

# Examining the driving factors of industrial CO<sub>2</sub> emissions in Chinese cities using geographically weighted regression model

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## Research Article

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2     Examining the driving factors of industrial CO<sub>2</sub> emissions in Chinese  
3             cities using geographically weighted regression model

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9     **Abstract:** The industrial sector is the sector with the largest CO<sub>2</sub> emissions, and to reduce overall CO<sub>2</sub>  
10     emissions, analysis of the impact factors holds significance. Based on the 2015 industrial CO<sub>2</sub>  
11     emissions of 282 cities in China combined with economic and social data, and a geographically  
12     weighted regression (GWR) model, we analysed the characteristics of the spatial distribution of CO<sub>2</sub>  
13     emissions and the influencing factors of spatial heterogeneity. The results show that China's urban  
14     industrial CO<sub>2</sub> emissions present a significant spatial agglomeration state that includes Shandong,  
15     Beijing, Tianjin, Shanghai, Zhejiang, and Jiangsu, and the core of the coastal areas form a high-high  
16     (H-H) concentration; a low-low aggregation (L-L) is formed in less developed areas such as Guizhou,  
17     Yunnan, Sichuan and Guangxi. The influence of various factors on industrial CO<sub>2</sub> emissions has  
18     significant spatial heterogeneity. The Industrial scale, industry share of GDP, and share of the service  
19     industry in GDP are factors that promote industrial CO<sub>2</sub> emissions. The technological innovation,  
20     population density, and social investment in fixed assets are important factors that inhibit industrial  
21     CO<sub>2</sub> emissions, but their impact on industrial CO<sub>2</sub> emissions shows spatial differences. In contrast, the  
22     level of economic development, foreign direct investment, financial development and government  
23     intervention have a two-way impact on industrial CO<sub>2</sub> emissions.

24     **Keywords:** Industrial CO<sub>2</sub> Emissions; City-level; Geographically Weighted Regression; China  
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26  
27     **1. Introduction**

28             Rising concentrations of greenhouse gases in the atmosphere are the main cause of global  
29     warming, and CO<sub>2</sub> is the greatest greenhouse gas emitted. According to data released by the  
30     International Energy Agency (IEA), the total global CO<sub>2</sub> emissions in 2018 amounted to approximately  
31     33 billion tons, contributing up to 65% of the greenhouse effect. In particular, with the development of  
32     the global economy, the total amount of CO<sub>2</sub> emissions has been maintained at a high level. CO<sub>2</sub>  
33     emissions from the industrial sector are the major source of CO<sub>2</sub> emissions. Based on the estimation of  
34     IEA, in 2016, industrial CO<sub>2</sub> emissions (ICEs) accounted for 36% of energy CO<sub>2</sub> emissions globally,  
35     ranking first among all sectors and being far higher than construction (27%) and transportation (25%)  
36     (IEA 2018). At the same time, as China continues to industrialize, the industrial sector consistently  
37     ranks first among all sectors in China in terms of energy consumption and CO<sub>2</sub> emissions. According to

38 the National Bureau of Statistics, in 2017, China's industrial energy consumption reached 294,480,400  
39 tons of standard coal equivalent, accounting for 65.7% of the country's total energy consumption,  
40 indicating that the industrial sector relies too much on energy consumption. However, China's  
41 industrialization is far from complete. Scholars believe that China's industrialization is, overall, in a  
42 transitional stage from the middle to the later stage, with approximately 80% of the industrialization  
43 level basically having been completed, and there is still nearly 20% room for growth. Based on the  
44 experience of the industrialization process and CO<sub>2</sub> emissions of developed countries, as well as the  
45 judgement on influencing factors such as China's industrialization and urbanization process, the  
46 emissions of the industrial sector will increase gradually and reach a peak around 2040. Even under a  
47 low-carbon scenario, China's total industrial sector emissions will peak as soon as around 2030

48 At present, the Chinese government is actively formulating and implementing various carbon  
49 emission reduction policies to deal with climate change and its impacts. Since 2013, seven regions,  
50 including Beijing, Shanghai, Tianjin, Hubei, Guangdong, Shenzhen and Chongqing, have established  
51 carbon markets and started substantial trading. Since its inception in 2013, the carbon markets have  
52 increasingly grown. By the end of August 2020, the cumulative turnover of the seven pilot carbon  
53 market quotas was 406 million tons, with a cumulative turnover of approximately 9.28 billion yuan. A  
54 total of 2,837 key emitters, 1,082 non-compliant organizations and 11,169 natural persons participated  
55 in the pilot carbon markets. In 2016, nearly 200 countries signed the Paris Agreement, and China  
56 promised to peak its CO<sub>2</sub> emissions around 2030 and to reduce its CO<sub>2</sub> emissions per unit of GDP by  
57 60%-65% compared to the 2005 level (Feng and Chen 2018). In the face of such a tough emission  
58 reduction target, the industrial sector, as the largest carbon emitter, should assume the primary  
59 responsibility for CO<sub>2</sub> emission reduction. Only by reducing the CO<sub>2</sub> emissions of the industrial sector  
60 can the overall goal of CO<sub>2</sub> emission reduction be achieved. Cities are the core area of relatively  
61 complete basic space units and industrial development in China, and they are also the most important  
62 source of energy consumption and CO<sub>2</sub> emissions. Excessive energy consumption and serious CO<sub>2</sub>  
63 emissions have become important factors hindering urban development (Glaeser and Kahn 2010).  
64 Therefore, studying the characteristics of the spatial distribution and influencing factors of ICEs in  
65 Chinese cities holds great significance for reducing CO<sub>2</sub> emissions and realizing a low-carbon way of  
66 life.

67 In existing research, it is believed that the factors influencing CO<sub>2</sub> emissions mainly include the  
68 industrial structure, urbanization, energy structure, energy consumption, technological innovation and  
69 so on. Some scholars believe that economic growth is positively correlated with CO<sub>2</sub> emissions. For  
70 example, Al-Mulali (2012) discussed the influencing factors of CO<sub>2</sub> emissions in 12 Middle Eastern  
71 countries, and the research results showed that GDP and the total trade volume were the main reasons  
72 for CO<sub>2</sub> emissions. Mousavi et al. (2017) used the logarithmic mean Divisia index (LMDI) to study the  
73 relationship between energy consumption and CO<sub>2</sub> emissions in Iran, and they found that economic

74 activity was the largest driving force. Lin and Benjamin (2019) found that economic growth has a  
75 positive effect on CO<sub>2</sub> emissions in the long run. However, some scholars believe that economic  
76 growth can help reduce CO<sub>2</sub> emissions. For example, Qin et al. (2019) found that per capita GDP and  
77 the CO<sub>2</sub> emissions of northern China and the southeast coastal region present negative correlations,  
78 showing that a city's economic development has the potential to reduce carbon dioxide emissions.  
79 Some scholars used the environmental Kuznets curve (EKC) to analyse the relationship between  
80 economic growth and CO<sub>2</sub> emissions, arguing that CO<sub>2</sub> emissions show an inverted U-shaped  
81 relationship with per capita GDP (Ghazali and Ali 2019). For example, Liddle (2015) confirmed the  
82 inverted U-shaped relationship between CO<sub>2</sub> emissions and economic growth according to the EKC  
83 hypothesis. Other scholars believe that there is no connection between the two. For example, Freitas  
84 and Kaneko (2011) studied the relationship between CO<sub>2</sub> emissions and economic growth in the UK  
85 using a decoupling index of energy and environmental pressure, and they found that the relationship  
86 between the two was completely disconnected.

87 The impact of urbanization on CO<sub>2</sub> emissions is also a key research area (Knight et al. 2013; Pata  
88 2018). Jorgenson and Clark (2010) and Knight et al. (2013) found that urbanization is the main driving  
89 force promoting the increase in CO<sub>2</sub> emissions. Zhang et al. (2018) argued that the population and  
90 industrial scale brought by urban expansion have expanded the consumption of fossil fuels and that  
91 urbanization and industrialization have staged effects on ICEs and the emission intensity. Lin and  
92 Benjamin (2019) found that urbanization accelerated CO<sub>2</sub> emissions in China and India. Wang et al.  
93 (2019) argued that different levels of urban development in China would obviously lead to different air  
94 quality pollution conditions. Su et al. (2020) found that the higher the level of urbanization, the greater  
95 the CO<sub>2</sub> emissions in the urban areas of Fujian. Energy structure is considered to be an important factor  
96 affecting CO<sub>2</sub> emissions (Zhang et al. 2018; Wen and Li 2020). Li and Moubarak (2014) argued that  
97 China, which has abundant natural resources, could increase its investment in clean energy and  
98 renewable energy (solar energy), optimize the energy structure, and thus promote carbon emission  
99 reduction. Moutinho et al. (2015) found that the optimization of the energy mix would lead to a  
100 significant reduction in CO<sub>2</sub> emissions in four regions of Europe. Zhang et al. (2018) found that the  
101 coal-based energy structure was the main cause of high ICEs and that adjustment of the energy  
102 structure was a powerful measure for reducing environmental pollution and promoting ICEs reduction.  
103 Wen and Li (2020) argued that the development of clean energy greatly improved the energy structure  
104 and reduced the consumption of fossil energy; additionally, adjustment of the energy structure could  
105 limit the increase in CO<sub>2</sub> emissions. In other words, adjusting the energy structure has a significant  
106 effect on reducing CO<sub>2</sub> emissions, which is of great significance for China's sustainable development  
107 strategy (Dong et al. 2018). Some scholars have found that CO<sub>2</sub> emissions are closely related to the  
108 industrial structure and have a long-term positive correlation with the proportion of the secondary  
109 industry because the secondary industry is considered to be a major user of energy and a major

110 contributor to global CO<sub>2</sub> emissions (Lin and Benjamin 2019). Griffin et al. (2016) found that 19% of  
111 the greenhouse gas emissions in the UK came from the steel industry, which had the second largest  
112 amount of emissions; the steel industry consumed more energy than the service industry and had a  
113 higher carbon emission level. Su et al. (2020) found that an increased proportion of the tertiary industry  
114 could significantly restrain CO<sub>2</sub> emissions. Most CO<sub>2</sub> emissions come from the secondary industry, and  
115 Kumbaroglu (2011) adopted the Shapely index decomposition method and found that the increase in  
116 CO<sub>2</sub> emissions mainly comes from the scale effect of electricity, manufacturing and transportation  
117 industries.

