable for a long time and the number has shown a declining trend in general.

(2) Space Dimension

As reflected by their relatively high values of local Moran's *I* indexes of carbon emissions, in the Harbin–Changchun urban agglomeration, counties in Daqing of Heilongjiang Province, and Jilin, Changchun, and Siping of Jilin Province have the most concentrated carbon emissions. These four cities are all core cities of the Harbin–Changchun urban agglomeration, with relatively advanced development level, especially the capital city of Jilin Province, Changchun. Changchun has relatively higher economic development level with a large population in the urban area, resulting in its higher carbon emission levels. In addition, the secondary industry accounts for a relatively large proportion in Changchun's economy, which has also caused a significant increase in its energy consumption. According to the statistics released by the Changchun Statistics Bureau, in 2017, the city's total energy consumption increased by 3.06% year by year [58], which has further confirmed the impact of industrial structure on the spatial clustering and distribution of carbon emissions. By calculating the local Moran's *I* indexes, this paper has found that Changchun has the largest number of "High–High Clusters" of carbon emissions in the Harbin–Changchun urban agglomeration, and these "High–High Clusters" are mainly concentrated in Changchun City or its neighboring areas, which to some extent confirms that there is a strong spatial correlation in the distribution of carbon emissions. The clustering characteristics of carbon emissions in the counties of the Harbin–Changchun urban agglomeration also indicate that the core cities and areas have relatively stronger spillover effects, especially in the areas with "High–High Clusters" of carbon emissions. The reasons are that areas with higher levels of urban economy, population size, and technology development are more likely to establish relationships with surrounding areas through industrial transfer, technology spillovers, etc., and thus forming more carbon emission relationships with neighboring areas.

Based on the calculation result of the local Moran's *I* indexes, this paper has found that from 1997 to 2017, the carbon emissions of counties in Qiqihar City of Heilongjiang Province have shown significant characteristics of "Low–Low Clustering". Since 1999, the carbon emissions of counties in Mudanjiang City of the same province have also started to show a pattern of "Low–Low Clustering" in terms of the spatial distribution of carbon emissions, a phenomenon which has continued until 2017. This is mainly related to the economic structure, industrial development level, and population decline of Qiqihar and Mudanjiang. In the economic structure of both cities, the secondary industry is relatively less developed, and the tertiary industry accounts for a large proportion. The output of the tertiary industry of Qiqihar accounted for about 40% of its total economic output, whose proportion even reached 48.8% in 2017 [59]. The proportion of the tertiary industry in Mudanjiang has remained above 40% from 1997 to 2017. The proportion has shown an increasing trend from 1997 to 2002 and has reached about 50% of the total economic output between 2002 and 2007. After that, this proportion started to decline and reached 42.6% in 2012, the lowest value in the past five years, then this proportion rose to about 50% again [60]. At the same time, both cities are facing the pressure of population reduction and labor loss. The population of Qiqihar has been showing a downward trend from 2009 to 2017, which declined from 5.716 million in 2009 to 5.337 million in 2017 [61]. Mudanjiang has experienced two stages of population decline. In the first stage, its population declined from 2.712 million in 2001 to 2.663 million in 2005; in the second stage, its population declined from 2.706 million in 2009 to 2.548 million in 2017 [60].

4. Conclusions

This paper has conducted global and local autocorrelation analysis on a spatial level by utilizing the carbon emission values estimated from the night light data from 1997 to 2017 based on the relevant data of 103 counties in the 11 cities of the Harbin–Changchun urban agglomeration. This paper has studied whether spatial correlation exists in the carbon emissions of different counties by using global and local Moran's *I* indexes; examined and measured the spatial distribution type of carbon emission values and whether spatial agglomeration and interdependence exist for carbon emissions of different counties; and obtained the geographical distribution characteristics and patterns of carbon emissions of these counties in order to further determine the spatial correlation and spatial clustering location. Through further analysis of the relevant calculation results, this paper has reached the following conclusions: (1) the main characteristic of carbon emission clustering in the Harbin–Changchun urban agglomeration is similar clustering; (2) the changes in carbon emissions of the Harbin–Changchun urban agglomeration have a strong correlation with relevant policies; (3) the areas where high carbon emission values cluster together ("High–High Cluster") and low carbon emission values cluster together ("Low–Low Cluster") in the Harbin–Changchun urban agglomeration are highly concentrated.

In view of this, this paper has provided the following policy recommendations:

(1) Energy-saving and emission-reduction policies should be formulated based on the actual situation of the Harbin–Changchun urban agglomeration to encourage energy-saving and emission reduction actions in the region and effectively control carbon emissions. According to the analysis above, relevant policies may have influence on the changes in carbon emissions of the Harbin-Changchun urban agglomeration. For example, the significant turning point of the county-level carbon emissions in 2012 and the correlation between the carbon emissions and energy conservation and emission reduction policies in the "Twelfth Five-Year Plan" can provide important guidance for the formulation of relevant policies and guidelines.

(2) Formulate preferential policies for talents and technologies; promote the transformation and upgrading of regional industries; and effectively reduce carbon emissions in the region. In response to the increasing carbon emissions caused by the high population density in core cities and spillover effects on neighboring cities, this paper proposes that more preferential policies should be formulated in order to attract talents and develop high−tech industries. This region can encourage technological advances in energy and other production fields to offset the increase in carbon emissions brought about by the population growth of urban agglomerations [62,63]. In this way, the carbon emissions of core cities can reach a balance and the spillover effect on neighboring areas can also be mitigated. In addition, increasing the density of road network and developing public transportation can also reduce the pressure on energy and carbon emissions within the region. The increase in the density of road network can help reduce energy consumption and carbon emission by private cars caused by substantial increase in the population density of core cities.

(3) Optimize regional investment structure and promote industrial transformation and upgrading. According to the analysis above, domestic and foreign investment can bring new vitality to urban areas, but they will also increase carbon emissions while stimulating regional economic growth. The migration of industries from the core cities to neighboring areas will have the same impact. In response to this, this paper believes that when it comes to local investment in fixed assets and foreign investment, this region should take the long-term development into consideration. This region should make careful decisions on the planning of regional development direction and investment structure optimization, and motivate investment to flow into industries related to energy conservation and emission reduction as well as relevant technological researches while promoting local economic growth and employment. This is not only the primary solution to reducing regional carbon emissions and preventing the expansion of areas where high carbon emission values cluster together ("High–High Cluster"), but also the primary condition for the sustainable development of the regional economy.

Therefore, I consider further integrating economic growth factors in future research, analyzing the impact of county-level carbon emission reduction in specific areas of China, and exploring how to improve the county-level industrial layout under the goal of "carbon neutrality".

