Original Research

Using a Geographically Weighted Regression Model to Explore the Influencing Factors of CO$_2$ Emissions from Energy Consumption in the Industrial Sector

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Abstract

This study presents the methodology as well as a quantitative analysis of the influence of social and economic factors, namely GDP, population, economic growth rate, urbanization rate, and industrial structure on CO$_2$ emissions as a result of energy consumption in the 101 counties of Inner Mongolia's industrial sector based on a geographically weighted regression model (GWR) and geographical information systems (GIS) from the perspectives of energy and environmental science. The results show significant differences in the measured CO$_2$ emission levels among different counties. Utilizing the GWR method (which was tested on the smallest scale that has been published thus far), the relationship between CO$_2$ emissions and these five explanatory variables produced an overall model fit of 99%. The GWR results showed that the parameters of variables in the GWR varied spatially, suggesting that the influencing factors had different effects on the CO$_2$ emissions among the various counties. Overall, population, GDP, and urbanization rates positively affect CO$_2$ emissions, industrial structure, and economic growth rate, and affect CO$_2$ emissions both positively and negatively. We also characterize the fact that varying industrial structures and economic growth rates result in different effects on the CO$_2$ emission of various regions.

Keywords: geographically weighted regression, influencing factors, industrial sector, energy consumption, CO$_2$ emissions

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Introduction

In the 21st century, global climate change has become an increasingly serious issue. Carbon emissions are mainly attributed to elevated global warming as well as other greenhouse gases. Yet all the while, reducing CO_2 emissions and maintaining stable economic growth has not only given rise to heated debate but has also been one of the major concerns of energy and environmental protection policies in all corners of the world [1]. The industrial sector in Inner Mongolia Province, as one of the three high-energy consumption sectors (construction, transportation, and production), faces a devastating resource and environmental challenge. Industrial energy consumption has occupied roughly 40% of overall global energy use [2]. However, the Chinese government has promised to reduce CO_2 emission intensity 40-45% by 2020 as compared to the 2005 levels at the COP15 United Nations Climate Change Conference [3]. Thus, it is urgent for academics and practitioners to intensively assess energy consumption CO_2 emissions all over the world – especially in rapidly developing countries [4]. However, in order to achieve the carbon emission reduction targets in the Inner Mongolia autonomous region, we need to conduct a scientific analysis of the province's (municipalities and autonomous regions) characteristics and regional differences in CO_2 emissions, economic development, industrial structure, and energy efficiency, and the need to investigate the spatial and temporal characteristics of Inner Mongolia CO_2 emissions, potential influencing factors, and how to develop a low-carbon economy [5]. According to literature, the Logarithmic Mean Divisia Index (LMDI) and Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) have been widely used recently in the fields of energy and environmental research [6-11]. However, all these studies focus on CO_2 emissions at the global and national levels rather than at the county level. In particular, their main objective is to develop an effective formula and model to estimate the total amount of CO_2 emissions but failed to explore the influencing factors and to better inform responsible politicians for the specific climate of political decisions regarding Inner Mongolian policies.

In previous studies, the relationship between CO_2 emissions and socio-economic factors obtained by OLS was for the whole study area and represented the average situation, assuming that the relationship does not change over space [11]. However, this assumption is not true when we compared the results from different studies. The traditional regression techniques estimate a single set of spatial trend parameters for all locations, which ignores localized differences across data points. Geographically weighted regression, which was proposed by geographers Brunsdon et al. [12] and fully described by Fotheringham et al. [13], is essentially a spatially weighted estimation of regression coefficients, repeated across space, with each (weighted) regression centered on a point in the data set. Compared with some new statistical models such as the linear mixed model, generalized additive model, multi-layer perception neural network, and radial basis function neural network, the GWR model can estimate regression coefficients at any one spatial location, and it produces better predictive performance for the response variable. The GWR model has become increasingly popular in the fields of geography, environment, and energy. The geographically weighted regression (GWR) proposed by Brunsdon et al. [12] is a local regression model that can examine non-stationary relationships between dependent and explanatory variables across the study area and improve the spatial accuracy of the regression model by calibrating errors of global models at different locations.

The dependent and explanatory variables at the county level are aggregated at a different spatial range as compared to the national level. In addition, the residuals of the GWR model have more desirable spatial randomness than those derived from other models [14]. Geographically weighted regression was specifically designed to deal with the spatial non-stationarity of regression coefficients between the target variable and explanatory variables by measuring those coefficients using local data [15]. In addition to its prediction capabilities, GWR produces a suite of parameter estimates over space (one set for each centering data point) and the effects of covariates become a continuously varying surface [16]. The GWR technique has been used to account for the spatial heterogeneity in the CO_2 emissions at the county level. An evaluation of the performance of the GWR modeling technique (particularly for the county-level panel data) is important to safety researchers. However, none of previous studies have used the GWR for the influencing factors of CO_2 emission analysis at the county level in Inner Mongolia Province. The findings can help Inner Mongolia's government agencies select appropriate methods to develop the low-carbon economy at the county level.