118 Technological innovation can improve energy utilization efficiency and reduce the energy  
119 intensity of China's industry, thus reducing the CO<sub>2</sub> emissions (Poumanyvong and Kaneko 2010; Wen  
120 and Li 2020). For example, Dauda et al. (2019) suggested that improving energy technology and  
121 related equipment could greatly improve energy efficiency, thereby reducing urban carbon dioxide  
122 emissions. Rahman et al. (2017) argued that improving clean energy technologies was crucial for  
123 reducing carbon dioxide emissions and that industrial technological innovation should be encouraged,  
124 especially to solve the carbon emission problem in carbon-intensive industrial sectors. Åhman et al.  
125 (2016) studied Belgium and Sweden and found that to significantly reduce greenhouse gas emissions  
126 after 2050, it is necessary to rely on disruptive technologies in the steel industry. Therefore, to reduce  
127 CO<sub>2</sub> emissions, it is necessary to promote the intensive development of industries with low energy  
128 consumption, promote the extensive application of advanced technologies, and eliminate  
129 energy-intensive industries (Lin and Benjamin 2019). Other scholars believe that factors such as the  
130 industrial scale, population density, social fixed asset investment and foreign direct investment (FDI)  
131 will have a certain impact on CO<sub>2</sub> emissions.

132 Taking 282 Chinese cities as samples, this paper uses exploratory spatial data analysis (ESDA) to  
133 analyse the characteristics of the spatial and temporal distribution of ICEs, and it uses a geographically  
134 weighted regression (GWR) model to study the spatial heterogeneity of the influencing factors of ICEs.  
135 This article makes three major contributions to the existing literature on ICEs. First, existing research  
136 basically takes a provincial- or national-level perspective to study ICEs, but data at the national and  
137 provincial scales fail to reveal the spatial differences at the city scale. The city is the main body of ICEs,  
138 and it is necessary to explore the relationship between ICEs and important measures of social and  
139 economic development. Therefore, this article discusses the differences in ICEs at the city level and  
140 compensates for the inadequacy of existing research at the ground level and above the city level.  
141 Second, the territory of China is vast in size, and cities are interconnected and influenced by each other  
142 in geographical space. However, the spatial correlation between cities has been ignored in most  
143 existing studies. This paper adopts ESDA to reveal the spatial clustering characteristics of urban ICEs.  
144 Third, the existing literature mostly adopts an ordinary least squares (OLS) panel regression model to  
145 analyse the influencing factors of ICEs. The model of the estimated coefficient can reflect the influence

146 extent as a whole and cannot reflect the differences in influence between cities. This paper introduces a  
 147 GWR model to consider the parameters of local spatial heterogeneity and the industrial emissions of  
 148 social and economic factors based on a more meticulous and comprehensive understanding of spatial  
 149 scales.

150

## 151 2. Materials and Methods

### 152 2.1 Models

#### 153 2.1.1 Global spatial autocorrelation

154 Spatial autocorrelation test can accurately reflect the characteristics of the spatial distribution and  
 155 agglomeration of ICEs in Chinese cities. Global spatial autocorrelation can reflect the agglomeration  
 156 characteristics of an economic variable in the whole space. It is represented by Moran's I, and the Z  
 157 score is calculated to judge the significance of the result. Moran's I is used in this paper to describe the  
 158 global spatial correlation of ICEs in Chinese cities. The formula is as follows:

$$159 \quad I = \frac{n \sum_i \sum_{j \neq i} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n \sum_{j \neq i} w_{ij}} \quad (1)$$

$$160 \quad Z(I) = \frac{[I - E(I)]}{\sqrt{Var(I)}} \quad (2)$$

161 where  $n$  is the number of cities,  $w_{ij}$  is the spatial weight matrix,  $x_i$  and  $x_j$  are the ICEs of  
 162 cities  $i$  and  $j$ , respectively, and  $\bar{x}$  is the average industrial emissions of each city. The value  
 163 range of Moran's I is  $[-1,1]$ . When Moran's I  $>0$ , it represents positive spatial correlation. The greater  
 164 the value is, the more obvious the spatial correlation is. When Moran's I  $<0$ , it represents negative  
 165 spatial correlation. The smaller the value is, the greater the spatial difference. When Moran's I = 0, it  
 166 represents the randomness of space.

#### 167 2.1.2 Local spatial autocorrelation

168 Global spatial autocorrelation is a global indicator that measures spatial autocorrelation. It reflects  
 169 only the differences in spatial mean values and may ignore the atypical characteristics of ICEs in some  
 170 cities in local areas (Elhorst 2012). Local spatial autocorrelation test can be used to test the local  
 171 agglomeration characteristics of ICEs. The formula is as follows:

$$172 \quad I_i = \frac{n(x_i - \bar{x})}{\sum_{j=1}^n (x_j - \bar{x})^2} \sum_{j=1}^n W_{ij} (x_j - \bar{x}) \quad (3)$$

173 where  $I_i$  is the local Moran's I,  $i$  reflects the correlation between a city and its surrounding  
 174 cities, and the other indicators have the same meaning as those in formula (1). When  $I_i > 0$ , it

175 represents a positive correlation between the ICEs of city  $i$  and those of its surrounding cities; that is,  
176 the CO<sub>2</sub> emissions present high-high (H-H) or low-low (L-L) agglomeration. When  $I_i < 0$ , it means  
177 that the ICEs of city  $i$  are negatively correlated with those of its surrounding cities; that is, CO<sub>2</sub>  
178 emissions present H-H or L-L agglomeration.

### 179 2.1.3 Geographically weighted regression model

180 In traditional regression analysis, the OLS method is commonly used, but the regression coefficient  
181 obtained by an OLS model is the average value of the whole study area, and local regional  
182 characteristics cannot be obtained. A GWR model is a local form of a linear regression model that is  
183 used to analyse spatial variation relationships. When analysing influencing factors, a GWR model  
184 sufficiently considers the spatial effects and can reflect the heterogeneity of the regression coefficients  
185 in different spaces. Due to the vast size of China, there are huge differences in industrial development  
186 and ICEs between cities. Therefore, a GWR model is adopted in this paper to analyse the influencing  
187 factors of ICEs. The formula is as follows:

$$Y_i = c(u_i, v_i) + \sum_j^m b_j(u_i, v_i) x_{ij} + \varepsilon_i \quad (4)$$

189 where  $Y_i$  represents the ICEs value of city  $i$ ,  $(u_i, v_i)$  represents the latitude and longitude  
190 coordinates of city  $i$ ,  $c(u_i, v_i)$  represents the constant term,  $b_j(u_i, v_i)$  represents the regression  
191 parameter of the influence of city  $j$  on city  $i$ ,  $c(u_i, v_i)$  and  $b_j(u_i, v_i)$  are coordinate functions,  
192 and  $\varepsilon_i$  represents the residual term.

## 193 2.2 Description of the variables

### 194 2.2.1 Explained variable: Industrial CO<sub>2</sub> emissions (ICEs)

195 In this paper, data from the China High Resolution Emission Gridded Database (CHRED),  
196 composed of 76 units and 137 researchers, are used. Covering the enterprise, industry, and urban levels,  
197 these data on the levels of city greenhouse gas emissions from activities are collected, sorted and  
198 cleaned. At the same time, they are used to carry out a large number of cross-validation and data  
199 analyses. A dataset on the 2015 greenhouse gas emissions of Chinese cities is ultimately established.  
200 The CHRED references the international mainstream bottom-up spatial analysis method. It combines  
201 the actual situation in China and the characteristics of the data. The spatial analysis method is based on  
202 point emission sources from the bottom up (industrial enterprises, sewage treatment plants, landfills,  
203 livestock and poultry farms, coal mining, water transport ships, etc.) and other line source (traffic  
204 source) and non-point source (such as agriculture, life source) data, as well as other greenhouse  
205 emissions grid data at a 1 km resolution and methods of spatial data accuracy and uncertainty analysis.  
206 The spatial position accuracy of point source data is controlled by two methods: the longitude and  
207 latitude data on emission sources and spatial coordinates, and address matching verification is carried  
208 out based on application programming interface (API) geocoding technology. CHRED data highlight

209 the spatialization and spatial distribution pattern of emissions and emphasize the spatial accuracy of  
210 emissions data.

