



Differentiation research of CO₂ emissions from energy consumption and their influencing mechanism on the industrial enterprises above designated size in Chinese industrial cities: based on geographical detector method

Wang Zhang¹ · Pengfei Feng²

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Abstract

Industry is one of the three fields of CO₂ emissions in Chinese cities. By measurement and analysis of data, the inter-city differentiation of CO₂ emissions from energy consumption and their influencing mechanism of the industrial enterprises above designated size (IEDS) in 59 non-resources-based industrial cities at prefecture level and above in different regions and types is obvious. In terms of CO₂ emissions from energy consumption per unit of employment, central and western industrial cities are above the average level of all industrial cities and cities of chemical and petrochemical, metallurgy and building materials see the same pattern; in terms of CO₂ emissions from energy consumption per unit of output, northeast industrial cities are all above the average level of all industrial cities, and it is the same for metallurgy and building materials industrial cities, chemical and petrochemical industrial cities. With geographical detector method, the size of each influencing factors of CO₂ emissions from energy consumption of the IEDS in industrial cities is probed. The results show that energy consumption structure and economic scale are the main influencing factors of CO₂ emissions from energy consumption of the IEDS in industrial cities; the influencing factors of CO₂ emissions in industrial cities from different regions and types are significantly spatially varying, and one factor also has diverse influence on CO₂ emissions in cities from different regions and types. Therefore, different countermeasures and actions to achieve low carbon transformation should be adopted according to the region and type of each industrial city.

Keywords Industrial cities · Industrial enterprises above designated size · CO₂ emissions from energy consumption · Inter-city differentiation · Geographical detector

✉ Wang Zhang
zhangwang0902@163.com

¹ College of Urban and Environmental Sciences, Hunan University of Technology, Zhuzhou 412007, Hunan, China

² College of Resource Environment and Tourism, Capital Normal University, Beijing 100048, China

1 Introduction

Cities are the main carriers of CO₂ emissions, and the top three largest amounts of urban energy consumption and CO₂ emissions are produced by industries (Eilperin 2007), constructions and transportation (Benjamin and Marilyn 2010). The industrial structures of most Chinese cities, especially the small and medium-sized ones, are dominated by industries as contemporary China is still in the process of industrialization. With the rapid development of urbanization and industrialization in China, the city demand for resources and energy is projected to rapidly soar, and thus, the energy consumption and CO₂ emissions from cities will significantly increase. Therefore, nowadays and even in the near and relatively far future, the industrial sectors naturally become the main areas for cities to reduce energy consumption and CO₂ emissions.

By far, there are two main characteristics in the research literatures about industrial CO₂ emissions: Firstly, in the perspective of space scales, most papers mainly paid attention to levels of countries (Ren et al. 2014; González and Martínez 2012), provinces (Zhang and Shang 2017; Shao et al. 2014) and regions (Sun 2015; Ye et al. 2013). However, even though the energy consumption by the industrial enterprises above designated size (IEDS) accounts for the major of the whole industry consumption in cities, the industrial researches, based on data of cities at prefecture level and above, are still rare. While studies normally have been involved to typical areas (Sun et al. 2015; Liu et al. 2015) or typical cities (Cong et al. 2013; Deng 2011), there are still no studies on CO₂ emissions in terms of industrial cities in a whole country. Secondly, in the perspective of research methods, the industry was regarded as an independent city sector to estimate its CO₂ emissions (Dodman 2009), and after that, the influencing mechanism of CO₂ emissions was revealed generally by the method of LMDI, which is usually used to decompose the total effect into three factors: scale, structure and intensity (Wang et al. 2012, 2015), and the Model of STIRPAT, which can be used to recognize the influencing factors of CO₂ emissions (Ren et al. 2012; Li and Zhang 2014).

However, although Chinese cities share common characteristics in general, cities from different regions have their own characteristics and thus industrial types of different cities are likely to be diverse. As a result, CO₂ emissions, as well as the types and degree of the influencing factors, are also different among cities with specific features. So, it is not very suitable to use LMDI and STIRPAT methods to analyze panel data carrying spatial attributes, predicting the mechanisms and its possible differentiation. Instead, this paper, on the basis of estimation and comparison of the CO₂ emissions from energy consumption of the IEDS in all non-resource-based industrial cities at prefecture level and above in China, adopts a new method called geographical detector to quantitatively explore and analyze the common characteristics and inter-city differences of the mechanisms of the CO₂ emissions from cities belonging to different regions and industrial types. Its results, which will exhibit important theoretical value and practical significance, can be used to provide policies suggestions about the adoptions of differential accesses to low carbon development for industrial cities where CO₂ emissions are huge and intense. Following the framework of this whole research (Fig. 1) was “Pattern-mechanism-Regulation”, that is, on the basis of accounting and comparison of the CO₂ emission from industrial energy consumption in all of non-resource-based industrial cities in China, this paper adopts a new method of geographical detector to quantitatively explore and analyze the common characteristics and inter-city differences of CO₂ emission mechanism in different regions and types of industrial cities, and then put forward some macro-level control measures. It will have important

