Spatial heterogeneity analysis of CO2 emissions in China's thermal power industry: GWR model

Lei Wen, and Fang Liu*

Department of Economics and Management, North China Electric Power University, Hebei 071003, China

Abstract. The thermal power industry is a major contributor to China's CO2 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 CO2 emissions. The empirical results show that standard coal consumption is a decisive factor affecting thermal power industry's CO2 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 CO2 emission mitigation. However, the urbanization level and per capita electricity consumption have a slight effect on CO2 emissions. These findings furnish constructive reference and policy implications to achieve emission abatement targets of different regions.

Keywords: Thermal power industry; CO2 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 CO2 discharges [1]. In 2015, the Chinese government proposed to peak CO2 emissions around 2030 and committed to decrease CO2 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 CO2 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 CO2 emissions.

Many scholars have attempted to make an in-depth study on the power sector's CO2 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 CO2 emissions and its driving forces [3, 4]. However, there is no report on the application of GWR model in thermal power sector's CO2 emissions.

In this paper, the primary drivers of CO2 emissions from thermal power sector have been conducted based on the GWR model. It not only explores the drivers of CO2 emissions from
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:

\[ y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j(u_i, v_i)x_{ij} + \epsilon_i \]  

(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. \( \epsilon_i \) means the random error term.

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

(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:

\[ W_i = \Phi \left( \frac{d_i}{\sigma \theta} \right) \]  

(3)

Exponential distance function:

\[ W_i = \exp \left( -\frac{d_i}{\theta} \right) \]  

(4)

Tricube distance function:

\[ W_i = \frac{1 - \left( \frac{d_i}{q_i} \right)^3}{1 + \left( \frac{d_i}{q_i} \right)^3} \quad I(d_i < q_i) \]  

(5)

where \( \sigma \) refers to the standard deviation of distance vector \( d_i \). \( \theta \) represents the bandwidth. \( \Phi (\cdot) \) 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.

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

(6)

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

2.2 Model construction

According to the extended STIRPAT model, this research takes five drivers of CO2 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:

\[
LCO_{2i} = \beta_0 \left(u_i, v_i\right) + \beta_1 \left(u_i, v_i\right) LURB_i + \beta_2 \left(u_i, v_i\right) LPEC_i + \beta_3 \left(u_i, v_i\right) LPSC_i + \\
\beta_4 \left(u_i, v_i\right) LTUH_i + \beta_5 \left(u_i, v_i\right) LTIC_i + \epsilon_i
\]

where \( LCO_{2i} \) is thermal power industry's CO2 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 CO2 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.

| Variables     | Definitions                                             | Units   |
|---------------|---------------------------------------------------------|---------|
| CO2           | CO2 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 CO2 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 CO2 emissions and propose policy recommendations from a regional perspective, China's 30 areas are separated into three parts (see Table 2).

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

Table 2. Regional divisions.
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.

| 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 R² obtained by using Exponential function is the largest (0.9989), so this function is finally selected (see Figure 1).

| Distance weight functions | Gaussian | Exponential | Tricube |
|---------------------------|----------|-------------|---------|
| Bandwidth                 | 1.2596   | 4.4721      | -       |
| R²                        | 0.9928   | 0.9991      | 0.9910  |
| Adjusted R²               | 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 CO₂ 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 CO₂ emissions. The effect of power demand on CO₂ 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 CO₂ emissions in these provinces. Besides, Liaoning, Jilin, and Heilongjiang provinces played a dominant part in the suppression of the total industrial CO₂ 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 CO₂ emissions for all provinces. They are positively correlated with CO₂ 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 CO₂ emissions. Meanwhile, there is a two-sided connection between urbanization level or per capita electricity consumption with the CO₂ emissions. Provinces with positive coefficients need to further control the urbanization process, or adjust the economic structure to reduce per capita electricity consumption.

![Graph of power demand impact on CO₂ emissions](image1.png)

**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 CO₂ emissions are different at the regional level. The biggest effect of standard coal consumption on CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions is gradually weakening in the central region (0.491), eastern region (0.273), and western region (0.219).

![Graph of regional estimation results](image2.png)

**Fig. 2.** The regional estimation results of GWR model.
4 Conclusions

This study discusses the thermal power industry's significant factors affecting CO₂ 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 CO₂ 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 CO₂ emissions, and this factor has a greatest impact in the central region. Thermal power installed capacity has great potential to lessen CO₂ 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 CO₂ 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 CO₂ emissions from the power industry.

References

1. Q.Y. Yan, Y.X. Wang, Z.Y. Li, et al, Coordinated development of thermal power generation in Beijing-Tianjin-Hebei region: Evidence from decomposition and scenario analysis for carbon dioxide emission. J. J Clean Prod 232, 1402-1417 (2019).
2. Intended Nationally Determined Contribution (INDC): Enhanced Actions on Climate Change: China's Intended Nationally Determined Contributions. Z. United Nations Framework Convention on Climate Change (UNFCCC), (2015).
3. Y.N. Wang, W. Chen, Y.Q. Kang, et al, Spatial correlation of factors affecting CO₂ emission at provincial level in China: A geographically weighted regression approach. J. J Clean Prod 184, 929-937 (2018).
4. H.T. Qin, Q.H. Huang, Z.W. Zhang, et al, Carbon dioxide emission driving factors analysis and policy implications of Chinese cities: Combining geographically weighted regression with two-step cluster. J. Sci Total Environ 684, 413-424 (2019).
5. B. Xu, L. Xu, R.J. Xu, et al, Geographical analysis of CO₂ emissions in China's manufacturing industry: A geographically weighted regression model. J. J Clean Prod 166, 628-640 (2017).
6. S. Georganos, A.M. Abdi, D.E. Tenenbaum, et al, Examining the NDVI-rainfall relationship in the semi-arid Sahel using geographically weighted regression. J. J Arid Environ 146, 64-74 (2017).
7. National Bureau of Statistics (NBS), China Energy Statistical Yearbook. J. Beijing: China Statistics Press, (2006-2018).
8. National Bureau of Statistics (NBS), China Statistical Yearbook. J. Beijing: China Statistics Press, (2006-2018).
9. National Bureau of Statistics (NBS), China Electric Power Yearbook. J. Beijing: China Statistics Press, (2006-2018).