### 211 2.2.2 Explanatory variables

212 On the basis of previous studies, this study takes 10 indicators, i.e., the industrial scale (IS), the  
213 share of industry in GDP (IR), the share of the service industry in GDP (RGDP) (TR), the economic  
214 development level, technology innovation (TI), population density (PD), foreign direct investment  
215 (FDI), social investment in fixed assets (FA), government intervention (FE), and financial development  
216 (FD), as influencing factors of China's urban ICEs. These indicators and their impact on ICEs can be  
217 simply described as follows: Industrial scale is expressed by the total industrial output value of each  
218 city. In general, the larger the industrial scale is, the higher the level of industrial output will be, and the  
219 higher the ICEs will naturally be. The share of industry in GDP is expressed by the proportion of  
220 industrial added value in GDP, reflecting the impact of the industrial structure on ICEs. The higher the  
221 proportion of the secondary industry is, especially the higher the proportion of heavy industry, the  
222 higher the ICEs will be. The share of the service industry in GDP uses the proportion of the added  
223 value of the service industry to GDP, reflecting the effects of ICEs from the upgrading of the industrial  
224 structure of the industry, especially the modern service industry relative to traditional industry, The  
225 service sector is characterized by low energy consumption, low pollution, and the accelerated  
226 development of finance, tourism, education, culture and other industries that can reduce ICEs.  
227 Economic development (RGDP) is measured by per capita GDP. According to the EKC hypothesis,  
228 due to different levels of economic growth, economic growth may increase or reduce ICEs, and there  
229 may be an inverted U-shaped relationship between the two. Technology innovation (TI), represented by  
230 the number of patents granted per 10,000 people, improves energy efficiency and promotes the  
231 development of high-tech industries, thereby effectively reducing ICEs. Population density is  
232 represented by the number of people per square kilometre. Human activities will result in an increase in  
233 ICEs. In general, population density is positively correlated with ICEs, but population agglomeration  
234 can also bring energy-intensive use, thus reducing ICEs. FDI, expressed in terms of the actual use of  
235 foreign capital as a share of GDP, brings advanced production technologies and managerial expertise,  
236 promotes technological progress in host-country industries, and thus increases and reduces ICEs. Social  
237 fixed asset Investment is expressed by the per capita fixed asset investment of the whole society. When  
238 investment is inclined towards industrial upgrading, it can bring advanced production equipment and  
239 technology to enterprises, thus reducing ICEs. Government intervention is expressed by the proportion  
240 of fiscal expenditure in GDP, and it reflects the government's intervention in economic activities. The  
241 government uses fiscal allocations to encourage enterprises to increase their research and development  
242 (R&D) and innovation, improve their energy efficiency and reduce their ICEs. In addition, China's  
243 fiscal decentralization system enables local officials to control the power of fiscal expenditure and  
244 resource allocation. The existing performance appraisal mechanism, with GDP as the core, also enables

245 local governments to relax environmental regulations on ICEs and to even support high-pollution  
 246 industries, leading to an increase in ICEs. Financial Development is expressed by the proportion of the  
 247 total amount of deposits and loans in GDP. Efficient financial intermediaries are usually more  
 248 conducive to the loan activities of consumers, making it easier for them to buy automobiles,  
 249 refrigerators, air conditioners and other big-box goods and increasing the amount of ICEs. At the same  
 250 time, the development of the financial market helps enterprises reduce their financing costs, increase  
 251 their financing channels, and optimize the structure of their assets and liabilities to introduce new  
 252 equipment, increase technological innovation, and thus reduce ICEs.

253

### 254 2.3 Data Sources

255 282 Chinese cities are selected as samples in this paper. The data are collected from the China  
 256 City Statistical Yearbook, China Energy Statistical Yearbook, and Yearbook Of China Transportation  
 257 & Communications, as well as provincial statistical yearbooks. The Statistical description of the  
 258 variables are shown in Table 1.

259

Table. 1 Statistical description of variables.

	Description	Max	Min	Mean	Std. Dev.
ICEs	Industrial CO <sub>2</sub> emissions(10 <sup>4</sup> ton)	16641.15	10.10	3110.74	3093.49
IS	Industrial scale (10 <sup>4</sup> Yuan)	7991.77	46.33	1139.94	1301.91
IR	Share of industry in GDP ( % )	71.45	15.17	46.71	9.47
TR	Share of service industry in GDP ( % )	79.65	24.17	40.94	8.68
RGDP	Per capita GDP ( Yuan )	207163.00	10987.00	51125.54	29543.82
TI	Number of patent authorization per 10 <sup>4</sup> people ( unit )	118225.00	73.00	6204.68	13576.52
PD	Population density ( people/km <sup>2</sup> )	2501.14	5.77	436.64	338.21
FDI	Share of FDI in GDP ( % )	20.72	0.00	2.03	2.59
FA	total social fixed assets investment per capita (Yuan)	173987.40	6799.22	42814.45	26561.95
FE	Share of financial development in GDP (%)	84.56	2.27	20.72	10.09
FD	Share of total deposit and loan in GDP (%)	743.60	91.05	242.32	110.23

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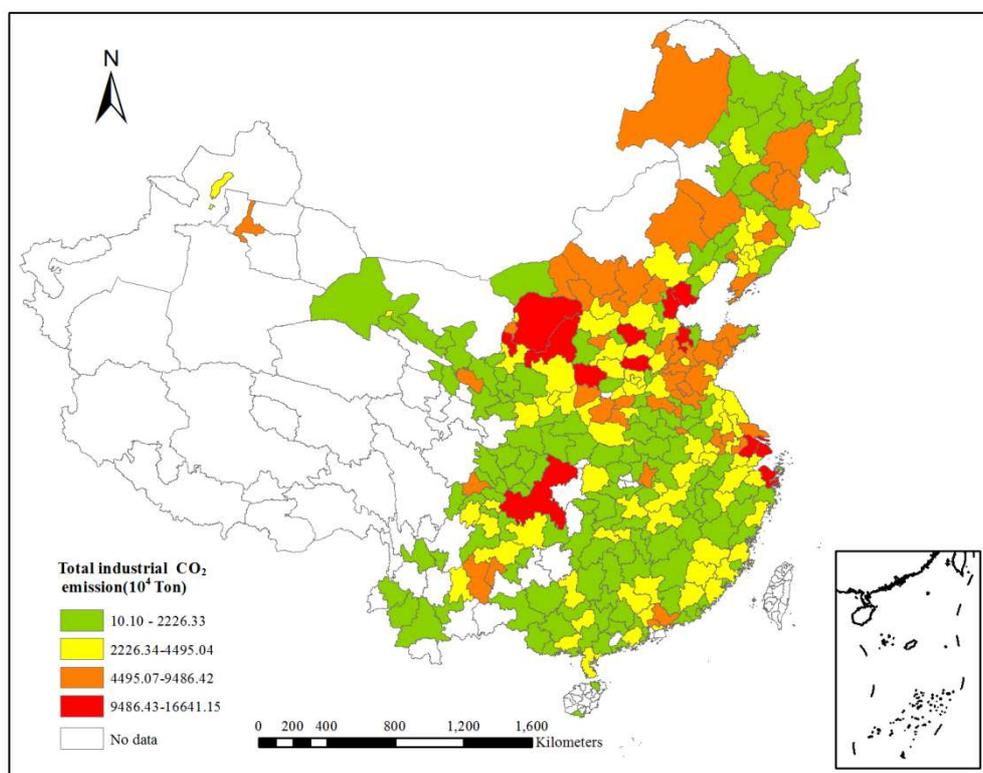
## 262 3. Empirical results and analysis

### 263 3.1 Spatial distribution pattern of ICEs

#### 264 3.1.1 Characteristics of the spatial distribution

265 The spatial distribution of ICEs in Chinese cities is shown in Figure 1. Chongqing, Tianjin,  
 266 Tangshan, Binzhou, Shanghai, Wuxi, Ningbo, Shijiazhuang, Handan, Linfen, Yinchuan, Ordos and  
 267 Yulin are the cities with the highest ICEs. Cities with high ICEs are mainly located in Shandong, Inner  
 268 Mongolia, Yunnan, Henan, Hubei, Shanxi, Jiangsu, Guangzhou and the Beijing-Tianjin-Hebei region.

269 Cities with low ICEs are mainly located in underdeveloped regions, such as Gansu, Ningxia, Qinghai,  
270 Heilongjiang, Jilin and other regions in Northwest and Northeast China. Therefore, the characteristics  
271 of the spatial distribution of ICEs are closely related to the level of regional economic development.  
272 The Beijing-Tianjin-Hebei region, Shanghai-Nanjing Hangzhou region, Suzhou-Xichang region and  
273 Pearl River Delta region are China's four major industrial bases. These four regions have high ICEs.  
274 Coastal areas have superior geographical environments, convenient traffic conditions, rapid economic  
275 development, and advanced levels of science and technology, which are conducive to industrial  
276 development. Shanxi, the western part of Inner Mongolia and the northern part of Shaanxi are the  
277 largest energy and chemical industry bases in China. The rich coal resources there provide abundant  
278 energy security for non-ferrous metal smelting, electric power, the chemical industry and other  
279 energy-intensive industries; thus, the ICEs are relatively high. Compared with Eastern China,  
280 Northwest China has a poor ecological environment, weak carrying capacity, and weak industrial base;  
281 it is unsuitable for large-scale industrialization. In Northeast China, although there are steel, heavy  
282 machinery, automobile, shipbuilding, aviation, and defence industries as well as other major industrial  
283 projects, since the 1990s, the industrial structure has been monolithic, with traditional products  
284 constituting the bulk. The institutional and structural contradictions are increasingly apparent. The old  
285 industrial base of enterprise equipment in Northeast China is ageing. The level of competitiveness is  
286 declining. There is an obvious contradiction in employment. Cities rich in resources and with leading  
287 industries are in recession. Economic development is still occurring at a slower pace. The gap between  
288 the regions and developed coastal areas is expanding.