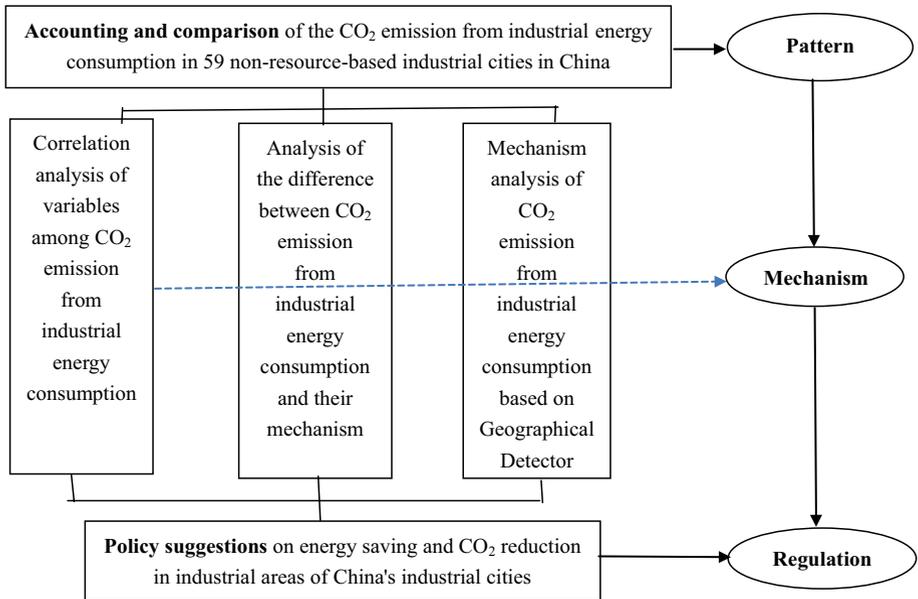


Fig. 1 The framework of this whole research

theoretical value and practical significance to adopt differential actions of low carbon development to guide industrial cities with high emission and intensity of CO₂.

2 Data processing and research methods

2.1 Data sources and processing

Referencing to Chinese 649 county-level and above cities that were scientifically classified according to functional types by Xu and Zhou (2010), and excluding the resource-based cities defined by the Sustainable Development Planning of Resource-based Cities in China (2013–2020), this paper finally chose 59 industrial cities at prefecture level and above in China (Fig. 2). The basic data are mainly derived from Statistical Yearbook 2016 of these 59 cities, and the energy types of these cities include coal, coke, clean coal, petrol, kerosene, diesel, fuel oil, liquefied petroleum gas, natural gas, heating power, electricity, etc.

2.2 Research methods

2.2.1 Measurement of CO₂ emissions from industrial energy consumption

To measure the CO₂ emissions from industrial energy consumption by the IEDS in industrial cities, this study uses the method in the IPCC Guideline for Greenhouse Gas Emission Inventory (IPCC 2007), whose equation is as follows:

$$C = \sum_i F_i \times a_i \tag{1}$$

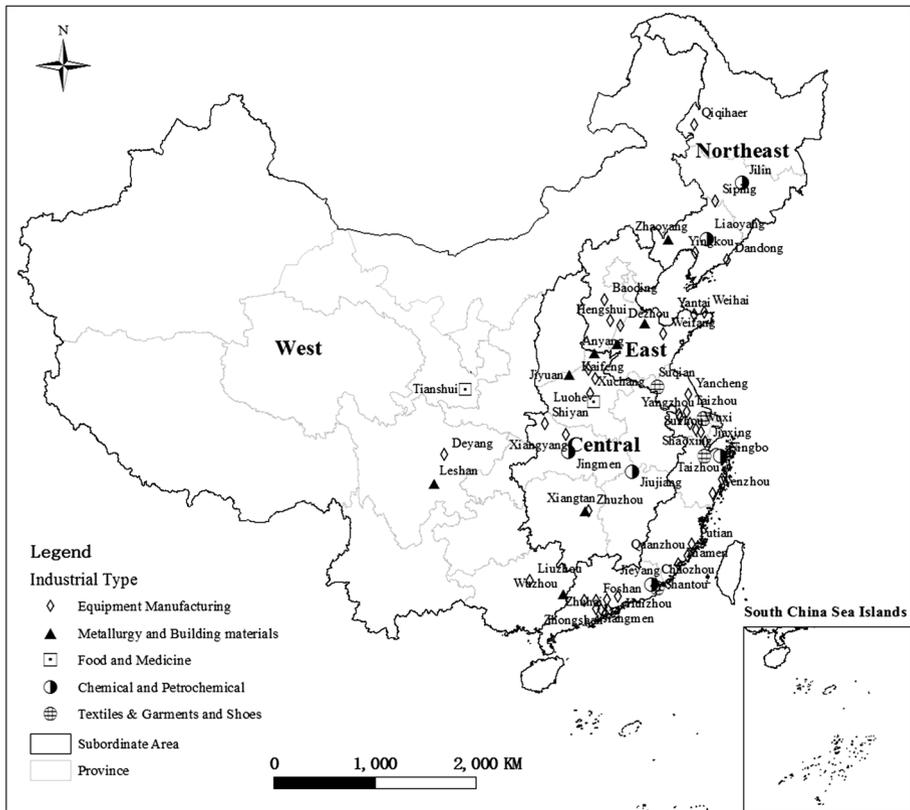


Fig. 2 The spatial distribution of which subordinate areas and types of leading industries for 59 non-resources-based industrial cities at prefecture level and above. *Note* The subordinate areas were divided into 4 regions: “east, central, west, northeast”, according to regional development in China; the leading industries types were classified to five categories as “equipment manufacturing, chemical and petrochemical, metallurgy and building materials, textiles & garments and shoes, food and medicine”, based on the biggest proportion industry for each city. Equipment manufacturing industry includes general equipment manufacturing, special equipment manufacturing, aerospace manufacturing, railway transport equipment manufacturing, transportation equipment and other transportation facilities manufacturing, electrical machinery and equipment manufacturing, communications equipment & computer and other electronic equipment manufacturing, instrumentation and cultural office supplies manufacturing

In this formula, C represents the total CO_2 emissions from industrial energy consumption (10^4t); i represents the type of energy consumption; F_i represents the total amount of terminal consumption for i type energy (10^4t tce); a_i represents the coefficient of CO_2 emissions for i type energy (calculated as per ton) = average low calorific value of unit fuel \times potential CO_2 emission factor \times oxidation rate in combustion process $\times 44/12$. The coefficients for respective types of fossil energy, including the average low calorific value, the potential carbon emission factor and the oxidation rate in the process of fuel combustion, are derived from the *Study on key issues of city carbon emission inventory* (Cai 2014), and the average calorific value of various fuels, which was converted into standard coal coefficients, was derived from the Yearbook of Energy Statistics 2016 in China.

2.2.2 Geographical detector technology

Geographical detector technology is a statistical method which can be used to detect spatial heterogeneity and reveal the driving forces behind it, developed by Wang Jingfeng and Xu Cheng dong. This method is a powerful tool for driving force, factor analysis and spatial analysis. Based on these advantages, the technology is used to explore the explanatory variables of CO₂ emissions in this study, so it is adept at analysis when the dependent variable *Y* is a type of numerical data (e.g., CO₂ emissions) and independent variable *X* is a type of categorical data (e.g., Land use graph) (Wu et al. 2016). If the dependent variable *Y* and the independent *X* are both numerical values, the *X* can be converted to categorical values by discretization. Therefore, geographical detector technology can be used to predict a more reliable relationship between *Y* and *X* than the classical regression does, especially when the sample volume is < 30 (Wang and Xu 2017). After the development of geographical detector software, this method has been widely used in natural sciences, social sciences, environmental sciences and human health areas. Based on these advantages, the tool is used to explore the explanatory variables of CO₂ emissions in this study. While according to the improved STIRPAT model (Dietz and Rosa 1994), the factors affecting CO₂ emissions are population, scale, technology, structure, etc., we chose sector employment, economic scale, energy efficiency and energy structure as independent variables in the paper, thus defining: The CO₂ emissions from industrial energy consumption by the IEDS in industrial cities are the dependent variable (*Y*); for the independent variables, the first independent variable (*X1*) is sector employment in cities; the second independent variable (*X2*) is economic scale (ratio of industrial output value to sector employment) of city; the third independent variable (*X3*) is energy efficiency (the ratio of total energy consumption to industrial output) of city; the fourth independent variable (*X4*) is energy structure (sum of the ratios of energy consumption on coal to consumption on coal, petroleum, natural gas, heat and electricity, respectively) of city. According to the operation requirement of geographical detector technology, the four numerical independent variables are discretized and converted into categorical values through the equal spacing method.