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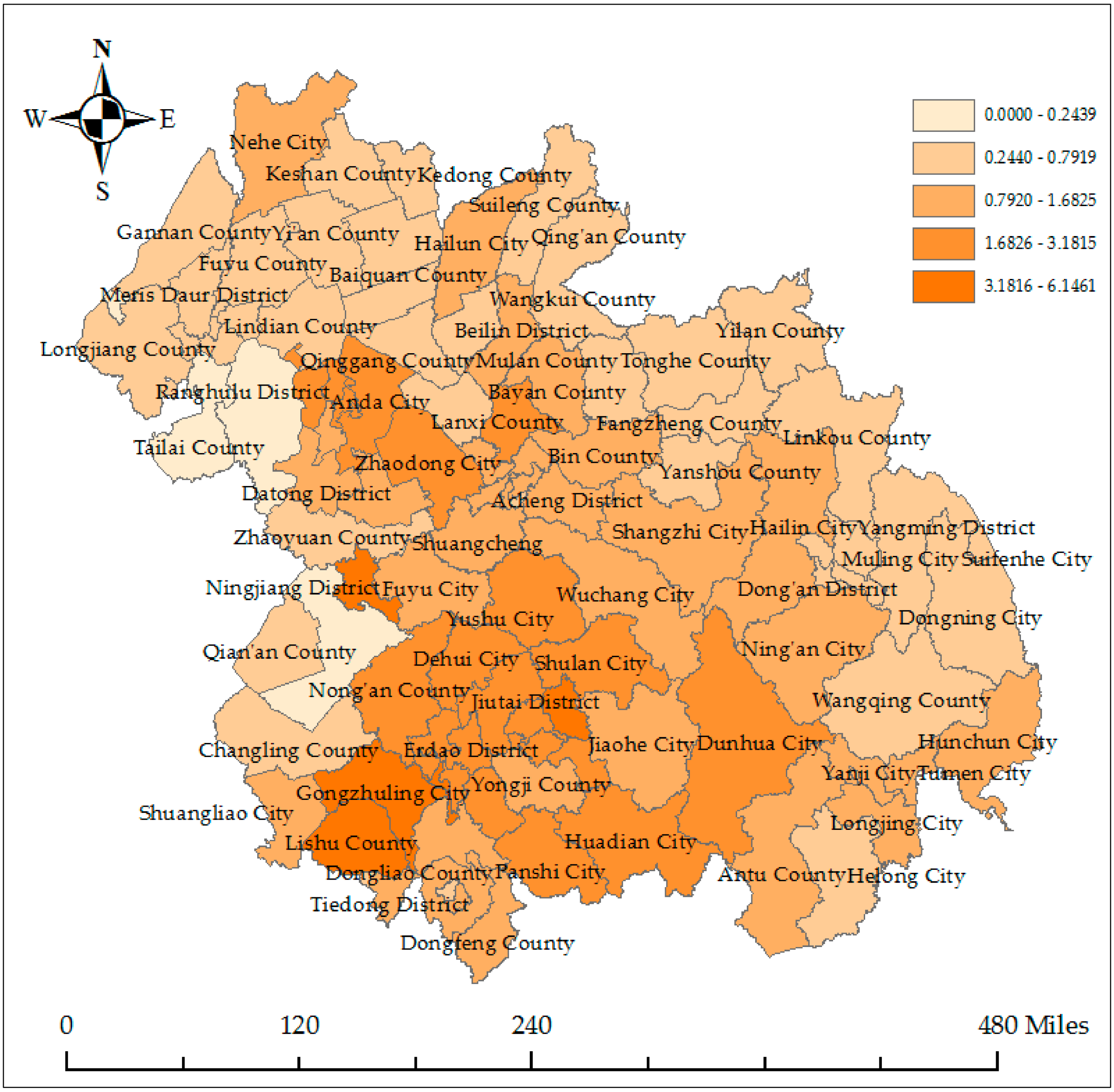
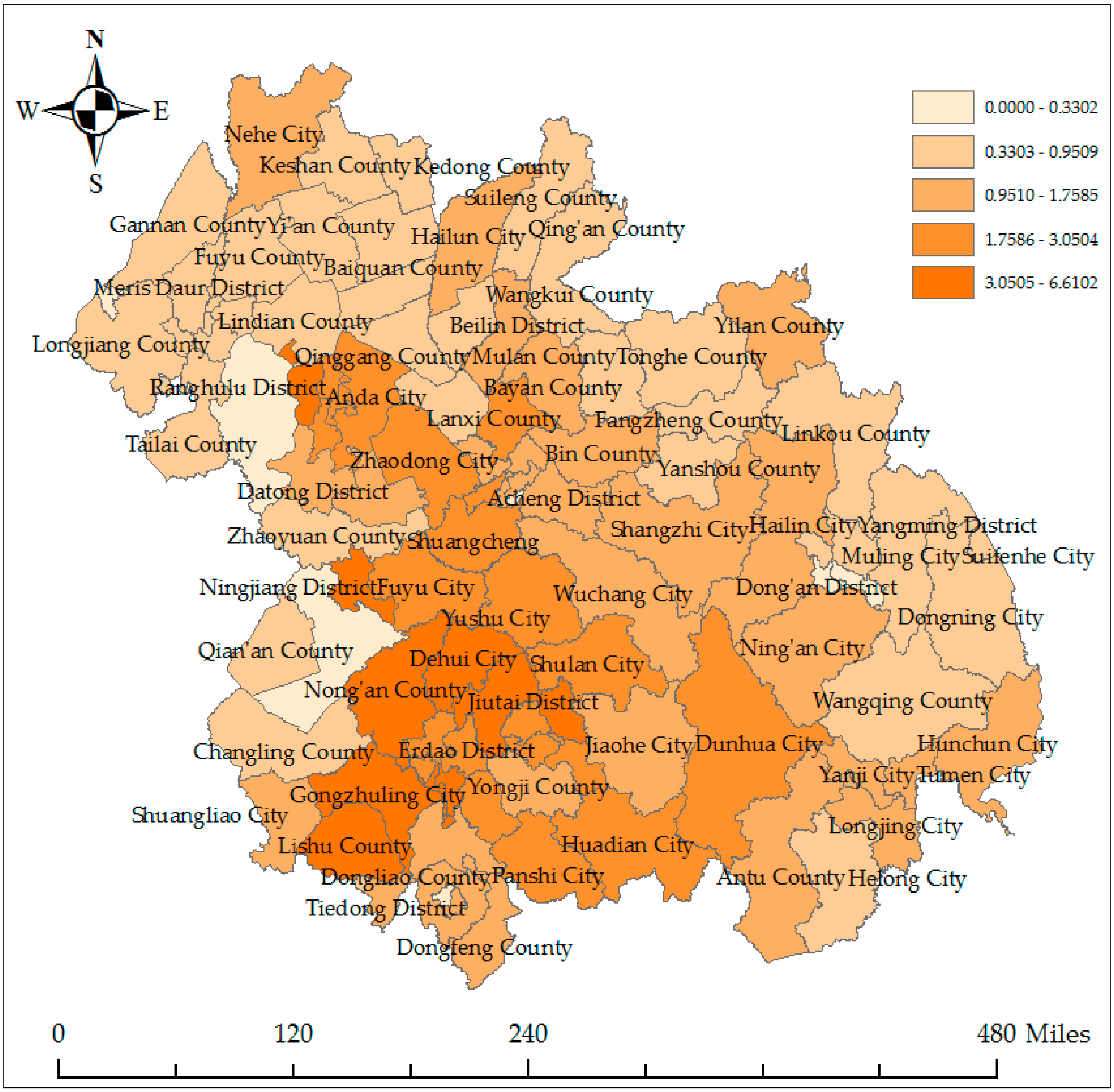
Conflicts of Interest: The author declares no conflict of interest.