A review of the literature shows that there is very limited study on the dynamic impacts between CO_2 emissions, economic growth rate, and other variables in Inner Mongolia. Thus, we develop an alternative method for the local analysis of relationships in multivariate data sets, which we term geographically weighted regression (GWR). The application of GWR is a new trial in the geographical field. The primary objective of this research is the application of the GWR modeling technique to evaluate the influencing factors of CO_2 emissions at the county level.

Material and Methods

Material

In this study, in order to take into account the variable influence of time lag, we selected the 2010-12 arithmetic mean values of the variables, which serve to smooth out the short-term effects of precipitating factors and present a more realistic description of the effects of each city's socio-economic factors on CO_2 emissions. The selected data is panel data from 101 counties in Inner Mongolia

and includes coal, coke, crude, gasoline, kerosene, diesel, fuel oil, and gas of final energy consumption data and socio-economic indicators, namely GDP, population, economic growth rate, urbanization rate, and industrial structure, respectively, in 2010-12. The economic growth, urbanization rate, and industrial structure indicators are calculated by the annual data collected from the Inner Mongolia Autonomous Region statistics website. The total energy consumption in Inner Mongolia Province's industrial sector and social economic factors are published in the Inner Mongolia Statistics Book (2010-12) [17-19].

Description of Regression Variables

Our study uses annual time series data from 2010 to 2012 for 101 counties of Inner Mongolia as obtained from the Inner Mongolia Statistics Book (2010-12) [17-19]. In the study we define CO_2 emissions as the dependent variable and GDP, economic growth rate, urbanization rate, and population and industrial structure as explanatory variables. The CO_2 emissions are estimated by the IPCC [20], and the economic growth rate is calculated by averaging the gross domestic products of 2010, 2011, and 2012. This indicator is a good measure of a region's economic development, as economies in different periods might demand different sources of energy and energy efficiency. The urbanization rate is defined as the ratio of urban population to the total population and the industrial structure is defined to the ratio of secondary industry GDP and tertiary industry GDP.

Calculation of CO_2 Emissions

The Intergovernmental Panel on Climate Change [20] provided fundamental guidelines and internationally unified standards of assessment for CO_2 emissions from greenhouse gases [21]. The IPCC method was used to calculate the statistical CO_2 emissions from the energy consumption of Inner Mongolia's industrial sector. The carbon emission coefficient method is good applicability for not enough detailed statistical data. All kinds of energy consumption within a study area during a certain period are multiplied by the corresponding carbon emission coefficients and are then summed up. We can obtain the CO_2 emissions of energy consumption in the study area over the study period. The formula is as follows:

$$C = \sum_{i=1}^{n} E_i \times c_i \tag{1}$$

…where C represents CO_2 emissions (10^4t), E_i represents the stand coal consumption of energy type i (tce), C_i represents the effective CO_2 emission coefficient of each energy type (t/tce), and i represents types of energy such as raw coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, and natural gas. According to the IPCC guidelines, various types of fuel consumption can be converted to standard coal consumption based on the calorific value

Table 1. The standard coal and CO_2 coefficients of different types of energy.

Energy type	Standard coefficient	CO_2 emission coefficient
	kg/kg	kg/kg
Coal	0.6248	2.21
Coke	0.9714	3.14
Crude oil	1.4286	2.76
Gasoline	1.4714	2.2
Kerosene	1.4714	2.56
Diesel oil	1.4571	2.73
Fuel oil	1.4286	2.98
Nature gas	12.143	2.09

of each fuel type. The conversion coefficients of power generation coal to standard coal consumption (SCE) and CO_2 emission coefficient for different energy types are listed in Table 1.

CO_2 emissions are calculated by final energy consumption and CO_2 emissions coefficients during 2003-12.

Geographically Weighted Regression Model

In recent years, multiple regression models have been widely used in geographic analysis. The global regression model assumes that different regions of the explanatory power of the independent variable on the dependent variable are the same, which indicates that there is no change in the relationships between them according to their location [22]. Moreover, recent studies have shown that the relationships between spatially distributed environmental variables can vary across geographical space [12-13]. However, variations or spatial non-stationarity in relationships between the dependent and independent variables over space commonly exist in spatial data sets and the assumption of stationarity or structural stability over space may be unreliable [13].