The spatial heterogeneity of geographical objects normally is influenced by factors from natural environment or economy and society. And geographical detector method does make sense to explore the formative mechanism and analyze the influential factors. The first application of this method was to analyze the causes of local diseases (Wang et al. 2010), and the model formula is as follows:

$$P_{D,U} = 1 - \frac{1}{n\delta_U^2} \sum_{i=1}^m n_{D,i} \delta_{U_{D,i}}^2 \tag{2}$$

where $P_{D,U}$ is the influencing factor of the CO₂ emissions from industrial energy consumption by the IEDS in industrial cities, $n_{D,i}$ represents the number of samples of the secondary region (type), n is the number of samples of the whole region (type), and m is the number of secondary region (type); δ_U^2 represents the variance of CO₂ emissions for the whole region (type), while $\delta_{U_{D,i}}^2$ denotes the variance of the secondary region (type). Assuming $\delta_{U_{D,i}}^2 \neq 0$, the model is established, and the value range of $P_{D,U}$ is [0,1]; if $P_{D,U} = 0$, it indicates that the distribution of CO₂ emissions is randomly distributed, and the larger the value of $P_{D,U}$, the greater the impacts of the subregion (type) factors on the CO₂ emissions. In the next of this paper, the extent to which the 4 types of potential influencing factors

(sector employment number, economy scale, energy efficiency and energy structure) affect CO₂ emissions is detected, respectively.

3 Results analysis

3.1 Correlation analysis of variables among CO₂ emission from industrial energy consumption

According to formula (1), the CO₂ emissions from industrial energy consumption of the IEDS in 59 industrial cities at prefecture level and above were calculated, while the data for influencing factors of CO₂ emissions were collected and collated from the Statistical Yearbook 2016 of each city. After that, we used Pearson (Spearman, Kendall) correlation coefficient to investigate the relative relationship among five variables, including dependent variable Y which means the CO₂ emissions from industrial energy consumption of the IEDS in industrial cities, and independent variables, including sector employment ($X1$), economic scale ($X2$), energy efficiency ($X3$) and energy structure ($X4$). The result shows that the correlation coefficient between CO₂ emissions from industrial energy consumption of the IEDS and sector employment is 0.293 (0.417, 0.277), while the correlation coefficient between economic scale and energy efficiency is 0.342 (0.443, 0.277), and these two correlation coefficients are statistically significant at the 0.01 level (bilateral); the correlation coefficient between CO₂ emissions from industrial energy consumption and energy efficiency is 0.389 (0.354, 0.256), while the correlation coefficient between sector employment and economic size is -0.506 ($-0.599, -0.401$); these two correlation coefficients are statistically significant at the 0.05 level (bilateral); the correlation coefficients between other variables are minimal (<0.2), and three groups of correlation coefficients are negative correlation, including groups between CO₂ emissions from industrial energy consumption and economic scale, sector employment and energy efficiency, the energy structure and energy efficiency; apart from that, the correlation coefficients for the remaining variables groups are positive. In general, the correlation coefficients of Pearson between the four independent variables are <0.51 , belonging to the relatively low values, which just indicates the variables are independent and also shows there exists low multi-collinearity. So, it is suitable to use the model of multivariate geographical detector model (Table 1).

Table 1 The results of the correlation test between the independent variables

	Y	$X1$	$X2$	$X3$	$X4$
Y	1				
$X1$	0.293* (0.417**, 0.277**)	1			
$X2$	-0.001 (0.010, 0.008)	-0.506 ($-0.599, -0.401$)**	1		
$X3$	0.187 (0.150, 0.099)	0.179 (0.191, 0.127)	0.041 (0.055, 0.040)	1	
$X4$	0.389** (0.354*, 0.256*)	-0.081 ($-0.048, 0.016$)	-0.342^* (-0.443^{**} , -0.277^{**})	-0.054 (-0.286 , 0.201*)	1

**Significant correlation at the 0.01 level (bilateral)

*Significant correlation at the 0.05 levels (bilateral)