Appendix A. The Spatial Distribution of the Carbon Emissions in Harbin–Changchun Urban Agglomeration in 1997



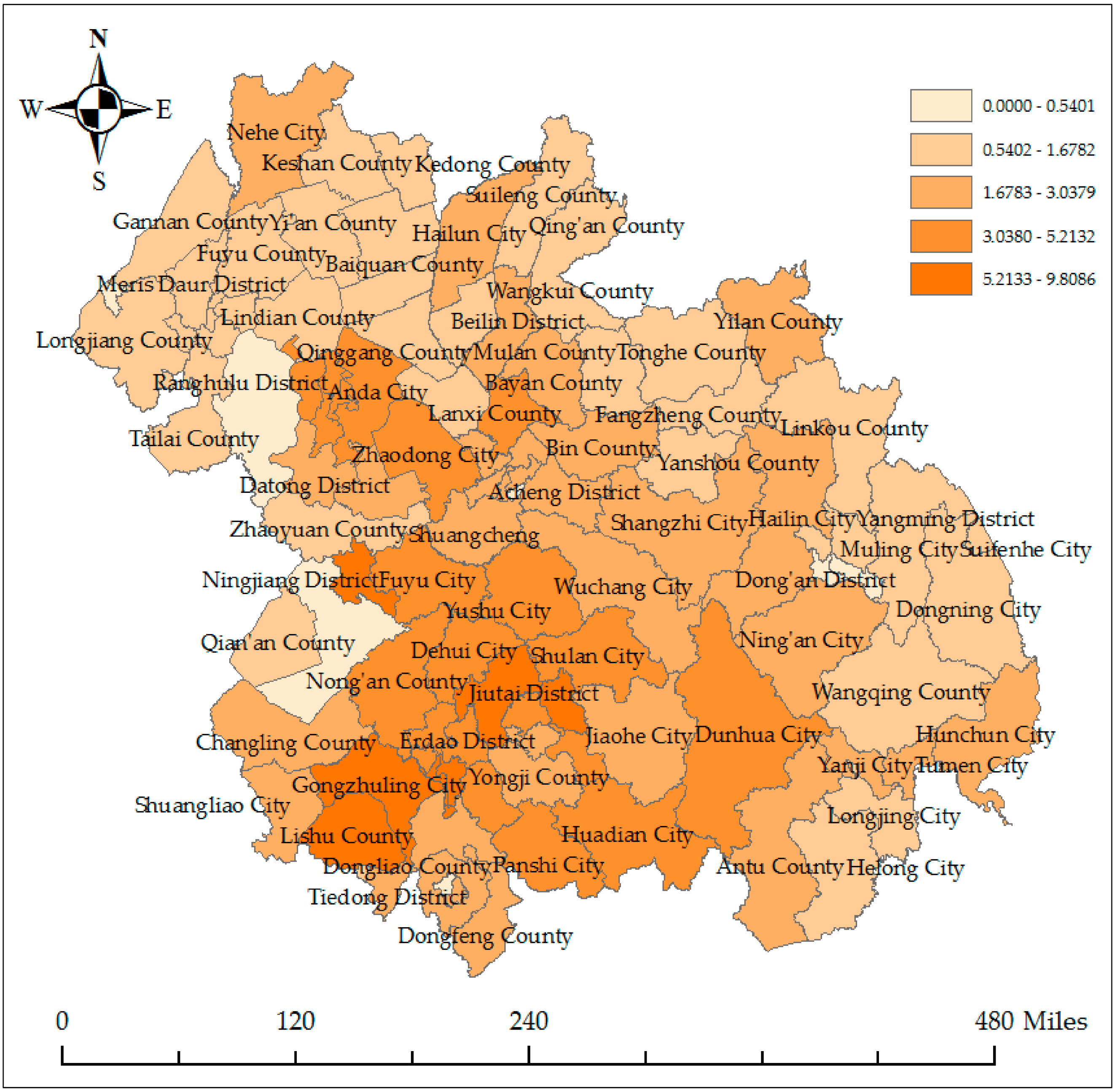
(**a**)

Figure A1. *Cont.*



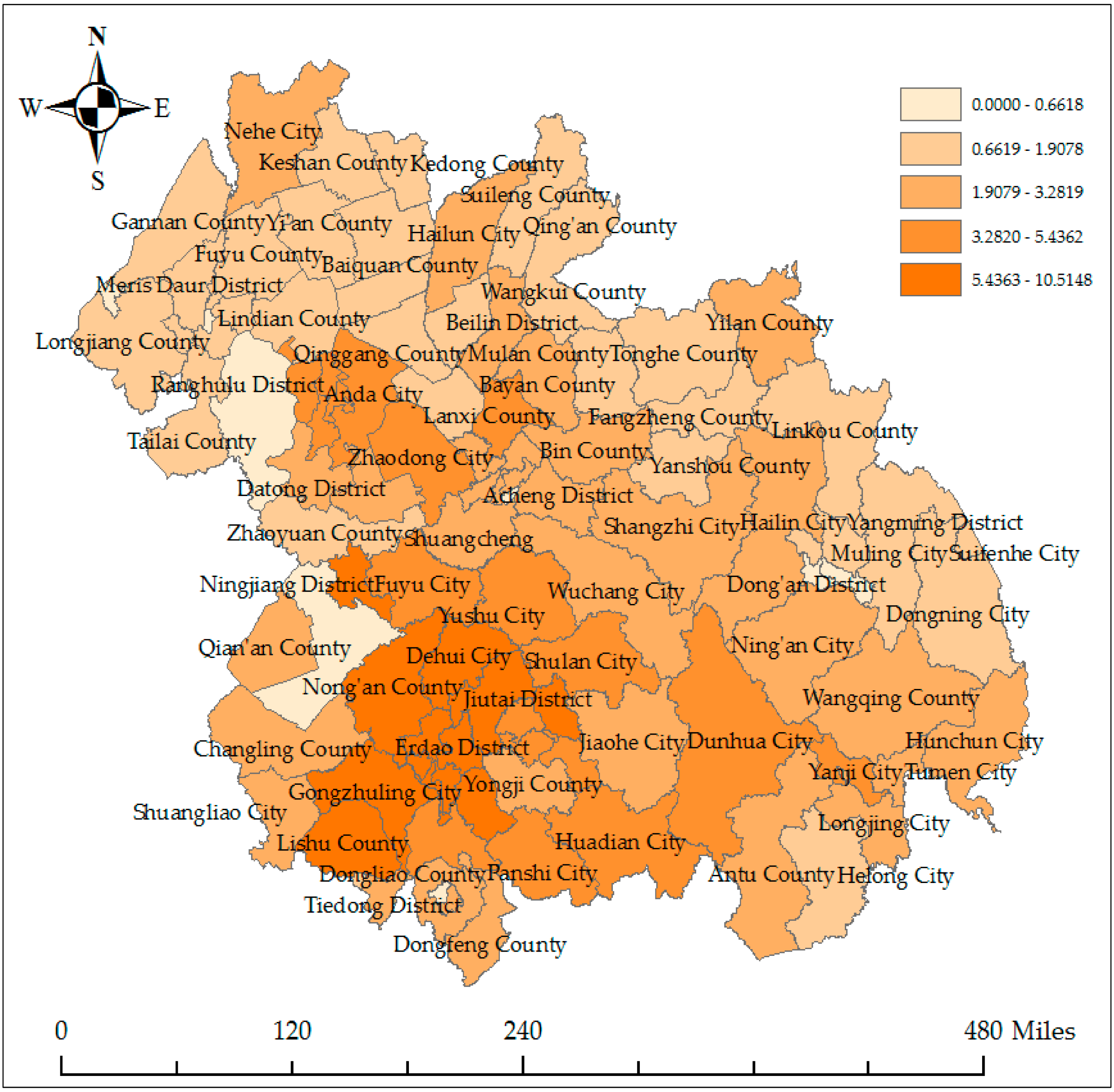
(**b**)