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Fig. 1 Spatial distribution of ICEs

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### 3.1.2 Global and local correlation

Based on the formulas (1) and (2), Moran's I is 0.24719, the P value is 0.000, and the Z score is 18.719. The results show that China's urban ICEs have significant spatial clustering characteristics and positive spatial autocorrelation. The global Moran's I reflects only the overall clustering characteristics of ICEs. This paper proceeds to use the local Moran's I to analyse the local characteristics of ICEs. Local indicators of spatial autocorrelation (LISA) agglomeration is shown in Figure 2. The results show that there are four types of spatial agglomeration, namely, H-H agglomeration (H-H), high-low (H-L) agglomeration (H-L), low-high (L-H) agglomeration and L-L agglomeration. The ICEs of high-agglomeration areas and peripheral cities are relatively high, and most of mainly distributed in the Beijing-Tianjin-Hebei region, the Yangtze River Delta region, Inner Mongolia, Shaanxi, Shanxi and other regions. This result may be due to the agglomeration of urban agglomerations and industrial zones in the Beijing-Tianjin-Hebei region and the Yangtze River Delta region, resulting in large ICEs. Inner Mongolia, Shaanxi and Shanxi are the largest energy and chemical bases in China. Local industries with high energy consumption, such as non-ferrous metal smelting, electric power and the energy and chemical industries, are relatively developed; thus, their ICEs are relatively high. The ICEs in H-L agglomeration areas are relatively high, while the ICEs in peripheral cities are relatively low, mainly distributed in cities such as Chongqing and Chengdu. L-H agglomeration areas have low ICEs, while the ICEs of peripheral cities are relatively high, mainly distributed in some cities in Hebei, Anhui and Sichuan. The ICEs of low-low-agglomeration areas and peripheral cities are relatively lower, mainly distributed in Guizhou, Yunnan and Guangxi, where the economy is less developed and the industrial base is weak; thus, the ICEs are also low.

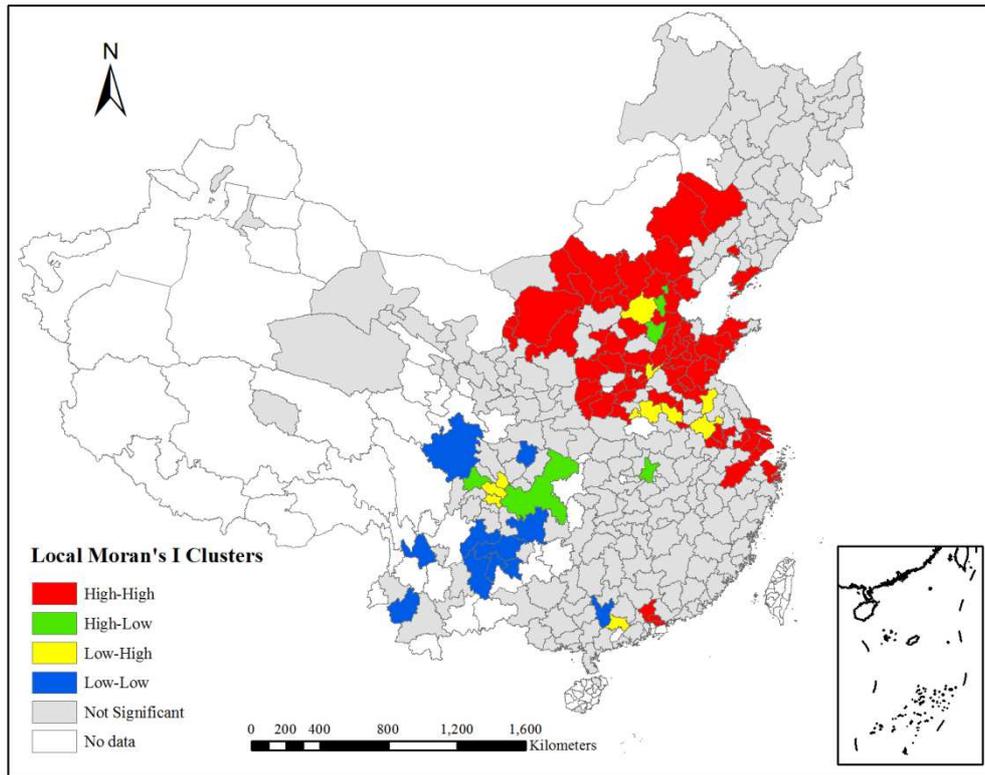


Fig. 2 Local Moran's I clusters of ICEs in China

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3.2 Spatial heterogeneity of the influencing factors of ICEs

3.2.1 OLS regression results

Table 2 OLS regression results

	Coefficient	Std. Error	t-value	p-value	VIF
IS	0.661	0.125	5.30	0.000	5.24
IR	1.454	0.413	3.52	0.001	3.45
TR	1.858	0.497	3.74	0.000	3.64
RGDP	1.129	0.254	4.44	0.000	6.27
TI	-0.101	0.022	-4.64	0.000	4.65
PD	-0.251	0.086	-2.91	0.004	2.29
FDI	0.004	0.044	0.10	0.923	1.46
FA	-0.245	0.169	-1.45	0.147	3.80
FE	-0.383	0.204	-1.87	0.062	2.87
FD	-0.038	0.193	-0.20	0.844	2.01
Constant	4.554	2.781	1.64	0.103	

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First, an OLS model was used for parameter estimation, and the results are shown in Table 2. The results of the ANOVA F test show that the model is strongly significant, and the variance inflation factor (VIF) values are less than 10, indicating that there is no serious collinearity problem in the model. The regression results show that the industrial scale, the share of industry in GDP, the share of service

322 industry in GDP and the level of economic development can significantly promote urban ICEs, and for  
323 each 1% increase in these four factors, the ICEs increase by 0.66%, 1.45%, 1.86% and 1.13%,  
324 respectively. At present, China's industrial output is as high as 39.0% of GDP, and industry is the  
325 sector with the largest CO<sub>2</sub> emissions. With the expansion of the industrial scale and the increase of the  
326 share of industry in GDP, the input of raw materials will increase, and in particular, energy  
327 consumption will greatly increase, which will naturally result in an increase in ICEs. The coefficient of  
328 the service industry is not consistent with expectations, which may be due to the high proportion of  
329 China's transportation industry in the service industry. In particular, in recent years, the rapid  
330 development of China's e-commerce and logistics industry has promoted the development of the  
331 transportation industry, which is the industry with the second largest ICEs after industry. With  
332 improved economic development, people will pursue better living standards, and the demand for  
333 household appliances, computers, automobiles and other industrial supplies will greatly increase, which  
334 will indirectly promote ICEs. At the same time, the figure shows that China is still on the left side of  
335 the EKC and has not reached the critical point of economic development to improve the environment.  
336 Technological innovation, population density, social fixed asset investment and government  
337 intervention are all important reasons for restraining ICEs; for every 1% rise in the four factors,  
338 accordingly the ICEs are reduced by 0.10%, 0.25%, 0.25% and 0.38%, respectively. Technological  
339 innovation, especially in energy conservation, environmental protection and low-carbon technologies,  
340 can improve energy efficiency and thus reduce carbon dioxide emissions. The higher the population  
341 density is, the more intensive the energy use, potentially reducing ICEs. Increased investment in fixed  
342 assets may promote the upgrading of production equipment and technology, which is conducive to  
343 reducing ICEs. An increase in government spending could encourage industrial enterprises to carry out  
344 technological innovations or to introduce advanced production lines to improve their energy efficiency  
345 and reduce their ICEs. The effects of FDI and on ICEs are not significant.

### 346 3.2.2 GWR regression results

347 In this paper, a GWR model is used to analyse the local heterogeneity of factors affecting ICEs. The  
348 R<sup>2</sup> values are shown in Figure 3. These values vary between 0.3731 and 0.8186, and there are  
349 significant differences in the fitting degree of different cities. The R<sup>2</sup> basically decreases from the  
350 marginal areas of Northeast China, Northwest China and the coast of Eastern China to Central China.  
351 The GWR model had the best fitting effect in Xinjiang, Gansu, Heilongjiang and Jilin, while the vast  
352 central region had the worst fitting effect. This result indicates that the relationship between the driving  
353 factors and ICEs is better reflected by the regression model in Xinjiang, Gansu, Heilongjiang and Jilin  
354 provinces.