3.2 Analysis of the inter-city differences about CO₂ emissions from industrial energy consumption and their mechanism

There are significant spatial differences in CO₂ emissions from the industrial energy consumption of the IEDS and the influencing factors (Table 2). In the perspective of CO₂ emissions from industrial energy consumption of the IEDS, there is a large gap between the highest and lowest values, with the maximum value (27,537.35 ten thousand tons) at Suzhou and the minimum value (823.13 ten thousand tons) at Wuzhou; the average value is at 5670.95 ten thousand tons; the standard deviation is at 5373.27 ten thousand tons. The second perspective is about sector employment. Its average and standard deviation values are at 72.54 and 58.84 ten thousand persons, respectively; the largest value is from Foshan, up to 243.17 ten thousand persons, while the lowest value is from Siping, at only 5.89 ten thousand persons. Thirdly, on the perspective of economy scale, the average and standard deviation values are at 81.57 and 78.75 ten thousand yuan per person, respectively; the biggest value is from Zhenjiang, reaching 305.69 ten thousand yuan per person, while the smallest value is from Dandong, down to 2.55 ten thousand yuan per person. The fourth is in terms of energy efficiency. The differences are also particularly uneven, as the most efficient city is Zhongshan with only 0.08 tons per ten thousand yuan, and the least efficient city is Jilin with 3.24 tons per ten thousand yuan; the average is at 0.68 tons per ten thousand yuan, and the standard deviation is at 0.67 per ten thousand yuan. Lastly, the descriptive statistics of energy structure are as follows: The average is at 1.69, and the standard deviation is at 1.09; the difference is also very big, as Huizhou, the nuclear power city, has a value at 6.65, and the value at Jiyuan is just at 1.03 where the clear majority of burning energy is coal.

The industrial cities in China are divided into 4 regions (Fig. 1) as “east, central, west and northeast” in order to compare and analyze the spatial differences of CO₂ emissions per unit of employment and CO₂ emissions per unit of output (Fig. 3). From the point of view on CO₂ emissions per unit of employment, the values of the industrial cities at the central and western areas in China exceed the overall level of industrial cities, while the values of the eastern and northeastern industrial cities are slightly lower than the overall level, with the largest value (128.61 ton per person) in western industrial cities, and the smallest value (71.38 ton per person) in eastern industrial cities. From the point of view on CO₂ emissions per unit of output, only the figure for northeast industrial cities (6.93 ton per ten thousand yuan) significantly exceeds the overall level of industrial cities (1.56 ton per ten thousand yuan). This is related to the high proportion of heavy chemical industries in old industrial base located in the northeast of China. By comparison, the figure for western industrial cities is slightly higher than the overall level, and figures for the eastern and central industrial cities are below the overall level of industrial cities. In short, the tasks to

Table 2 The statistical indexes about CO₂ emissions from energy consumption and influencing factors of IEDS in industrial cities

Variable	Average	Standard deviation	The biggest	The smallest
CO ₂ emissions (ten thousand tons)	5670.97	5373.27	27,537.35	823.13
sector employment (ten thousand persons)	72.54	58.84	243.17	5.89
scale of the economy (scale of the economy)	112.68	86.00	451.14	7.46
energy efficiency (tons per ten thousand yuan)	0.68	0.67	3.24	0.08
energy structure (number value ≥ 1, no unit)	1.69	1.09	6.65	1.03

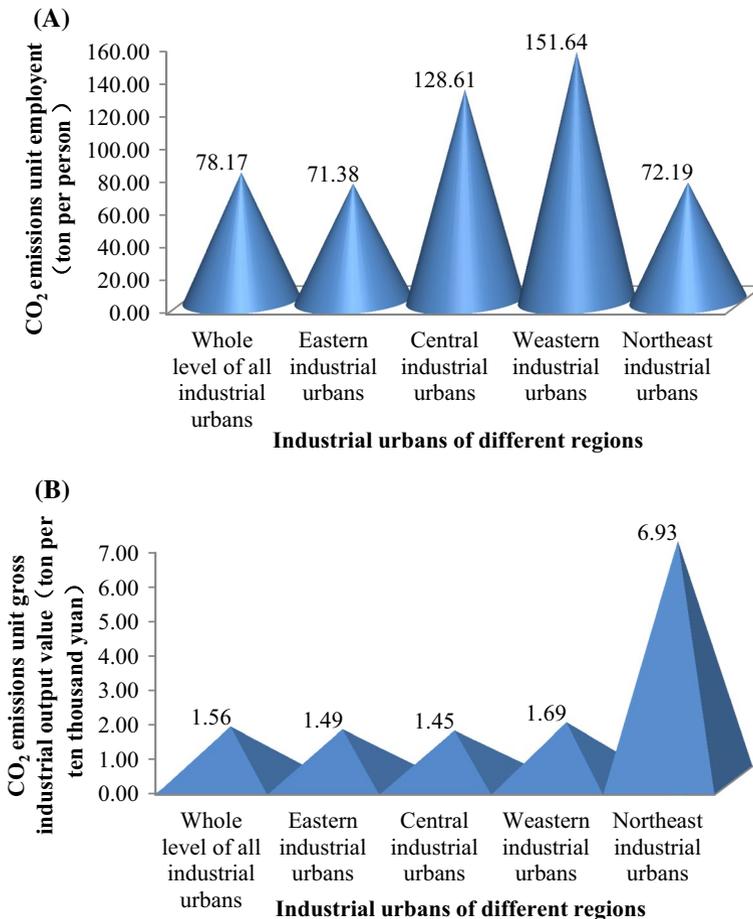


Fig. 3 CO₂ emissions from energy consumption per unit of employment and per unit of output of the IEDS in industrial cities of different regions