Figure A1. *Cont.*



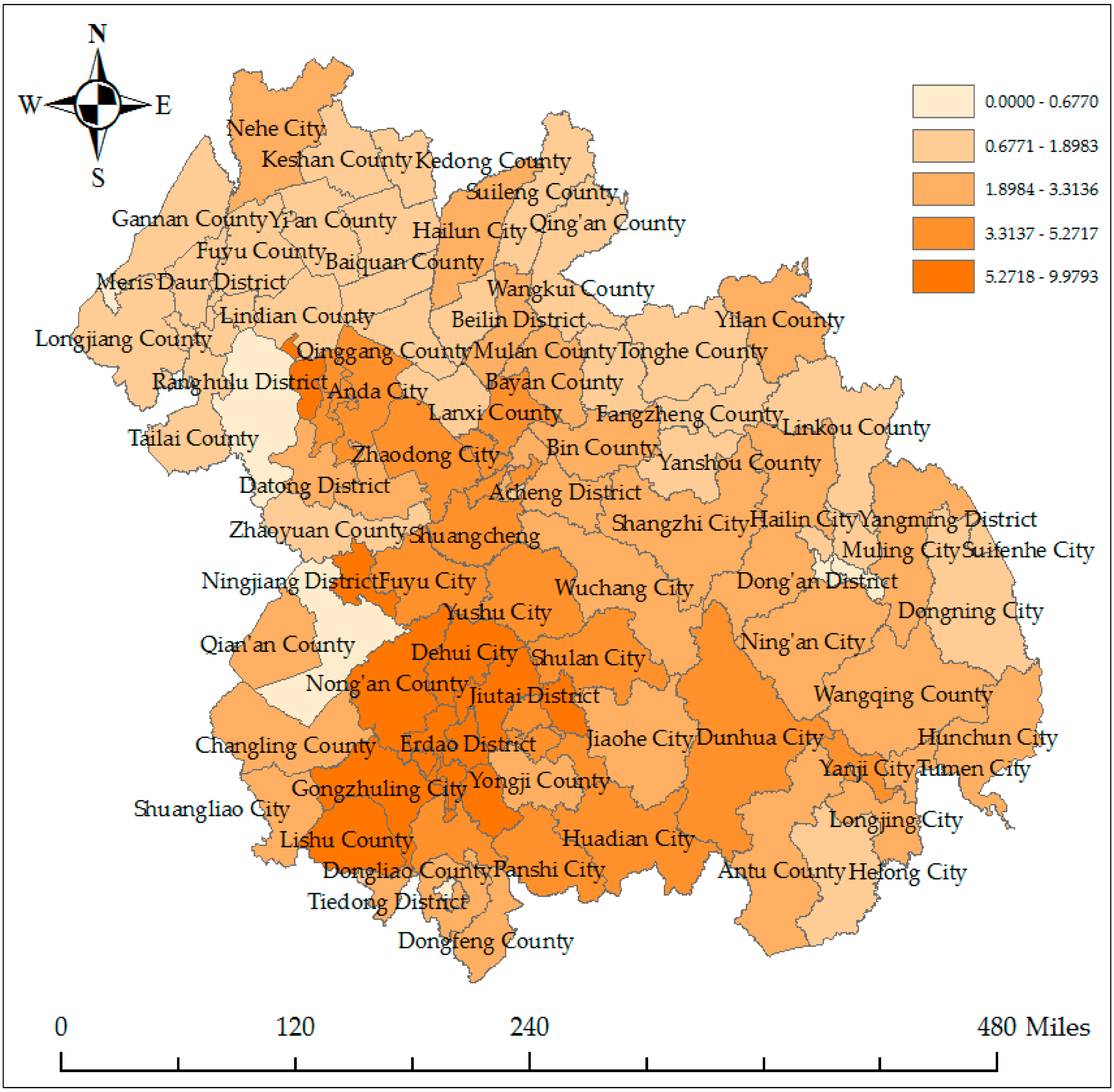
(c)

Figure A1. *Cont.*



(**d**)

Figure A1. *Cont.*



(e)

Figure A1. The spatial distribution of the carbon emissions in Harbin–Changchun urban agglomeration: (**a**) 1997; (**b**) 2002; (**c**) 2007; (**d**) 2012; (**e**) 2017.

Appendix B. Establish the Spatial Weight Matrix

The spatial weight matrix is the basis for analyzing the spatial distribution of carbon emissions in the Harbin–Changchun urban agglomeration by using spatial autocorrelation. Its purpose is to define the adjacent relations. The spatial weight matrix shows the degree of influence of a county on nearby counties. This paper has adopted a binary symmetrical spatial weight matrix $W_{103\times103}$ to represent the spatial adjacent relations among 103 counties, which is Equation (A1) below:

$$W_{103\times103} = \begin{bmatrix} w_{1,1} & \cdots & w_{1,103} \\ \vdots & \vdots & \vdots \\ w_{103,1} & \cdots & w_{103,103} \end{bmatrix} \quad \text{(A1)}$$

in which w_{ij} $(i = 1,2,\ldots,103; j = 1,2,\ldots,103)$ represents the spatial weight of the ith county and the jth county. There are many methods for the establishment of spatial weight matrixes, and this paper uses the Euclidean distance d_{ij} $(i = 1,2,\ldots,103; j = 1,2,\ldots,103)$ between two points to determine the weight.

Step 1: Calculate the Euclidean distance d_{ij}, as shown in Equation (A2) below:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}, i = 1,2,\ldots,103; j = 1,2,\ldots,103 \quad \text{(A2)}$$

Step 2: Construct weight matrixes based on different situations. When $i \neq j$, the spatial weight w_{ij} is determined by using the reciprocal of the distance, as shown in Equation (A3) below:

$$w_{ij} = w_{ji} = \frac{1}{d_{ij}}, i = 1,2,\ldots,103; j = 1,2,\ldots,103 \quad \text{(A3)}$$

in which when $i = j$, $w_{ij} = 0$.

Appendix C

Table A1. The global Moran's *I* indexes of the Harbin–Changchun urban agglomeration from 1997 to 2017.

Year	The Global Moran's *I* Indexes
1997	0.4852
1998	0.4831
1999	0.4928
2000	0.5071
2001	0.5067
2002	0.5022
2003	0.5065
2004	0.5083
2005	0.5114
2006	0.5143
2007	0.5202
2008	0.5236
2009	0.5237
2010	0.5389
2011	0.5724
2012	0.5687
2013	0.5089
2014	0.5127
2015	0.5145
2016	0.5111
2017	0.5527

Table A2. The local Moran's *I* indexes of the Harbin–Changchun urban agglomeration from 1997 to 2007.