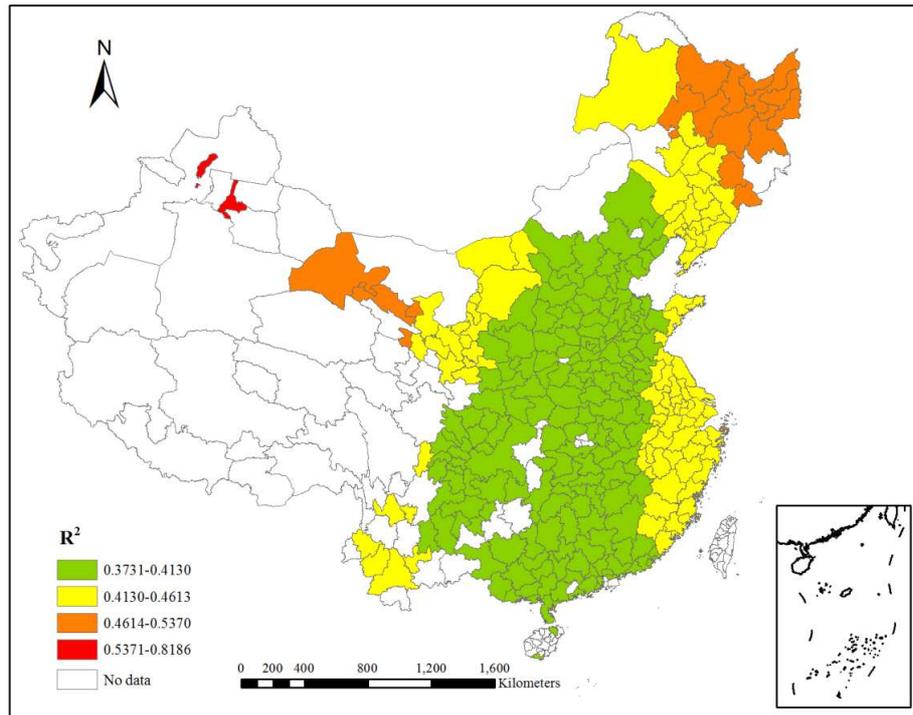


Fig. 3 Spatial distribution of  $R^2$  values

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The GWR model can calculate the coefficient of the influence of the explanatory variables on the explained variables in each city, making it possible to more clearly analyse the local characteristics of the coefficient of influence. The descriptive statistics of the coefficient of the influence for each variable on ICEs is shown in Table 3. The standard deviation of the estimated coefficient varies over a wide range, with the minimum (FD) value being 0.026 and the maximum (TI) value being 0.147. The greater the variation range of the coefficient is, the greater the spatial difference in the influence extent of various factors on ICEs, which better reflects the superiority of the GWR model. Table 3 also calculates the proportion of the number of cities with significant coefficients ( $P < 0.10$ ) and the proportion of cities with positive and negative coefficients.

Table 3 Descriptive statistics of GWR regression coefficient

	Coefficients				Percent of cities by significance of T-test		
	max	Min	mean	Std. Dev.	P<0.1	+(%)	-(-%)
IS	1.780	0.610	0.896	0.109	100	100	0
IR	0.515	0.178	0.321	0.087	86.01	100	0
TR	0.618	0.207	0.436	0.102	94.76	100	0
RGDP	0.225	-0.379	-0.215	0.142	53.5	0	100
TI	-0.115	-1.074	-0.403	0.147	93.36	0	100
PD	-0.033	-0.281	-0.088	0.036	9.79	0	100
FDI	0.147	-0.261	-0.003	0.067	19.23	50.91	49.09
FA	0.111	-0.227	0.008	0.077	5.24	0	100
FE	0.034	-0.109	-0.061	0.028	22.73	0	100
FD	-0.018	-0.128	-0.075	0.026	27.97	0	100

367 The article also describes the spatial characteristics of the estimated coefficients of each  
368 influencing factor, as shown in Figure 4. Cities whose estimated coefficients are significant at the 10%  
369 level are also marked with slashes. In all cities, the industrial scale, the share of industry in GDP and  
370 the share of service industry in GDP all promote ICEs, while technological innovation, population  
371 density and social fixed asset investment all restrain ICEs. In contrast, the level of economic  
372 development, FDI, financial development and government intervention have a two-way impact on  
373 ICEs, and there are significant differences in different cities. which is inconsistent with the results  
374 estimated by the OLS regression model. These results are different from those of OLS regression  
375 model. The specific analysis is as follows.

376 The coefficient of the IS is all positive and significant in 100% of the cities under study, indicating  
377 that industrial scale expansion significantly promotes ICEs, which is basically consistent with the OLS  
378 model estimation results. Among them, in cities such as Gansu and Xinjiang, the influence of the  
379 industrial scale on ICEs is the highest, while the influence on the ICEs of coastal areas such as Guangxi,  
380 Guangdong and Fujian is relatively low. Overall, the coefficient of influence for northern cities is  
381 obviously higher than that for southern cities. One possible reason for this result is that in recent years,  
382 with upgrading of industrial structure, energy-intensive enterprises in the eastern coastal areas have  
383 gradually moved to western regions. Gansu and Xinjiang are the two major energy and chemical bases  
384 in China, and the scale of energy-intensive industries continues to expand; thus, the impact on ICEs is  
385 higher than that in other regions.

386 The coefficient of the IR is positive and significant in 86.01% of the cities under study, and the  
387 influence extent gradually decreases from west to east. Among them, the share of industry in GDP has  
388 the highest influence on ICEs in Inner Mongolia, Gansu, Ningxia, Shanxi, Shaanxi and other western  
389 regions. This result may be because Western China is rich in energy resources, and the  
390 energy-intensive industries related to these resources, such as the energy and chemical industry, the  
391 equipment manufacturing industry and the non-ferrous metal smelting and processing industry, are  
392 relatively developed. Therefore, an increase in the share of industry in GDP will promote ICEs. In  
393 addition, to catch up and go beyond, western cities tend to weaken their environmental regulations  
394 when undertaking industrial transfer from eastern regions, and they introduce some  
395 high-energy-consuming enterprises into local areas. Therefore, with the development of industry,  
396 especially heavy industry, ICEs will inevitably increase.

397 The coefficient of the TR is positive and significant in 94.76% of cities, indicating that an increase  
398 in the share of the service industry in GDP will promote ICEs, and the influence extent successively  
399 decreases from west to east. In western cities such as those in Inner Mongolia, Gansu and Shaanxi, the  
400 share of the service industry in GDP has the highest impact on ICEs, while in eastern cities, the impact  
401 is much smaller. One possible reason is related to the internal structure of the service industry. In  
402 Western China, low-end service industries such as transportation, storage and logistics, accommodation

403 and catering account for a higher proportion. In Eastern China, financial, legal consulting, real estate  
404 and other services are more developed. Therefore, an increase in the share of the service industry in  
405 GDP in Western China will cause more ICEs compared to Eastern China.

406 The level of economic development has a two-way effect on ICEs. In Jiangsu, Zhejiang, Fujian,  
407 Guangdong, Hunan and other eastern coastal cities, the coefficient is significantly negative, showing  
408 that economic development can restrain ICEs, which conforms to the law described in the right part of  
409 the EKC. The main reason may be that the economic level of the eastern coastal areas has reached a  
410 certain degree and exceeded a certain critical point. Therefore, people will pursue better living  
411 standards and have a higher demand for green and low-carbon products, the government will have  
412 strong environmental regulations, and enterprises will tend to adopt green and low-carbon technologies;  
413 thus, ICEs can be restrained. The impact coefficient of RGDP in other cities is not significant,  
414 indicating that economic development in these cities has difficulty curbing ICEs.

415 The coefficient of TI is negative and significant in 93.36% of the cities under study, and the  
416 influence extent increases successively from east to west. In western regions such as Inner Mongolia,  
417 Gansu, Ningxia and Qinghai, technology innovation has the highest impact on ICEs, while its impact is  
418 relatively low in Heilongjiang, Hainan and other places. This result may be because of the rich  
419 resources in Western China; the high proportion of energy-intensive industries, such as flue gas  
420 enterprises; and the comprehensive utilization of solid waste, the energy savings and the reduced  
421 consumption in key areas, such as the independent development of new technologies, new processes,  
422 and new equipment, which promote the development of low-carbon technology, improve the efficiency  
423 of energy utilization, and curb ICEs.

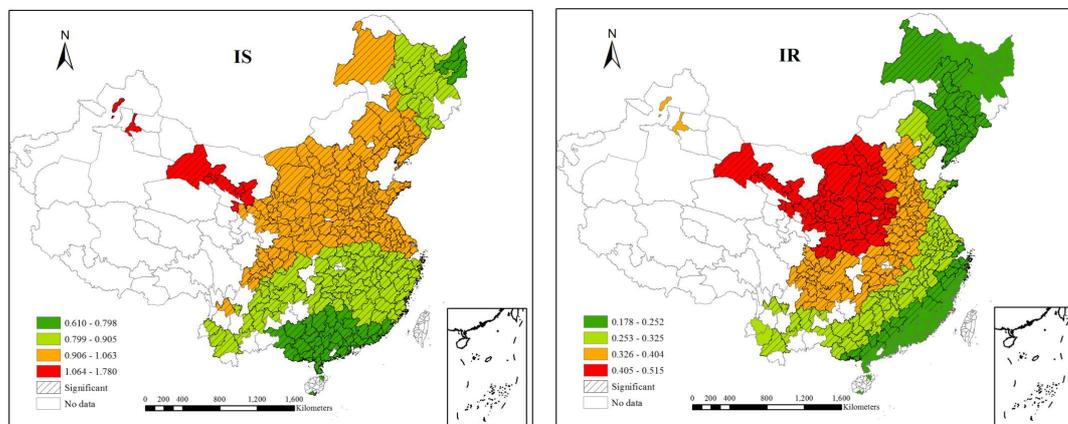
424 The impact coefficient of PD is negative and significant in only 9.79% of cities, indicating that PD  
425 can suppress ICEs in very few cities, which are mainly concentrated in western regions such as Ningxia,  
426 Gansu, Shaanxi and Inner Mongolia. One possible reason is that Western China is sparsely populated,  
427 with a low population density, and CO<sub>2</sub> emissions mainly come from the bioenergy in rural. With the  
428 advancement of urbanization and the increase in population density, energy is utilized intensively, and  
429 the utilization efficiency is greatly improved; thus, ICEs will also be reduced accordingly.