reduce CO₂ emissions and low carbon transformation in the northeast and west industrial cities are more onerous than cities located in the central and east.

According to the type of the leading industry in each industrial city, 59 cities are divided into five categories, which are equipment manufacturing, chemical and petrochemical, metallurgical and building materials, textiles & garments and shoes, food and medicine, but food and medicine is excluded because the number of these types of cities is only 2 which do not have statistical significance. A comparative analysis in terms of CO₂ emissions per unit of employment and per unit of output was carried out in the remaining 57 cities (Fig. 4). Results in terms of CO₂ emissions per unit of employment show that values in chemical and petrochemical, metallurgical and building materials industrial cities are far larger than the overall level of industrial cities, while the remaining two categories are both lower than the overall level of industrial cities, with the least value for equipment manufacturing industrial cities (63.60 ton per person). Results from CO₂ emissions per unit of output show the similar trends that the values in metallurgical and building materials,

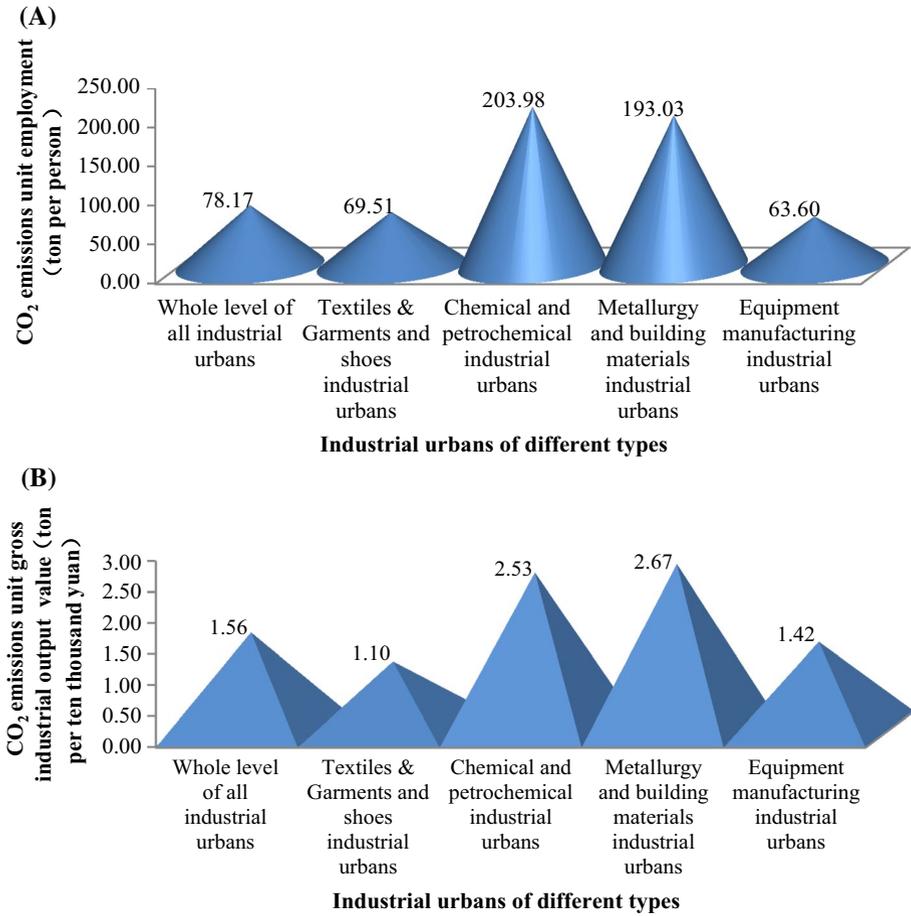


Fig. 4 CO₂ emissions from energy consumption per unit of employment and unit of output of the IEDS in different types of industrial cities

chemical and petrochemical industrial cities are higher than the overall level of industrial cities, while the values in the remaining two categories of cities are lower than the overall level of industrial cities, where figure for textiles & garments and shoes industrial cities is the least, at only 1.10 ton per ten thousand yuan. In sum, it can be predicted that the characteristics of high CO₂ emissions are obvious and the pressure of reducing CO₂ emissions is larger in chemical and petrochemical, metallurgical and building materials industrial cities.