	1997	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Nanguan District	1.1472	1.1229	1.2333	1.7679	1.9064	1.8735	1.9701	1.9629	1.9984	2.0023	2.0497
Kuancheng District	1.4101	1.4195	1.5842	1.7003	1.6623	1.5881	1.5579	1.5403	1.5182	1.4775	1.5026
Chaoyang District	0.5172	0.4594	0.4206	0.5652	0.5582	0.5418	0.6803	0.6722	0.6660	0.6462	0.6425
Erdao District	2.1768	2.1643	2.1903	2.3354	2.3161	2.2385	2.2513	2.2349	2.2592	2.2968	2.2516
Green Park	2.0109	2.0496	2.2101	2.5766	2.5501	2.4561	2.4430	2.4449	2.4114	2.3607	2.4119
Shuangyang District	0.9306	0.8921	0.8689	0.9104	0.9175	0.8793	0.8944	0.8898	0.9022	0.9671	1.0225
Jiutai District	2.6626	2.6197	2.5774	2.5189	2.4771	2.4075	2.4321	2.4606	2.8466	3.1332	3.2639
Nong'an County	3.7080	3.7104	3.7266	3.6664	3.6161	3.5145	3.4446	3.4404	3.4692	3.4202	3.3435
Yushu City	0.5579	0.5671	0.5345	0.4763	0.4652	0.4546	0.4565	0.4500	0.4720	0.4947	0.5030
Dehui City	2.3409	2.3463	2.3499	2.2625	2.2295	2.1819	2.1596	2.1812	2.2841	2.3136	2.2852
Changyi District	0.8172	0.7713	0.8110	0.7654	0.7325	0.6916	0.7200	0.7752	0.7729	0.7562	0.7698
Longtan District	2.1984	2.1211	2.1073	1.9698	1.9088	1.8486	1.8247	1.8385	1.8747	1.8845	1.8566
Ship camp area	0.6130	0.5577	0.5429	0.4922	0.4675	0.5202	0.5114	0.5260	0.5120	0.4893	0.4821
Fengman District	0.6664	0.6206	0.5963	0.5781	0.5614	0.5357	0.5189	0.5145	0.5070	0.4968	0.4572
Yongji County	−0.1160	−0.1421	−0.1515	−0.1732	−0.1588	−0.1747	−0.1940	−0.2047	−0.2043	−0.2178	−0.2512
Jiaohe City	−0.2824	−0.2801	−0.2455	−0.2303	−0.2239	−0.2360	−0.2263	−0.2177	−0.2188	−0.2054	−0.1340
Huadian City	0.1935	0.1788	0.1758	0.1567	0.1507	0.1380	0.1361	0.1341	0.1391	0.1430	0.1607
Shulan City	0.8738	0.8730	0.8456	0.7278	0.7046	0.6631	0.6393	0.6309	0.6224	0.6045	0.5644
Panshi City	0.1166	0.0956	0.0789	0.0526	0.0481	0.0381	0.0344	0.0316	0.0311	0.0346	0.0373
Tiexi District	−0.4386	−0.4552	−0.4600	−0.4335	−0.4388	−0.4412	−0.4420	−0.4427	−0.4335	−0.4269	−0.4112
Tiedong District	−0.0062	−0.0116	−0.0181	−0.0168	−0.0119	−0.0107	−0.0091	−0.0090	−0.0098	−0.0110	−0.0135
Lishu County	1.6621	1.5647	1.5013	1.3565	1.3159	1.2366	1.2132	1.1971	1.1363	1.0657	0.9989
Yitong Manchu Autonomous County	0.2486	0.2137	0.1929	0.1434	0.1368	0.1151	0.1046	0.0975	0.0887	0.0759	0.0797
Gongzhuling City	4.1096	4.0099	4.0441	4.0850	4.0603	3.9234	3.9010	3.8767	3.7765	3.6419	3.5585
Shuangliao City	0.4887	0.4313	0.4571	0.3640	0.3464	0.3046	0.2944	0.2868	0.2626	0.2343	0.1821
Longshan District	0.0604	0.0790	0.0963	0.1283	0.1372	0.1566	0.1632	0.1638	0.1624	0.1554	0.1681
Xi'an District	−0.0904	−0.0556	−0.0259	0.0162	0.0223	0.0499	0.0548	0.0576	0.0610	0.0620	0.0788
Dongfeng County	−0.0180	−0.0116	−0.0039	0.0202	0.0260	0.0348	0.0373	0.0384	0.0401	0.0417	0.0426
Dongliao County	0.0486	0.0689	0.0863	0.1288	0.1376	0.1581	0.1657	0.1673	0.1697	0.1729	0.1904
Ningjiang District	0.0867	0.1328	0.1716	0.2043	0.1954	0.1778	0.1968	0.2137	0.2635	0.3333	0.4601
Changling County	0.0989	0.1192	0.1009	0.1262	0.1272	0.1328	0.1319	0.1289	0.1068	0.0833	0.0558
Qian'an County	−0.7776	−0.7806	−0.7201	−0.7102	−0.7081	−0.7072	−0.7027	−0.7057	−0.6914	−0.5949	−0.4891
Fuyu City	0.4841	0.5077	0.4971	0.4760	0.4672	0.4458	0.4545	0.4646	0.4717	0.5010	0.5745
Yanji City	−0.0560	−0.0452	−0.0389	−0.0573	−0.0496	−0.0542	−0.0525	−0.0518	−0.0450	−0.0484	−0.0737
Tumen City	0.0426	0.0523	0.0632	0.0607	0.0669	0.0697	0.0738	0.0760	0.0750	0.0756	0.0614
Dunhua City	−0.2454	−0.2532	−0.2244	−0.2388	−0.2355	−0.2451	−0.2353	−0.2263	−0.2325	−0.2196	−0.1471
Hunchun City	−0.0431	−0.0309	−0.0146	0.0131	0.0210	0.0336	0.0400	0.0419	0.0166	0.0090	−0.0255
Longjing	0.0946	0.1115	0.1244	0.1066	0.1141	0.1194	0.1223	0.1251	0.1270	0.1276	0.1214
Helong	0.1494	0.1673	0.1844	0.1674	0.1776	0.1869	0.1889	0.1922	0.1892	0.1853	0.1725
Wangqing County	0.0196	0.0335	0.0505	0.0400	0.0487	0.0536	0.0595	0.0622	0.0591	0.0589	0.0398
Antu County	0.1608	0.1637	0.1853	0.1898	0.1979	0.2073	0.2079	0.2117	0.2022	0.1999	0.1836
Daoli District	−0.0043	−0.0052	−0.0055	−0.0225	−0.0340	−0.0290	−0.0260	−0.0227	−0.0229	−0.0219	−0.0228
Nangang District	0.0289	0.0289	0.0323	0.0289	0.0262	0.0246	0.0248	0.0243	0.0302	0.0321	0.0380
Daowai District	−0.0007	0.0002	0.0000	0.0000	−0.0001	−0.0001	−0.0005	−0.0011	−0.0023	−0.0026	−0.0028
Bungalow area	−0.1092	−0.1178	−0.1120	−0.1319	−0.1452	−0.1600	−0.1626	−0.1659	−0.1447	−0.1372	−0.1193
Songbei District	0.0001	0.0002	0.0003	0.0001	−0.0002	0.0020	0.0039	0.0092	0.0076	0.0066	0.0041
Xiangfang District	−0.0129	−0.0130	−0.0155	−0.0185	−0.0209	−0.0246	−0.0229	−0.0210	−0.0181	−0.0165	−0.0124
Hulan District	−0.0743	−0.0652	−0.0658	−0.0624	−0.0592	−0.0691	−0.0789	−0.0783	−0.0941	−0.1006	−0.1104
Acheng District	−0.0050	−0.0036	−0.0070	−0.0048	−0.0013	0.0027	0.0042	0.0051	0.0027	0.0011	−0.0023
Shuangcheng	0.0144	0.0202	0.0185	0.0254	0.0294	0.0320	0.0328	0.0347	0.0285	0.0296	0.0298
Yilan County	0.4380	0.3679	0.3187	0.3024	0.3130	0.2806	0.2647	0.2546	0.2343	0.2237	0.1637
Fangzheng County	0.5903	0.5382	0.4732	0.4924	0.5020	0.5102	0.5151	0.5170	0.5132	0.5084	0.4879
Bin County	0.0272	0.0242	0.0279	0.0267	0.0196	0.0206	0.0190	0.0196	0.0115	0.0142	0.0149
Bayan County	−0.0094	−0.0206	−0.0205	−0.0183	−0.0161	−0.0128	−0.0106	−0.0089	−0.0057	−0.0046	−0.0055
Mulan County	0.1252	0.0877	0.0732	0.0859	0.0834	0.0706	0.0602	0.0605	0.0480	0.0490	0.0387
Tonghe County	0.6691	0.6217	0.5304	0.5469	0.5578	0.5639	0.5686	0.5728	0.5647	0.5506	0.5127
Yanshou County	0.3055	0.2758	0.2687	0.2751	0.2709	0.2775	0.2795	0.2815	0.2741	0.2835	0.2744
Shangzhi	0.0450	0.0288	0.0360	0.0357	0.0391	0.0362	0.0357	0.0378	0.0407	0.0483	0.0397
Wuchang City	0.0639	0.0828	0.0733	0.0666	0.0623	0.0561	0.0550	0.0520	0.0497	0.0441	0.0426

