Spatial heterogeneity analysis of CO_2 emissions in China's thermal power industry: GWR model

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Abstract. The thermal power industry is a major contributor to China's CO_2 emissions, and its absolute emissions are still increasing year by year. Hence, this paper introduced a geographically weighted regression model to explore the spatial heterogeneity of different driving factors for this industry's CO_2 emissions. The empirical results show that standard coal consumption is a decisive factor affecting thermal power industry's CO_2 emissions, and its response to the western region is at the forefront. The average utilization hours of thermal power equipment in the central region exert a profound impact, while the western region devotes a lot to the installed capacity, and these two variables have great potential for CO_2 emission mitigation. However, the urbanization level and per capita electricity consumption have a slight effect on CO_2 emissions. These findings furnish constructive reference and policy implications to achieve emission abatement targets of different regions.
Keywords: Thermal power industry; CO_2 emissions; GWR model.

1 Introduction

On account of the rapid economic growth and enormous energy consumption, China overtook the United States in 2006 to become the world's biggest emitter of CO_2 discharges [1]. In 2015, the Chinese government proposed to peak CO_2 emissions around 2030 and committed to decrease CO_2 launches per unit of GDP in 2030 by 60% to 65% from the 2005 level [2]. To our knowledge, the power generation accounts for the maximum share in fuel consumption and CO_2 emissions. Meanwhile, the thermal power as an important part of power supplies, it is of vital importance to discuss the drivers of this industry's CO_2 emissions.

Many scholars have attempted to make an in-depth study on the power sector's CO_2 emission through the analysis of contributing factors. As we all know, the researches mainly focus on the index decomposition analysis (IDA) method and econometric model. In recent years, some scholars have realized the importance of spatial effect and have begun to fully study spatial econometric methods. Notably, GWR model has gained increasing popularity on CO_2 emissions and its driving forces [3, 4]. However, there is no report on the application of GWR model in thermal power sector's CO_2 emissions.

In this paper, the primary drivers of CO_2 emissions from thermal power sector have been conducted based on the GWR model. It not only explores the drivers of CO_2 emissions from

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the provincial and regional point of view, but also carries enough attention to spatial heterogeneity between the research regions, which will facilitate to develop targeted policies for the realization of energy conservation and abatement targets.

2 Methodology and data

2.1 Geographically weighted regression model

The geographically weighted regression (GWR) model expands the general linear regression, taking the spatial properties of the sample data into account [5]. The form is:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j(u_i, v_i) x_{ij} + \varepsilon_i \quad (1)$$

where $\beta_j(u_i, v_i)$ represents the spatial geographic location function, which is the regression parameter of the j-th impact factor at the i-th region. ε_i means the random error term.

$$\hat{\beta}(u_i, v_i) = [X'W(u_i, v_i)X]^{-1} X'W(u_i, v_i)Y \quad (2)$$

where X and Y represent the vectors of independent and dependent variables, respectively. $W(u_i, v_i)$ is a diagonal matrix with diagonal element W_{ij}. The decision of W_{ij} generally affects the adjacency, so its selection is vital [6]. In empirical research, the methods for calculating spatial weight functions are shown below:

Gaussian distance function:

$$W_i = \Phi\ (d_i / \sigma\theta) \quad (3)$$

Exponential distance function:

$$W_i = \sqrt{\exp\ (-d_i/\theta)} \quad (4)$$

Tricube distance function:

$$W_i = [1 - (d_i/q_i)^3]^3 \quad \mathrm{I}\ (d_i < q_i) \quad (5)$$

where σ refers to the standard deviation of distance vector d_i. θ represents the bandwidth. Φ $(\cdot)$ represents the standard normal density. q_i means the distances of the q-th nearest neighbor to the i-th region. I $(\cdot)$ denotes an indicator function. If the condition is true, that is equal to 1; otherwise, it is 0.

To confirm the suitable bandwidth, the commonly used cross-validation (CV) method is adopted in this paper.

$$CV = \sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(\theta)]^2 \quad (6)$$

where $\hat{y}_{\neq i}(\theta)$ indicates the fitted value of y_i. When CV acquires the minimum, θ-value is the appropriate bandwidth.

2.2 Model construction

According to the extended STIRPAT model, this research takes five drivers of CO_2 emissions from the thermal power sector into account, which not only includes the traditional power supply side, but also considers incentives from power demand. Specifically, urbanization level, per capita electricity consumption, and standard coal consumption for power supply denote population size, economic level, and technical progress indicators, respectively. In addition, the average utilization hours of thermal power equipment and the installed capacity of thermal power efficiency closely related to the thermal power industry are also considered. Table 1 shows the description of the final selected variable.

All variables are processed using natural logarithm to remove possible heteroscedasticity. Finally, the research formula is as follows:

$$LCO_{2i} = L\beta_0(u_i,v_i) + \beta_1(u_i,v_i)LURB_i + \beta_2(u_i,v_i)LPEC_i + \beta_3(u_i,v_i)LPSC_i + \beta_4(u_i,v_i)LTUH_i + \beta_5(u_i,v_i)LTIC_i + \varepsilon_i \tag{7}$$

where CO_{2i} is thermal power industry's CO_2 emissions of the *i*-th province. URB and PEC are expressed as urban population or total electricity consumption divided by total population, respectively. PEC is one of the important technical indicators. Under the same conditions, the less it consumes, the less CO_2 emissions are generated. TUH refers to the utilization degree of power generation equipment in thermal power plants. TIC is an indicator of thermal power efficiency.