430 FDI has a two-way impact on ICEs. The impact is significantly positive in Hainan, Guangdong,  
431 Fujian and other south-eastern regions, indicating that FDI can promote ICEs. However, it is  
432 significantly negative in Heilongjiang, Jilin, Liaoning and other north-eastern regions, indicating that  
433 FDI can curb ICEs. This means that FDI has an impact on ICEs only in specific cities and that OLS  
434 models cannot reveal this feature. This may be because in the eastern coastal areas with developed  
435 industries, FDI inflows are mainly to industrial enterprises; thus, an increase in FDI will promote ICEs.  
436 In Northeast China, traditional industries, with high energy consumption and backward technology, are  
437 dominant. FDI inflow can bring advanced technology and management experience, promote the  
438 technological progress of local industrial enterprises, and thus reduce ICEs.

439 Social fixed asset investment has a two-way impact on ICEs. The coefficient of influence for  
 440 Inner Mongolia, Ningxia, Gansu and other northwest regions is significantly negative, while in most  
 441 other cities, it is not significant. This result shows that social fixed asset investment is an important  
 442 factor in restraining ICEs in Northwest China, possibly because the industrial enterprises in Northwest  
 443 China are at a critical stage of eliminating their backward production capacity and transforming and  
 444 upgrading. A large amount of social fixed asset investment can bring advanced production equipment  
 445 and technology to enterprises, which may increase their economic income and give them more funds  
 446 for environmental governance, thereby reducing their ICEs.

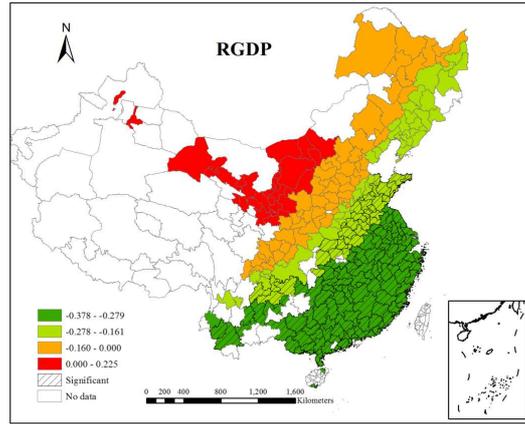
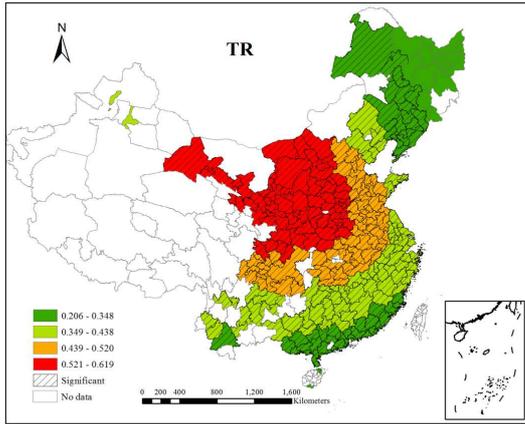
447 The coefficient of FE is negative and significant only in 22.73% of the cities under study, which  
 448 are mainly located in eastern regions such as Shanghai, Shandong, Zhejiang, Anhui, and Jiangsu. The  
 449 impact of government intervention is not significant in most other cities. This result suggests that  
 450 government intervention is currently able to curb ICEs in Eastern China. One possible reason is that the  
 451 eastern region has a relatively developed economy, and local governments have relatively high  
 452 financial revenues. They typically use tax incentives and subsidy policies to encourage enterprises to  
 453 innovate. Under the encouragement of preferential policies from the government, enterprises will  
 454 invest more money in scientific innovation and technological innovation and introduce green and  
 455 low-carbon technologies to reduce their CO<sub>2</sub> emissions.

456 The influence of financial development on ICEs is negative and significant only in 27.97% of the  
 457 cities under study. This result shows that financial development could inhibit ICEs. The cities in which  
 458 financial development has an impact are mainly in Chongqing, Hunan, Guangdong, Guangxi, Yunnan,  
 459 southern Sichuan, and Guizhou; the influence of financial development is not significant in most other  
 460 cities. One possible reason is that the degree of regional financial development is higher, and therefore,  
 461 financial institutions provide financial support for green credit business, technological transformation  
 462 and innovation, especially in terms of green technology R&D and promotion. Financial institutions will  
 463 give preferential access to credit, low interest rates and other support, improving the hatching rate and  
 464 survival rate and improving technology innovation to reduce ICEs.

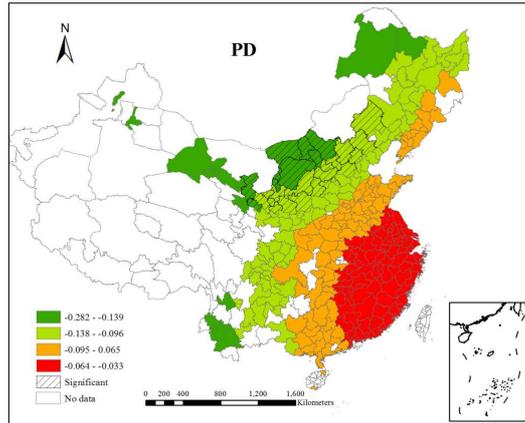
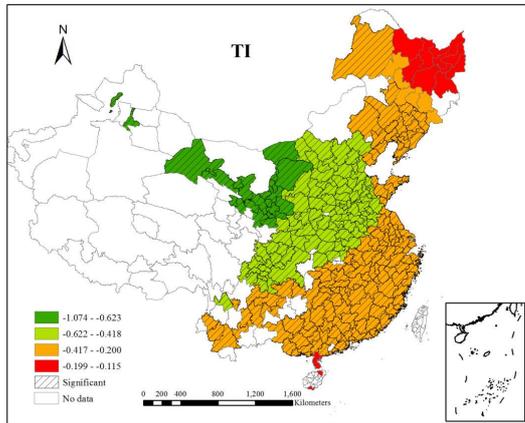


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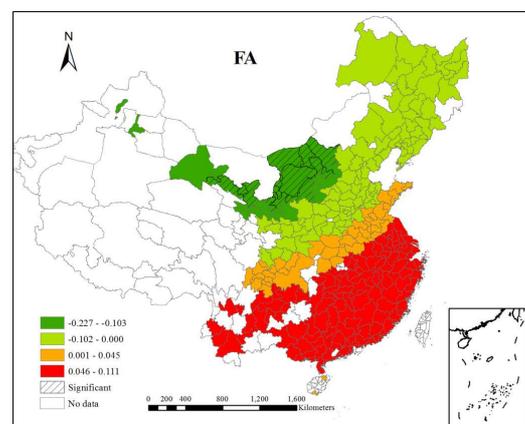
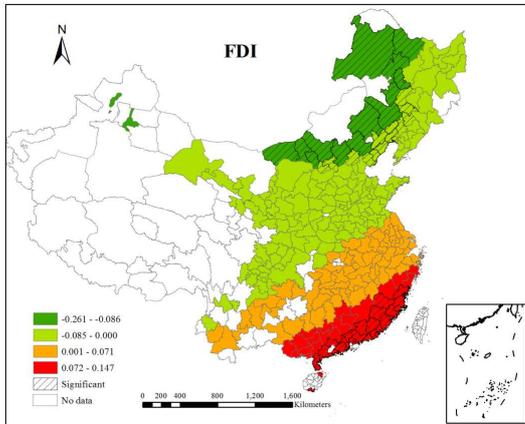
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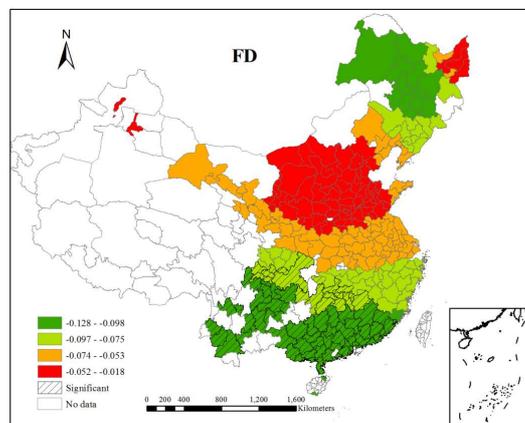
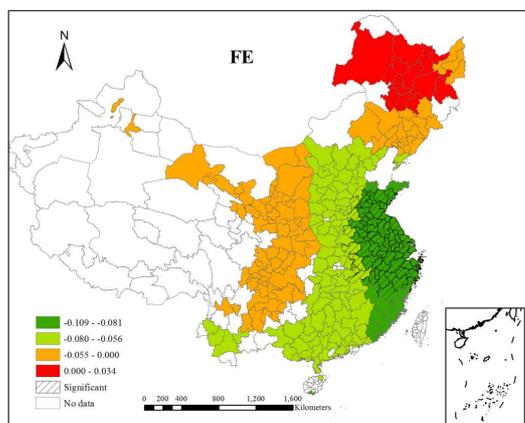


Fig. 4 Spatial distribution of regression coefficients

## 471 **4. Conclusion and Policy Implications**

### 472 *4.1 Conclusion*

473 In this paper, the spatial and temporal distribution characteristics of ICEs are discussed by ESDA  
474 method, and the spatial heterogeneity of influencing factors of ICEs is studied by GWR model. The  
475 main conclusions are as follows.