Table A2. *Cont.*

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Longsha District	0.8353	0.8814	0.9013	0.9498	0.9599	0.9716	0.9822	0.9937	1.0053	1.0144	1.0503
Jianhua District	0.7399	0.7821	0.7943	0.8460	0.8545	0.8569	0.8664	0.8769	0.8893	0.8957	0.9271
Tiefeng District	0.6035	0.6318	0.6351	0.6614	0.6578	0.6353	0.6380	0.6470	0.6590	0.6625	0.6943
Ang'angxi District	0.7344	0.7696	0.7815	0.8006	0.8047	0.7994	0.8070	0.8180	0.8316	0.8375	0.8681
Fularki District	0.5800	0.6172	0.6388	0.6851	0.7009	0.7113	0.7233	0.7362	0.7541	0.7666	0.8041
Nianzishan District	1.0104	1.0550	1.0687	1.1210	1.1321	1.1361	1.1452	1.1544	1.1585	1.1665	1.2049
Meris Daur District	0.7199	0.7575	0.7694	0.8035	0.7895	0.7720	0.7776	0.7815	0.7899	0.7902	0.8216
Longjiang County	0.8093	0.8425	0.8434	0.8316	0.8426	0.8416	0.8417	0.8489	0.8500	0.8584	0.8861
Yi'an County	0.7358	0.7453	0.7452	0.7759	0.7625	0.7493	0.7515	0.7441	0.7357	0.7311	0.7629
Tailai County	0.9439	0.9792	0.9952	0.9321	0.9054	0.8973	0.8943	0.8939	0.8744	0.8808	0.8702
Gannan County	0.7187	0.7093	0.7034	0.7501	0.7213	0.6550	0.6586	0.6455	0.6235	0.6141	0.6388
Fuyu County	0.7581	0.7828	0.7772	0.7956	0.7613	0.7084	0.7015	0.6967	0.6910	0.6866	0.7111
Keshan County	0.4438	0.4344	0.4445	0.4935	0.4934	0.4819	0.4854	0.4834	0.4816	0.4801	0.5133
Kedong County	0.5081	0.4946	0.4927	0.5313	0.5304	0.5341	0.5410	0.5401	0.5508	0.5475	0.5727
Baiquan County	0.6860	0.6675	0.6696	0.7049	0.7006	0.7045	0.7041	0.6884	0.6910	0.6829	0.7062
Nehe	0.1360	0.0895	0.0966	0.1285	0.1145	0.0984	0.0869	0.0784	0.0529	0.0465	0.0710
Sartu District	0.3422	0.3827	0.4710	0.5252	0.5857	0.7500	0.7805	0.7779	0.7219	0.7244	0.6863
Longfeng District	0.2975	0.3430	0.4223	0.4788	0.5112	0.6104	0.6546	0.6562	0.6236	0.6196	0.5894
Ranghulu District	0.3275	0.3717	0.4741	0.5659	0.6306	0.8148	0.8499	0.8455	0.7771	0.7745	0.7254
Honggang District	0.2309	0.2737	0.3335	0.4735	0.5041	0.5843	0.6012	0.6094	0.5696	0.5775	0.5616
Datong District	−0.0478	−0.0365	−0.0186	0.0234	0.0372	0.0684	0.0825	0.0811	0.0681	0.0684	0.0558
Zhaozhou County	−0.1668	−0.1356	−0.1234	−0.1168	−0.1224	−0.1189	−0.1138	−0.1015	−0.0704	−0.0474	0.0077
Zhaoyuan County	−0.4936	−0.5085	−0.4942	−0.4610	−0.4561	−0.4610	−0.4455	−0.4499	−0.4466	−0.4426	−0.4564
Lindian County	0.1860	0.1833	0.1531	0.1413	0.1209	0.0778	0.0701	0.0711	0.0824	0.0836	0.1009
Dong'an District	0.7520	0.7967	0.8245	0.8505	0.8737	0.9084	0.9246	0.9398	0.9549	0.9704	1.0074
Yangming District	0.6260	0.6646	0.6894	0.7202	0.7410	0.7713	0.7854	0.7989	0.8151	0.8301	0.8652
Aimin District	0.5224	0.5567	0.5802	0.6076	0.6285	0.6560	0.6693	0.6814	0.6980	0.7113	0.7359
Xi'an District	0.7241	0.7686	0.7956	0.8246	0.8479	0.8822	0.8980	0.9127	0.9270	0.9417	0.9762
Linkou County	0.1326	0.1372	0.1488	0.1198	0.1280	0.1368	0.1394	0.1419	0.1544	0.1638	0.1746
Suifenhe	0.7718	0.8018	0.8239	0.8350	0.8485	0.8450	0.8463	0.8492	0.8376	0.8256	0.7785
Hailin	0.1979	0.2084	0.2246	0.1920	0.2062	0.2201	0.2252	0.2303	0.2493	0.2616	0.2738
Ning'an	0.0972	0.1080	0.1283	0.0367	0.0481	0.0615	0.0722	0.0808	0.0971	0.1114	0.1373
Muling City	0.4701	0.4813	0.5063	0.5064	0.5241	0.5441	0.5565	0.5675	0.5772	0.5896	0.6139
Dongning City	0.7629	0.7939	0.8131	0.8197	0.8309	0.8347	0.8357	0.8398	0.8285	0.8226	0.7857
Beilin District	−0.0397	−0.0482	−0.0454	−0.0449	−0.0484	−0.0581	−0.0540	−0.0509	−0.0442	−0.0440	−0.0411
Wangkui County	0.2384	0.1891	0.1925	0.1923	0.1849	0.1768	0.1776	0.1760	0.1790	0.1809	0.1784
Lanxi County	−0.0585	−0.0710	−0.0743	−0.0846	−0.0908	−0.1093	−0.1187	−0.1275	−0.1259	−0.1252	−0.1208
Qinggang County	0.1857	0.1490	0.1330	0.1317	0.1193	0.0924	0.0837	0.0806	0.0883	0.0891	0.0961
Qing'an County	0.2940	0.2415	0.2277	0.2227	0.2182	0.2154	0.2211	0.2263	0.2395	0.2430	0.2628
Mingshui County	0.5393	0.5108	0.5009	0.4974	0.4777	0.4618	0.4566	0.4433	0.4425	0.4377	0.4420
Suileng County	0.4650	0.4051	0.3845	0.3764	0.3666	0.3695	0.3745	0.3789	0.3933	0.3963	0.4244
Anda City	0.1750	0.2097	0.2546	0.2992	0.3203	0.3965	0.4329	0.4409	0.4277	0.4261	0.4075
Zhaodong City	0.0103	0.0296	0.0371	0.0577	0.0630	0.0811	0.0915	0.1012	0.0974	0.0990	0.0994
Hailun City	0.2666	0.2200	0.2107	0.2011	0.1810	0.1750	0.1743	0.1703	0.1796	0.1758	0.1919