3.3 Mechanism analysis of CO₂ emission from industrial energy consumption based on geographical detector

According to the steps of geographical detector technology, every independent variable should be firstly discretized by equal spacing method, and then, the formula (2) can be used to calculate the influence coefficients of each factor on CO₂ emissions from

industrial energy consumption of the IEDS in all industrial cities (Table 3). $P_{D,U}$ values of all factors in the result are arranged in order from big to small: energy structure (0.9267), economic scale (0.7153), energy efficiency (0.7111), sector employment (0.6741). Thus, energy structure and economic scale generally constitute the main factors that affect CO₂ emissions from industrial energy consumption in all industrial cities. To explore the mechanism of CO₂ emissions from industrial energy consumption in industrial cities, this paper divides industrial cities into four regions and four types to analyze the differences of influencing coefficients.

3.3.1 Analysis of the mechanism and their inter-city differences on CO₂ emissions from industrial energy consumption in different regional industrial cities

After the analysis of CO₂ emissions from industrial energy consumption by using geographical detector, $P_{D,U}$ values of each factor in different regional industrial cities are reported as follows (Table 3): For the eastern industrial cities, the influencing coefficients of CO₂ emissions from industrial energy consumption of the IEDS show that the sector employment, energy efficiency, energy structure and economic scale are at 0.9541, 0.8876, 0.7135 and 0.5417, respectively; the figures for the central industrial cities are energy efficiency (0.8403), economic scale (0.7991), sector employment (0.6937) and energy structure (0.3141); the figures for western industrial cities are sector employment (0.5510), energy structure (0.4233), economic scale (0.4102) and energy efficiency (0.0966); the figures for northeast industrial cities are sector employment (0.6115), economy scale (0.6023), energy structure (0.0922) and energy efficiency (0.0906).

Comparing with each other, the degrees of the same influencing factor on industrial cities in different regions are different: The influence of sector employment is arranged in order from large to small as east (0.9541), the central (0.6937), northeast (0.6115) and the west (0.5510) for industrial cities; the influence of economic scale is arranged in order from large to small as central (0.7991), the northeast (0.6023), the east (0.5417) and the west (0.4102); the influence of energy efficiency is arranged in order from large to small as east (0.8876), central (0.8403), west (0.0966) and northeast (0.0906). The influence of energy structure is east (0.7135), the west (0.4233), the central (0.3141) and the northeast (0.0922).

Table 3 The result of geographical detector analysis about the different influencing factors of CO₂ emissions from industrial energy consumption in industrial cities of different regions

Region name	Sector employment	Economy scale	Energy efficiency	Energy structure
Eastern industrial cities	0.9541	0.5417	0.8876	0.7135
Central industrial cities	0.6937	0.7991	0.8403	0.3141
Western industrial cities	0.5510	0.4102	0.0966	0.4233
Northeast industrial cities	0.6115	0.6023	0.0906	0.0922
Whole level of all industrial cities	0.6714	0.7153	0.7111	0.9267

3.3.2 Analysis of the mechanism and inter-city differentiation on CO₂ emissions from industrial energy consumption in different types of industrial cities

With the application of geographical detector, $P_{D,U}$ values of each factor that is related to CO₂ emissions from industrial energy consumption in different types of industrial cities have been analyzed, and the results are as follows (Table 4): The influencing factors of CO₂ emissions from industrial energy consumption of the IEDS for cities of textiles & garments and shoes industrial show economic scale (0.8989), sector employment (0.4958), energy efficiency (0.4902) and energy structure (0.4317), but reducing the size of the economy is not advisable, which indicate that the key ways to low carbon for cities of textiles & garments and shoes are likely to increase labor efficiency and reduce energy intensity. For chemical and petrochemical industrial cities, the results of variables are energy structure (0.7153), sector employment (0.4682), energy efficiency (0.0467) and economic scale (0.0403), which indicate that the main means of reducing CO₂ emissions in chemical and petrochemical industrial cities are likely to optimize energy structure and achieve the goal of efficiency and downsizing. For metallurgical and building materials industrial cities, the figures are energy structure (0.6956), economy scale (0.6134), employment number (0.3993) and energy efficiency (0.3103), indicating that the reduction of the proportion of coal consumption and the capacity of metallurgy can be the core path to low carbon aim for metallurgical and building materials industrial cities; figures for equipment manufacturing cities are energy structure (0.8687), energy efficiency (0.8094), economic scale (0.8052) and sector employment (0.7405), indicating that the reduction of the proportion of coal consumption and the increase of the efficiency in energy consumption can be the main way to save energy and reduce CO₂ emissions in equipment manufacturing industrial cities.