In the geographically weighted regression model, the estimation of regression coefficients does not use global information and instead uses neighborhood information to estimate the local regression coefficient, which changes with spatial location. Furthermore, the GWR offers the possibility to promptly generate maps integrating diverse spatial information and visualize how potential radon factors influence changes over geographical space (Fig. 1).
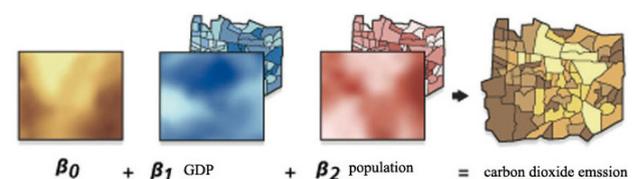
Fig. 1. Display of geographically weighted regression models.

As a local regression technique, GWR is an extension of the global regression technique:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \tag{2}$$

…where y_i, y_{ik}, and ε_i represent the dependent variable, the independent variables, and random error term at different spatial points (the subscripts i and k stand for the spatial locations and the independent variable number, respectively); β_0 is the model intercept; and β_k is the slope coefficient for kth independent variable. This type of model is aspatial, i.e., no geographical location information is considered in the estimation of the model parameters, and all parameters are averages across the whole data set. Calibrating equation (2) would appear to be problematic because there are more unknowns than observed variables.

The GWR model extends the conventional global regression by adding a geographical location parameter. The model is rewritten as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)\chi_{ik} + \varepsilon_i \quad i = 1,2......,n \tag{3}$$

…where y_i is the dependent variable in the ith location (in this case CO_2 emission i at location i), χ_{ik} is the ith value of the kth independent variable, k represents the number of independent variables (GDP, industrial structure, economic growth rate, urbanization rate, and population), i represents the number of counties, ε_i represents the residual, (u_i, v_i) is the coordinate location of the i sampling point, $\beta_0(u_i, v_i)$ is the continued function, and a $\beta_k(u_i, v_i)$ is the value at the i point.

According to formula (3), the regression parameters of the geographically weighted regression model are different from the values in different sampling points. The total number of unknown parameters is $n * (p + 1)$, and the observational data is only n. A general estimation of parametric regression methods cannot solve this problem. According to Tobler's first law, geographical phenomena situated in geographical space near each other are likely to show more similar characteristics than points situated far away from each other [23].

Accordingly, Brunsdon proposed the following problem-solving idea based on previous research [24]: For sampling point i, select the point of sampling points and the surrounding neighborhood as an observation to establish the overall regression model and use the principle of least squares to obtain the point of regression parameters. Similarly, the regression parameters of the other point can be obtained using the same method.

We assume that w_{ij} is the weight value of ith and sampling point j. The ith of the regression parameters in the GWR model can be calibrated using the weighted least squares approach.

$$\sum_{j=1}^{n} w_{ij}\left(y_j - \beta_{i0} - \sum_{k=1}^{p} \beta_{ik} x_{ik} \right)^2 \tag{4}$$

We estimate it by the formula into minimum.

In matrix form, $\beta_i = [\beta_{i0}\beta_{i1}...\beta_{ip}]$, $W_i = diag(w_{i1}, w_{i2},...,w_{in})$ and these parameters at each location i are estimated by the equation:

$$\hat{\beta}_i = \left(X'W_i X \right)^{-1} X'W_i y \tag{5}$$

The most important aspect of the GWR model is how to decide the spatial weighting matrix, which can be calculated using many different methods. In this study, the weight of each point can be calculated by applying the Gaussian function [15]. This paper uses an adaptive bi-square function to generate the geographic weights:

$$w_{ij} = \begin{cases} [1-(d_{ij}/b)^2]^2 & d_{ij} \leq b \\ 0 & d_{ij} > b \end{cases} \tag{6}$$

… where w_{ij} is the weight of location j in the space at which data are observed in order to estimate the dependent variable at location i, b is referred as bandwidth, and d_{ij} is the distance between the ith and jth locations (namely the spatial geography distance between ith county and jth county in this study). This spatial geography distance is calculated by the longitude and latitude of each county.

Selecting the weighting function and optimal bandwidth depends on the parameter of data number of neighborhoods by comparing the performance of GWR and OCK. When processing the GWR regression models, weights and bandwidths decreased in the densely sampled places and increased in the sparsely sampled places. In this study, the adaptive method was employed to calculate kernels of GWR [13]. The parameter estimates under the GWR model can be solved by using a weighting scheme from a Kernel function that provides the most weight to locations closest in space to the focal location [13].