Table A3. The local Moran's *I* indexes of the Harbin–Changchun urban agglomeration from 2008 to 2017.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Nanguan District	2.0534	2.1459	2.2621	2.5088	2.4225	2.0186	2.1763	2.2697	2.2862	2.9442
Kuancheng District	1.5671	1.6855	2.1242	2.3795	2.5288	2.0948	2.2516	2.8109	2.8981	3.8136
Chaoyang District	0.6229	0.6798	0.8125	1.0219	0.9455	0.6462	0.7722	0.7828	0.7314	0.9955
Erdao District	2.2452	2.3231	2.3827	2.6291	2.5453	2.1079	2.2886	2.3878	2.4711	3.3565
Green Park	2.4558	2.5175	2.7235	2.9061	2.8244	2.3677	2.4941	2.9599	2.9399	3.6616
Shuangyang District	1.0957	1.1530	1.2484	1.4911	1.4483	1.0870	1.1369	1.0968	1.1356	1.4871
Jiutai District	3.3477	3.3334	3.5439	3.9332	3.9719	3.3809	3.3515	3.1254	3.0152	3.4565
Nong'an County	3.3543	3.3263	3.4882	3.7594	3.8796	3.4048	3.3435	3.1599	3.0129	3.4014

Table A3. *Cont.*

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Yushu City	0.5081	0.4796	0.5055	0.6062	0.6256	0.5731	0.5291	0.4283	0.3843	0.3827
Dehui City	2.2871	2.2236	2.3912	2.6224	2.6621	2.2185	2.1481	1.9383	1.8899	2.1927
Changyi District	0.7520	0.7388	0.7981	0.9338	0.8649	0.5537	0.5354	0.4544	0.4197	0.6427
Longtan District	1.8821	1.8361	1.8707	2.1707	2.1225	1.6213	1.6361	1.4386	1.3563	1.6459
Ship camp area	0.4669	0.4658	0.5212	0.6438	0.6017	0.3484	0.3475	0.3802	0.4300	0.6355
Fengman District	0.4538	0.4728	0.5213	0.6654	0.6450	0.4066	0.3954	0.3118	0.2898	0.3904
Yongji County	−0.2631	−0.2918	−0.3083	−0.1603	−0.1213	−0.2918	−0.2903	−0.3408	−0.3695	−0.2853
Jiaohe City	−0.0990	−0.1252	−0.1347	−0.0620	−0.0976	−0.2386	−0.2508	−0.2841	−0.2965	−0.2398
Huadian City	0.1918	0.2048	0.2150	0.3284	0.3090	0.1509	0.1331	0.0759	0.0550	0.1004
Shulan City	0.5635	0.5178	0.5008	0.6976	0.7335	0.5062	0.4696	0.3465	0.2889	0.3696
Panshi City	0.0544	0.0587	0.0734	0.1887	0.1909	0.0406	0.0423	0.0049	0.0005	0.0578
Tiexi District	−0.4128	−0.4004	−0.3803	−0.3916	−0.3809	−0.3817	−0.3855	−0.3439	−0.3185	−0.3300
Tiedong District	−0.0132	−0.0133	−0.0177	−0.0123	−0.0175	−0.0114	−0.0110	0.0043	0.0136	−0.0132
Lishu County	0.9812	0.9385	0.9872	1.2104	1.1682	0.8092	0.7998	0.6725	0.5812	0.7732
Yitong Manchu Autonomous County	0.1223	0.1467	0.2061	0.3984	0.3755	0.1982	0.1864	0.1288	0.1032	0.1864
Gongzhuling City	3.5228	3.5171	3.6880	4.0480	4.0831	3.4750	3.5325	3.4528	3.2950	3.8554
Shuangliao City	0.1669	0.1339	0.1297	0.2418	0.1912	−0.0105	−0.0072	−0.0734	−0.0883	0.0004
Longshan District	0.1692	0.1837	0.1739	0.0846	0.0866	0.2188	0.1641	0.1610	0.1585	0.0845
Xi’an District	0.0748	0.0900	0.0707	−0.0791	−0.0717	0.1415	0.1043	0.1496	0.1493	0.0089
Dongfeng County	0.0380	0.0491	0.0467	0.0057	0.0084	0.0820	0.0786	0.1089	0.1192	0.0592
Dongliao County	0.1942	0.2102	0.1984	0.1035	0.1028	0.2455	0.2223	0.2497	0.2402	0.1480
Ningjiang District	0.5236	0.5319	0.5472	0.6191	0.6251	0.5260	0.4704	0.3524	0.2935	0.3273
Changling County	0.0414	0.0418	0.0319	−0.0003	−0.0018	0.0548	0.0578	0.0970	0.1149	0.0526
Qian’an County	−0.4226	−0.3973	−0.3620	−0.2434	−0.1657	−0.2943	−0.3077	−0.3538	−0.3827	−0.3553
Fuyu City	0.6217	0.6094	0.6184	0.7207	0.6831	0.5539	0.5196	0.4224	0.3756	0.4470
Yanji City	−0.0724	−0.0834	−0.1020	−0.1174	−0.1172	−0.0865	−0.0849	−0.0600	−0.0486	−0.0854
Tumen City	0.0602	0.0663	0.0618	0.0161	0.0173	0.0935	0.1080	0.1540	0.1692	0.0873
Dunhua City	−0.1072	−0.1348	−0.1411	−0.0656	−0.1061	−0.2733	−0.2784	−0.3036	−0.3081	−0.2451
Hunchun City	−0.0339	−0.0248	−0.0235	−0.0440	−0.0462	0.0092	0.0215	0.0700	0.0959	0.0332
Longjing	0.1222	0.1313	0.1231	0.0521	0.0527	0.1422	0.1543	0.2017	0.2190	0.1278
Helong	0.1667	0.1716	0.1546	0.0452	0.0400	0.1579	0.1702	0.2328	0.2602	0.1480
Wangqing County	0.0405	0.0451	0.0418	0.0127	0.0128	0.0665	0.0815	0.1192	0.1345	0.0824
Antu County	0.1690	0.1671	0.1470	0.0245	0.0140	0.1180	0.1318	0.1919	0.2204	0.1237
Daoli District	−0.0245	−0.0225	−0.0249	−0.0066	−0.0085	−0.0195	−0.0257	−0.0055	0.0201	−0.0631
Nangang District	0.0483	0.0488	0.0593	0.1215	0.1166	0.0416	0.0313	−0.0026	−0.0146	0.0046
Daowai District	−0.0005	−0.0008	0.0041	0.0454	0.0440	−0.0023	−0.0026	0.0030	0.0062	−0.0045
Bungalow area	−0.0874	−0.0873	−0.0541	0.1048	0.0971	−0.1252	−0.1412	−0.2531	−0.3054	−0.1446
Songbei District	0.0001	−0.0001	−0.0055	0.0029	0.0005	0.0040	0.0082	0.0530	0.0783	0.0145
Xiangfang District	−0.0098	−0.0079	−0.0005	0.0477	0.0482	−0.0048	−0.0063	−0.0083	−0.0079	−0.0203
Hulan District	−0.1212	−0.1170	−0.1217	−0.1277	−0.1281	−0.1112	−0.1000	−0.0444	−0.0187	−0.0699
Acheng District	−0.0068	−0.0072	−0.0108	−0.0034	−0.0049	−0.0007	0.0021	0.0235	0.0349	0.0023
Shuangcheng	0.0226	0.0217	0.0144	−0.0046	−0.0051	0.0353	0.0404	0.0771	0.0919	0.0293
Yilan County	0.1388	0.1318	0.1511	0.2233	0.2196	0.1009	0.1216	0.1215	0.1273	0.2219
Fangzheng County	0.4859	0.4830	0.4846	0.5026	0.4997	0.4680	0.4846	0.4899	0.4949	0.5268
Bin County	0.0223	0.0191	0.0315	0.0901	0.0880	0.0117	0.0187	0.0152	0.0146	0.0611
Bayan County	−0.0046	−0.0057	−0.0029	0.0377	0.0385	−0.0061	−0.0039	−0.0029	−0.0018	0.0214
Mulan County	0.0509	0.0450	0.0776	0.2103	0.2093	0.0312	0.0554	0.0455	0.0481	0.1895
Tonghe County	0.5004	0.5010	0.5056	0.5289	0.5259	0.5011	0.5178	0.5241	0.5293	0.5564
Yanshou County	0.2839	0.2792	0.2986	0.3665	0.3629	0.2660	0.2874	0.2890	0.2944	0.3729
Shangzhi	0.0413	0.0394	0.0564	0.1283	0.1213	0.0306	0.0430	0.0422	0.0455	0.1183
Wuchang City	0.0333	0.0292	0.0118	−0.0435	−0.0289	0.0723	0.0539	0.0481	0.0414	−0.0155
Longsha District	1.0656	1.0855	1.0711	1.0039	1.0131	1.1563	0.9869	0.8681	0.8048	0.7472
Jianhua District	0.9370	0.9575	0.9512	0.9098	0.9174	1.0243	0.9465	0.8626	0.8142	0.7703
Tiefeng District	0.7046	0.7214	0.7294	0.7318	0.7394	0.7781	0.7003	0.6630	0.6283	0.6203
Ang’angxi District	0.8847	0.9006	0.8960	0.8648	0.8731	0.9601	0.9053	0.8447	0.8002	0.7559
Fularki District	0.8284	0.8503	0.8539	0.8295	0.8367	0.9156	0.8765	0.7839	0.7672	0.7368
Nianzishan District	1.2157	1.2408	1.2140	1.1062	1.1094	1.2763	1.2315	1.1880	1.1707	1.0717
Meris Daur District	0.8302	0.8471	0.8412	0.8124	0.8148	0.8788	0.8312	0.7947	0.7728	0.7504
Longjiang County	0.8957	0.9143	0.8821	0.8057	0.7934	0.8421	0.8299	0.8062	0.7981	0.7699