Table 1. Explanation of variables.

Variables	Definitions	Units
CO_2	CO_2 emissions from the thermal power industry	10^4 tons
URB	Urbanization level	Percent
PEC	Per capita electricity consumption	kWh
PSC	Standard coal consumption of power supply	g/kWh
TUH	Average utilization hours of thermal power equipment	Hour
TIC	Thermal power installed capacity	10^4 kW

Note: Tibet, Macao, Taiwan, and Hong Kong are precluded owing to unavailable data.

2.3 Data sources

In current paper, the data of CO_2 emissions are obtained based on three primary sources (coal, oil, and natural gas). The conversion factors of standard coal are 0.7143, 1.4286, 1.3300, and the carbon dioxide emission factors are 2.7412, 2.1358, 2.1650, respectively. In addition, the fossil energy consumption data of 30 provinces in the thermal power industry are derived from the Energy Balance Table of Sub-Regions in China Energy Statistical Yearbook (2006-2018) [7]. The provincial-level of urban and total population data from 2005 to 2017 is acquired by the China Statistical Yearbook [8]. Through the China Electric Power Yearbook over the period 2005-2017, we found the total electricity consumption, average utilization hours of thermal power equipment, standard coal consumption, and thermal power installed capacity in 30 provinces [9]. In order to discuss the drivers affecting CO_2 emissions and propose policy recommendations from a regional perspective, China's 30 areas are separated into three parts (see Table 2).

Table 2. Regional divisions.

Regions	Provinces
Eastern (11)	Beijing, Tianjin, Hebei, Hainan, Fujian, Liaoning, Shandong, Guangdong, Jiangsu, Zhejiang, Shanghai
Central (9)	Anhui, Jilin, Shanxi, Hubei, Jiangxi, Inner Mongolia, Henan, Hunan, Heilongjiang
Western (10)	Guizhou, Sichuan, Gansu, Guangxi, Ningxia, Yunnan, Xinjiang, Shaanxi, Qinghai, Chongqing

3 Results and discussion

3.1 Results of Multicollinearity test

In order to ensure that there are no multiple collinearity and redundant independent variables in the GWR model, it is necessary to check the multicollinearity of the selected variables. In this study, we adopted the variance expansion factor (VIF) to judge, and the results are expressed in Table 3. As can be seen, the tolerance of variables is greater than 0.1, and the VIF-value is much less than 10, indicating that there is no multicollinearity among variables.

Table 3. Results of multicollinearity test.

Variables	LURB	LPEC	LTUH	LPSC	LTIC
Tolerance	0.468	0.420	0.512	0.570	0.956
VIF	2.138	2.380	1.952	1.755	1.046

3.2 Results of the GWR model

Table 4 displayed the overall running results based on Gaussian, Exponential, and Tricube distance weight functions. As shown in Table 4, the value of adjusted R^2 obtained by using Exponential function is the largest (0.9989), so this function is finally selected (see Figure 1).

Table 4. The overall running results in view of three distance weight functions.

Distance weight functions	Gaussian	Exponential	Tricube
Bandwidth	1.2596	4.4721	-
R^2	0.9928	0.9991	0.9910
Adjusted R^2	0.9913	0.9989	0.9891

3.2.1 From a perspective of the provinces

In all explanatory variables, the technical indicator "standard coal consumption of power supply" has the strongest positive effect on CO_2 discharges from thermal power industry. The effect in Qinghai province is largest (5.194), followed by Gansu, Heilongjiang, and Jilin, while that in Xinjiang Autonomous Region is the least (0.210). However, Fujian Province does not pass the significance test, indicating that technology is not the decisive driver of Fujian Province's emission reduction. In other provinces, decreasing the standard coal consumption should be the priority, it is necessary to increase investment in R & D personnel and funds for technological innovation.

The power demand indicator "average utilization hours of thermal power equipment" is also an important contributor to thermal power generation's CO_2 emissions. The effect of power demand on CO_2 emissions in Beijing, Hebei, Inner Mongolia, Shanxi, and Tianjin does not pass the significance test. It denotes that power demand is not a primary driver affecting CO_2 emissions in these provinces. Besides, Liaoning, Jilin, and Heilongjiang provinces played a dominant part in the suppression of the total industrial CO_2 emissions. In addition, other provinces still need to arrange and adjust the average utilization hours of equipment according to the power demand.

The factor of installed capacity is the key to reducing CO_2 emissions for all provinces. They are positively correlated with CO_2 emissions. The coefficient of installed capacity ranges from 0.272 to 1.209. The elasticity of installed capacity in Qinghai province stands first (1.209), while that in Xinjiang Autonomous Region ranks final (0.272). In addition, most provinces have a coefficient greater than 1, the government should keep an eye on improving the efficiency of power supply in these provinces.