476 First, China's urban ICEs show significant spatial clustering characteristics. Areas with high ICEs  
477 are mainly concentrated in Chongqing, Tianjin, Shandong, Shanghai, Jiangsu, Zhejiang, Hebei, Shanxi,  
478 Yinchuan, Inner Mongolia, Shaanxi and other provinces, while low-emission areas are mainly  
479 distributed in less developed cities in Central and Western China, such as Sichuan, Gansu, Guizhou and  
480 Yunnan. Therefore, coordinated emission reduction policies should be formulated for areas with high  
481 ICEs.

482 Second, regarding ICEs, based on the influencing factors of the overall situation, industry scale, the  
483 share of industry in GDP, the share of service industry in GDP, and the level of economic development  
484 play a major role in promoting ICEs, while the technology innovation, population density, social fixed  
485 assets investment, government intervention play a major role in inhibiting ICEs. The influence of FDI  
486 and financial development on ICEs is not significant.

487 Third, the influencing factors of ICEs have spatial heterogeneity. The influence of the industrial  
488 scale on ICEs is always positive and significant in all cities evaluated, and the influence extent  
489 gradually decreases from north to south. The influence of the share of industry in GDP on ICEs is  
490 always positive and significant in 86.01% of the cities under study, and the influence extent gradually  
491 decreases from west to east. The coefficient of the share of service industry in GDP on ICEs is positive  
492 and significant in 94.76% of the cities, and the influence extent successively decreases from west to  
493 east. The economic development level has a two-way impact on ICEs. This impact is significant in  
494 53.8% of the cities, and the inhibitory effect of the economic development level is the strongest in  
495 eastern coastal cities. The impact of technology innovation on ICEs is negative and significant in 93.36%  
496 of the cities, and the influence extent increases from east to west. The impact of population density on  
497 ICEs is negative and significant in only 9.79% of the cities, which were mainly concentrated in  
498 Ningxia, Gansu, Shaanxi, Shanxi, Hebei and other regions. FDI has a two-way impact on ICEs, and  
499 this impact is significantly positive in Hainan, Guangdong, Fujian and other south-eastern cities and  
500 significantly negative in Heilongjiang, Jilin, Liaoning, Hebei, Inner Mongolia and other north-eastern  
501 regions. Social fixed asset investment has a two-way impact on ICEs. This impact is significant in only  
502 5.24% of the cities, which are mainly located in Inner Mongolia, Shaanxi, Ningxia and other  
503 north-western regions, while in most other cities, the impact of social fixed asset investment is not  
504 significant. Government intervention has a two-way impact on ICEs that is significant in only 22.73%  
505 of the cities, which are located in eastern regions such as Shanghai, Shandong, Zhejiang, Anhui,  
506 Jiangsu and Fujian. The impact of government intervention is not significant in most other cities.

507 Financial development has a negative impact on ICEs, and this impact is in 27.97% of the cities, which  
508 are located in southern regions such as Chongqing, Hunan, Guangdong, Guangxi, Yunnan, Sichuan and  
509 Guizhou.

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#### 511 *4.2 Policy implications*

512 According to the above conclusions, the influences of different factors on ICEs are spatially  
513 heterogeneous. Therefore, policies should be made according to the development characteristics of  
514 cities and according to local conditions. Therefore, the following suggestions are proposed: the  
515 industrial production scale and excessive proportion of industry are still one of the main sources of  
516 ICEs, and local governments should strictly control the industrial structure, especially the heavy  
517 industry output value, and maintain it within a reasonable scope. The choice of low-pollution,  
518 low-emission, and green industries should encourage enterprises in Central China to optimize and  
519 upgrade the industrial structure, reduce the proportion of the secondary industry in GDP, and actively  
520 develop the low-carbon economy. On the premise of encouraging industrial structure optimization,  
521 local governments should focus on developing high-end low-carbon service industries, such as finance,  
522 medical care, culture and entertainment, and information technology, while vigorously developing the  
523 service industry to avoid a shift in ICEs from industry to the service industry. As economic  
524 development has a significant restraining effect on ICEs, Central and Western China should vigorously  
525 develop their economy, improve people's living standards, alleviate the contradiction between people's  
526 growing demand for a better life and economic development, and promote people to cultivate green  
527 and low-carbon living habits. Technological innovation should be accelerated, with emphasis on the  
528 application of new energy technologies and low-carbon technologies, flue gas treatment and the  
529 comprehensive utilization of solid waste. Market mechanisms should be introduced to ensure the  
530 application of low-carbon technologies and to improve energy utilization efficiency. The government  
531 should encourage an appropriate increase in the population density of western cities and guide the  
532 population to flow into Western China through industrial transfer, talent introduction and other  
533 measures because this change in the population structure can not only relieve the environmental  
534 pressure brought by the population in Eastern China but also promote the balanced development of  
535 urbanization in Central and Western China. For the eastern coastal areas, foreign capital should be  
536 encouraged. When introducing foreign capital, attention should be paid to the investment structure of  
537 foreign investors, and they should be guided to flow to high-tech industries and service industries. For  
538 less developed regions such as Northeast China and Northwest China, the business environment should  
539 be further optimized to attract high-tech foreign-funded enterprises, and local enterprises should be  
540 encouraged to actively introduce advanced foreign technologies and conduct cooperations and  
541 collaborative innovation with foreign high-tech enterprises. Western China should increase the scale of  
542 social fixed asset investment, pay attention to optimizing the investment structure, accelerate the

543 transformation and upgrading of traditional industries in industrial investment, and encourage  
544 enterprises to introduce advanced production equipment and technological transformation. We will  
545 quickly promote investment in medium- and high-end manufacturing, reduce overcapacity and high  
546 energy consumption, and improve the quality of industrial investment. In Central and Western China,  
547 we should increase government financial expenditure, especially on science and technology and  
548 environmental governance. We should also set up innovation funds, use tax and fiscal subsidy policies,  
549 guide and encourage enterprises to adopt green and low-carbon technologies, and increase R&D. We  
550 should strengthen the financial development in the northern cities of China, give full play to the role of  
551 financial capital in allocating resources by means of the market, encourage financial institutions to  
552 provide financial support for innovative and green enterprises, and even offer certain preferential  
553 interest rates to alleviate the financing pressure of enterprises. For zombie enterprises with an excessive  
554 production capacity and severe pollution, loans should be prohibited.