Table A3. *Cont.*

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Yi'an County	0.7348	0.7419	0.7290	0.7002	0.6913	0.6190	0.6316	0.6366	0.6388	0.6455
Tailai County	0.8659	0.8760	0.8468	0.7680	0.7498	0.7609	0.7440	0.7125	0.7003	0.6826
Gannan County	0.6186	0.6278	0.6024	0.5918	0.5868	0.5354	0.5289	0.5155	0.5080	0.5389
Fuyu County	0.6783	0.6784	0.6654	0.6638	0.6674	0.6563	0.6430	0.6309	0.6188	0.6240
Keshan County	0.5071	0.5129	0.5226	0.5444	0.5369	0.4618	0.4781	0.4818	0.4838	0.5176
Kedong County	0.5574	0.5495	0.5529	0.5697	0.5652	0.5232	0.5389	0.5421	0.5400	0.5609
Baiquan County	0.6891	0.6857	0.6909	0.6759	0.6680	0.6402	0.6543	0.6614	0.6609	0.6619
Nehe	0.0663	0.0711	0.0918	0.1746	0.1687	−0.0205	0.0020	−0.0009	0.0036	0.1248
Sartu District	0.6469	0.6582	0.5452	0.1939	0.1959	0.7065	0.7606	1.0164	1.1622	0.5512
Longfeng District	0.5442	0.5538	0.4552	0.1603	0.1638	0.6072	0.6704	0.8596	0.9806	0.4491
Ranghulu District	0.6621	0.6683	0.5439	0.1515	0.1529	0.7121	0.7738	1.0739	1.2628	0.5618
Honggang District	0.5208	0.5290	0.4517	0.1566	0.1570	0.5786	0.6143	0.8396	0.9503	0.4337
Datong District	0.0375	0.0314	0.0111	−0.0415	−0.0407	0.0400	0.0334	0.0592	0.0658	−0.0441
Zhaozhou County	−0.0097	−0.0130	−0.0252	−0.0737	−0.0710	0.0080	−0.0105	0.0107	0.0155	−0.0640
Zhaoyuan County	−0.4456	−0.4345	−0.4133	−0.4115	−0.3951	−0.3935	−0.4012	−0.4153	−0.4277	−0.4495
Lindian County	0.1115	0.1137	0.1392	0.2392	0.2411	0.1030	0.0770	0.0167	−0.0216	0.0969
Dong'an District	1.0218	0.9950	0.9821	0.9151	0.9128	0.9939	0.9976	0.9926	0.9812	0.9206
Yangming District	0.8831	0.8646	0.8586	0.8115	0.8070	0.8538	0.8568	0.8372	0.8309	0.7974
Aimin District	0.7556	0.7494	0.7416	0.7292	0.7296	0.7560	0.7557	0.7186	0.6938	0.6811
Xi'an District	0.9952	0.9852	0.9701	0.9162	0.9159	0.9984	1.0022	0.9934	0.9828	0.9259
Linkou County	0.1702	0.1398	0.1304	0.1916	0.1804	0.0512	0.0673	0.0665	0.0709	0.1552
Suifenhe	0.8011	0.7523	0.7357	0.7106	0.6970	0.6999	0.7122	0.7157	0.7112	0.7056
Hailin	0.2613	0.2130	0.1937	0.2674	0.2522	0.0862	0.1102	0.1068	0.1117	0.2207
Ning'an	0.1727	0.1827	0.2019	0.2837	0.2614	0.1040	0.1313	0.1299	0.1363	0.2510
Muling City	0.6411	0.5195	0.5031	0.5201	0.5049	0.4307	0.4507	0.4497	0.4521	0.5065
Dongning City	0.8044	0.7644	0.7471	0.7172	0.7041	0.7115	0.7236	0.7287	0.7261	0.7165
Beilin District	−0.0427	−0.0483	−0.0399	0.0289	0.0297	−0.0490	−0.0454	−0.0503	−0.0530	0.0079
Wangkui County	0.1688	0.1597	0.1765	0.2513	0.2485	0.1550	0.1677	0.1624	0.1599	0.2345
Lanxi County	−0.1062	−0.1107	−0.0893	0.0263	0.0236	−0.1337	−0.1392	−0.1916	−0.2138	−0.1030
Qinggang County	0.0927	0.0878	0.1165	0.2172	0.2158	0.0757	0.0742	0.0470	0.0307	0.1459
Qing'an County	0.2705	0.2576	0.2721	0.3322	0.3270	0.2499	0.2650	0.2648	0.2664	0.3325
Mingshui County	0.4264	0.4226	0.4381	0.4805	0.4781	0.3845	0.3932	0.3792	0.3708	0.4361
Suileng County	0.4367	0.4170	0.4294	0.4653	0.4569	0.3972	0.4169	0.4217	0.4272	0.4798
Anda City	0.3705	0.3757	0.3004	0.0798	0.0818	0.4247	0.4314	0.5299	0.5831	0.2325
Zhaodong City	0.0775	0.0805	0.0521	−0.0361	−0.0336	0.1057	0.1109	0.1854	0.2139	0.0632
Hailun City	0.1992	0.1692	0.1803	0.2373	0.2284	0.1203	0.1388	0.1384	0.1419	0.2272

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