Compared horizontally, the degrees of the same influencing factor in different types of industrial cities are different: For the influence of sector employment, the coefficients are arranged in order from large to small in terms of city types as equipment manufacturing (0.7405), textiles & garments and shoes (0.4958), chemical and petrochemical (0.4682), metallurgical and building materials (0.3993); for the influence of economic scale, the figures are arranged in the same way as textiles & garments and shoes (0.8989), equipment manufacturing (0.8052), metallurgical and building materials (0.6134), chemical and petrochemical (0.0403); for the influence of energy efficiency, the figures are also arranged in the same way as equipment manufacturing (0.8094), textiles & garments and shoes (0.4902), metallurgical and building materials (0.3103), chemical and petrochemical (0.0467); for the influence of energy structure, figures for each types of cities are equipment manufacturing (0.8687), chemical and petrochemical (0.7154), metallurgical and building materials (0.6956), textiles & garments and shoes (0.4317).

4 Conclusions and discussion

This paper classified non-resource-based industrial cities at prefecture level and above into 4 regions and 5 types, calculated the CO₂ emissions of industrial energy consumption and analyzed its forming mechanism by using the geographical detector method to reveal the spatial differences of CO₂ emissions and influencing factors. Conclusions are as follows:

Table 4 The result of geographical detector analysis of the influencing factors on CO₂ emissions from industrial energy consumption in different types of industrial cities

Region name	Sector employment	Economy scale	Energy efficiency	Energy structure
Textiles & garments and shoes industrial cities	0.4958	0.8989	0.4902	0.4317
Chemical and petrochemical industrial cities	0.4682	0.0403	0.0467	0.7154
Metallurgy and building materials industrial cities	0.3993	0.6134	0.3103	0.6956
Equipment manufacturing industrial cities	0.7405	0.8052	0.8094	0.8687
Whole level of all industrial cities	0.6714	0.7153	0.7111	0.9267

1. The correlation coefficient between sector employment and economic scale is the largest, and the figure between CO₂ emissions from industrial energy consumption and energy efficiency of the IEDS is relatively large, while the correlation coefficients for groups between 4 independent variables, including sector employment, economy scale, energy efficiency and energy structure, are much smaller.
2. The CO₂ emissions from industrial energy consumption of the IEDS and their influencing factors are significantly different among industrial cities. The largest and smallest CO₂ emissions are produced by Suzhou and Wuzhou, respectively; the largest and least figures in terms of sector employment are for Foshan and Siping, respectively. The cities with the biggest and smallest economic scale are Zhenjiang and Dandong, respectively. The highest and the lowest figures in the energy efficiency are for Zhongshan and Jilin, respectively. The optimal and worst cities in energy structure are Huizhou and Jiyuan, respectively.
3. For CO₂ emissions per unit of employment, the figures for the central and western industrial cities far exceed the overall level of the whole industrial cities, and the figures for the chemical and petrochemical, metallurgical and building materials industrial cities also exceed the average level; for CO₂ emissions per unit of the output, the figures for northeast cities far exceed the overall level, and figures for metallurgical and building materials, chemical and petrochemical industrial cities show similar pattern.
4. Energy structure and economic scale are the main influencing factors of CO₂ emissions from industrial energy consumption of the IEDS in industrial cities. The spatial differentiation of factors that influence CO₂ emissions from industrial energy consumption in industrial cities is significant both in terms of city types and locations, and a same factor also has diverse influence on CO₂ emissions in cities from different regions and types. Therefore, we should adopt different countermeasures and actions to achieve low carbon transformation according to the region and type of each industrial city.

Based on previous article, policy recommendations of energy-saving and CO₂ emission reduction for industrial areas in Chinese industrial cities are: Firstly optimizing energy structure, the plan of improving energy efficiency and reducing CO₂ emissions action should be compiled; secondly in the premise of ensuring industrial development, it is the time to optimize the industrial structure, promote the introduction and application of energy-saving technology, use new and renewable energy and decouple the growth of CO₂ emissions from economic growth.

Due to the availability of data and length restriction of a paper, this paper just chose and analyzed the cross-sectional data of the IEDS in industrial cities in 2015, so dynamic research was not carried out and the characters of industry sectors were not explored. Thus, the following research should overcome this deficiency and gradually complement and improve it.

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