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563

564 **Compliance with ethical standards**

565 **Conflict of interest** *The authors declare no conflict of interest.*

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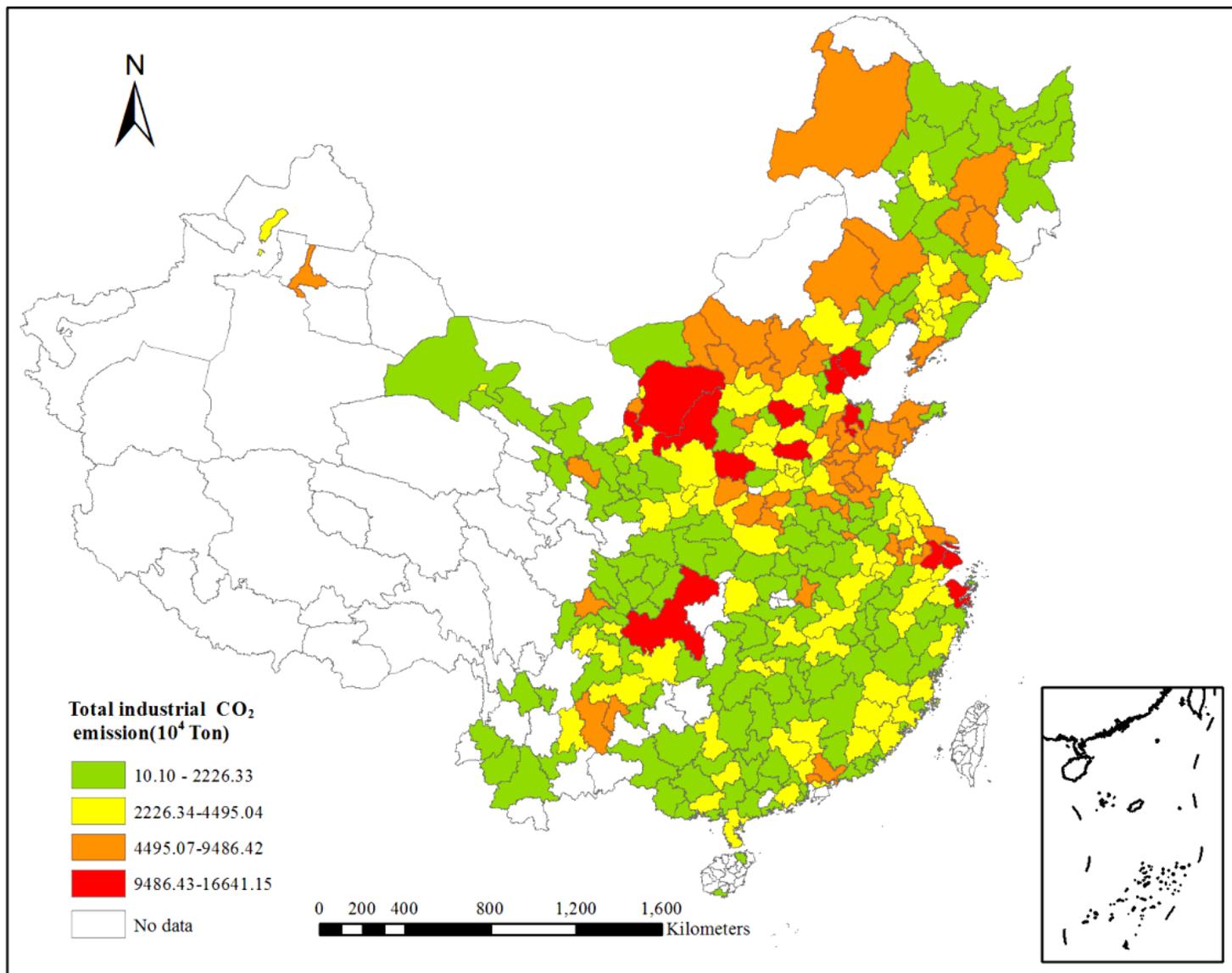
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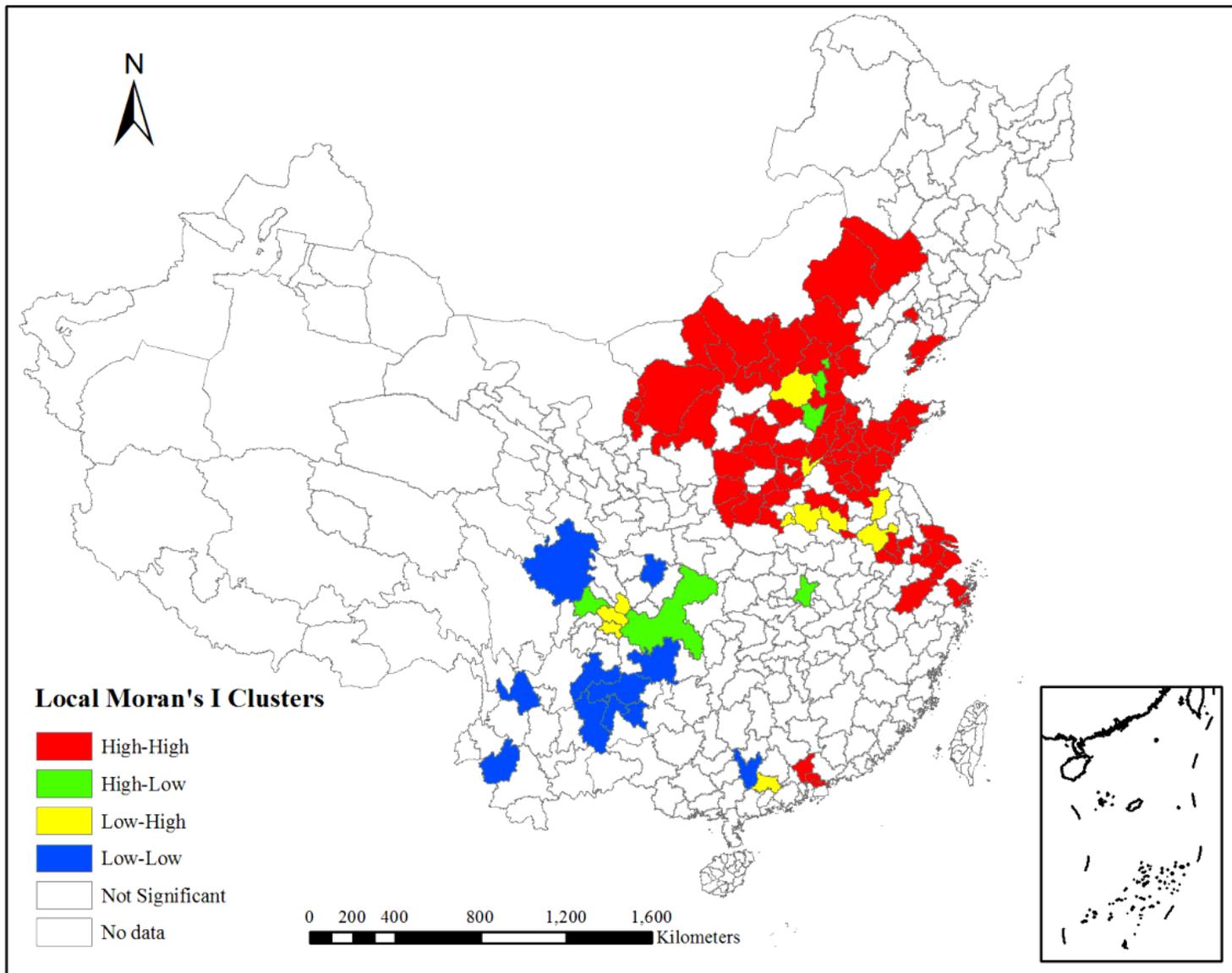
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# Figures



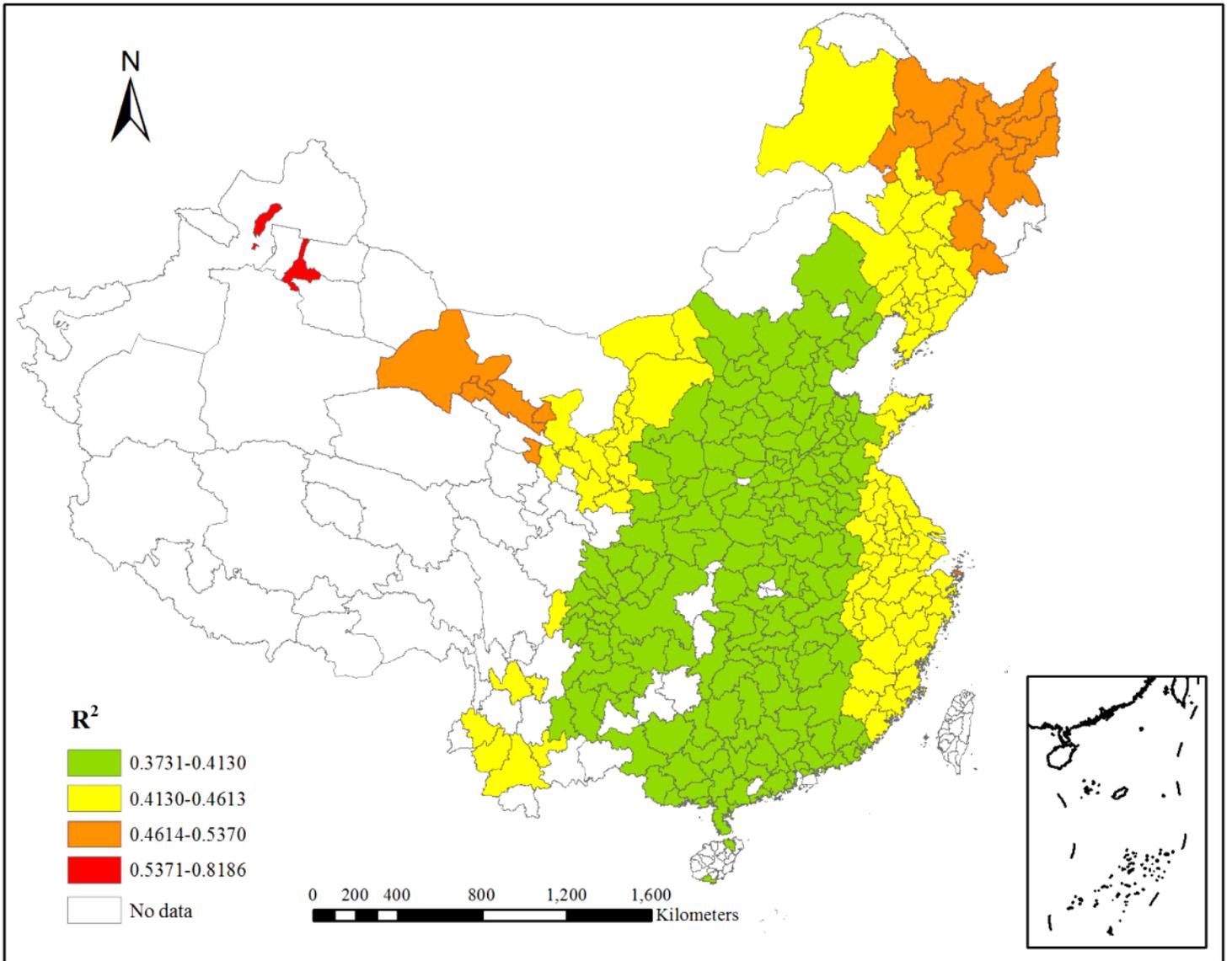
**Figure 1**

Spatial distribution of ICEs. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 2**

Local Moran's I clusters of ICEs in China. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 3**

Spatial distribution of  $R^2$  values. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



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