Except for Liaoning, Jilin, and Heilongjiang provinces, the coefficients of urbanization level and per capita electricity consumption are less than 1, indicating that these two factors have a slight impact on thermal power's CO_2 emissions. Meanwhile, there is a two-sided connection between urbanization level or per capita electricity consumption with the CO_2 emissions. Provinces with positive coefficients need to further control the urbanization process, or adjust the economic structure to reduce per capita electricity consumption.

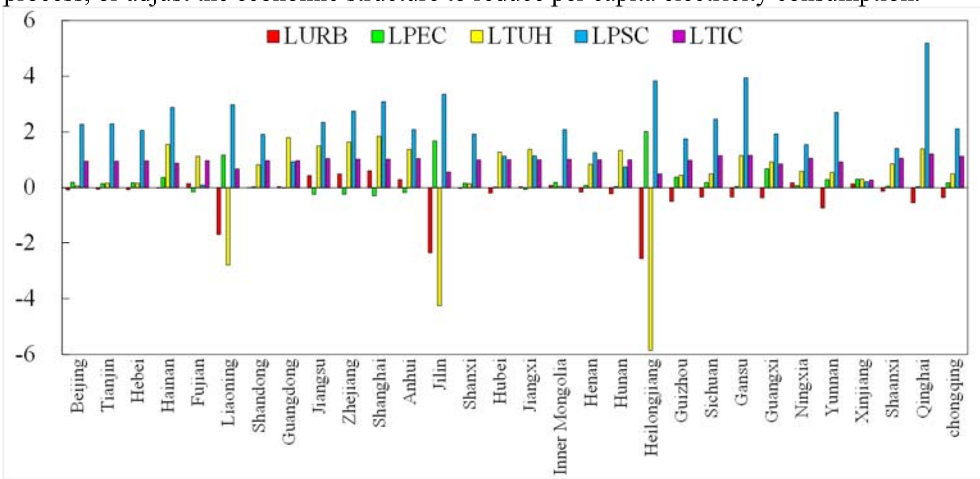

Fig. 1. The estimation result of GWR model based on Exponential function.

3.2.2 From a regional point of view

As shown in Figure 2, the effects of drivers on CO_2 emissions are different at the regional level. The biggest effect of standard coal consumption on CO_2 emissions is in the western region (2.325), stronger than that in the eastern region (2.145) and central region (1.951). The average utilization hour of thermal power equipment ranks first in the central region (1.834) for its response on CO_2 emissions, while the eastern region (1.223) and western region (0.721) continues to decline. The affect strength of thermal power installed capacity in the western region (0.977) is greater than those in the eastern region (0.946) and central region (0.901). The largest effect of urbanization level on CO_2 emissions is in the central region (0.656), with almost the same effect on the western region (0.361) and eastern region (0.329). The influence of per capita electricity consumption on CO_2 emissions is gradually weakening in the central region (0.491), eastern region (0.273), and western region (0.219).

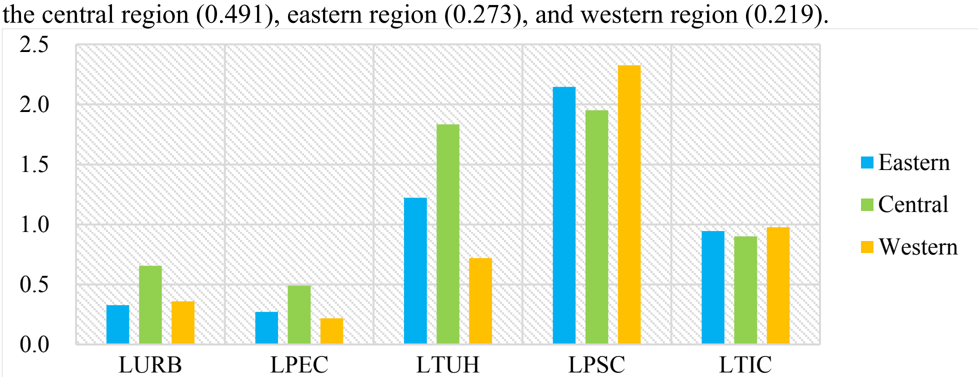

Fig. 2. The regional estimation results of GWR model.

4 Conclusions

This study discusses the thermal power industry's significant factors affecting CO_2 discharges through the GWR model. According to the empirical research that has been done, it can be concluded that standard coal consumption of power supply is a decisive factor influencing CO_2 emissions. It is worth noting that its response is larger in the western and eastern regions. The average utilization hours of thermal power equipment play an essential role in accelerating CO_2 emissions, and this factor has a greatest impact in the central region. Thermal power installed capacity has great potential to lessen CO_2 emissions, and its influence in the western region is the largest. The urbanization level and per capita electricity consumption only have a slight effect on the thermal power industry's CO_2 emissions, and that have been restraining emissions for most provinces. According to the above conclusions, the different policy suggestions are put forward from the aspects of power demand and supply. In the future research, we can add more power-related factors to study its impact on CO_2 emissions from the power industry.

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