Results and Discussion

The Statistics of CO_2 Emissions and Each Variable

There is a significant difference between the spatial pattern of CO_2 emissions and socio-economic factors of Inner Mongolia's 101 counties. Table 2 presents the quantitative statistics of CO_2 emissions and five socio-economic factors. The distribution of CO_2 emissions and influencing factors varied significantly across all of Inner Mongolia (Table 2). In addition, the maximum and minimum values of monthly mean temperature and

Table 2. The mean, standard, minimum, and maximum percentages of 25, 50, and 75 percent of CO_2 emission volumes and each variable.

Variables	Mean	STD	Min	25%	50%	75%	Max
CO_2 emissions (million t)	5.05	9.71	0.0002	0.25	0.80	6.08	69.99
GDP (billion CNY)	17.51	19.36	1.27	5.81	10.35	21.24	100.04
Economic growth rate (%)	13	3.44	4.2	11.1	13.3	15.1	24.9
Industrial structure (%)	2.42	1.77	0.2	1.3	1.9	3.1	9.4
Population (10^4) (million people)	24.86	16.74	1.79	10.9	23.26	33.95	88.96
Urbanization rate (%)	49.7	28.52	8.34	22.27	49.97	74.89	100

CO_2 emissions were greatly different as well. The CO_2 emissions of some counties were lower than 0.0002 million tons; emissions of other counties were as high as 69.99 million tons (emissions among the counties ranged from 0.00002 million tons to 69.99 million tons). The average CO_2 emissions are 5.05 million tons. The average GDP of each county in Inner Mongolia is 17.51 billion CNY. A significant wealth gap is present in Inner Mongolia and the highest GDP among the counties is 100.04 billion CNY, while the lowest is 1.27 billion CNY.

Spatial Distribution of Each Variable Based on ARCGIS

The five attributable indexes of data of this study and relevant statistics on cross-section data were obtained in accordance with county-level cities. Before the GWR modeling, a statistical description of each variable, preliminary understanding of the regional distribution, and spatial autocorrelation of these variables were necessary. This statistical descriptive analysis was achieved using ARCGIS software.

The Distribution of CO_2 Emissions

Fig. 2 shows that the average CO_2 emissions for a county in Inner Mongolia Province is 0.0463 million tons and the highest CO_2 emissions were recorded in Etuokeqi County. The counties with the next highest CO_2 emissions are mainly concentrated in the Huhhot and Baotou areas, which are the traditional industrial regions of Inner Mongolia. Due to rapid economic development, there is a high demand for energy and the energy consumption structure of our province is mainly comprised of coal, thus resulting in high levels of CO_2 emissions. However, emissions in central, eastern, and western parts of the whole region are below the provincial average value. The county with the lowest levels of CO_2 emissions is Hengxiangbaiqi County because it contains the grasslands and typical forests of Inner Mongolia, which are less developed economically, and its population abides by the traditional nomadic way of life. Consequently, the demand for energy is very low.

The Distribution of GDP

Table 2 and Fig. 2 reveal that the average GDP in Inner Mongolia is 15,012.18 million CNY and the highest GDPs are mainly concentrated in the southwest corner of Inner Mongolia. Baotou Kundulun District has the highest GDP, mainly because the regional economy is relatively developed and coal mining and the steel industry are concentrated here. However, GDP is lowest in the eastern and western regions of Inner Mongolia – far below the average level. The GDP in Aershan county of Hulunbeier League is the lowest. This area is a developing region where primary and tertiary industries concentrate.

The Distribution of Population

Fig. 2 indicates that population density is highest in the northeast region, and the most populous city is Tongliao in Keorqin County. This area is characterized by rich water resources, mild weather conditions, and flat terrain, and it is relatively developed to meet the basic needs of human life. The population density in the Western Region is lowest, and the least populous city is Ejinaqi in Alashan League. This area is characterized by poor weather conditions, a shortage of water resources, frequent drought, terrain desertification, and insufficient natural resources, and consequently has a low population.

The Distribution of Industrial Structure

From Table 2 and Fig. 2, we found that the average industrial structure of a county in our province is 2.29. The industrial structure in Wulatezhongqi is as high as 8.9, which shows that the proportion of secondary industry almost is almost four times that of tertiary industry. The counties with high industrial structures are mainly concentrated in the western and central regions, which are the traditional industrial districts in Inner Mongolia. This indicates that the industrial structure in Inner Mongolia is the typical rough development type and needs to be improved. The proportion of industrial output in the Eastern regions is much lower than other areas, and the urban industrial structure in Xincheng District is at least 0.15. The industrial structure in the eastern areas is below
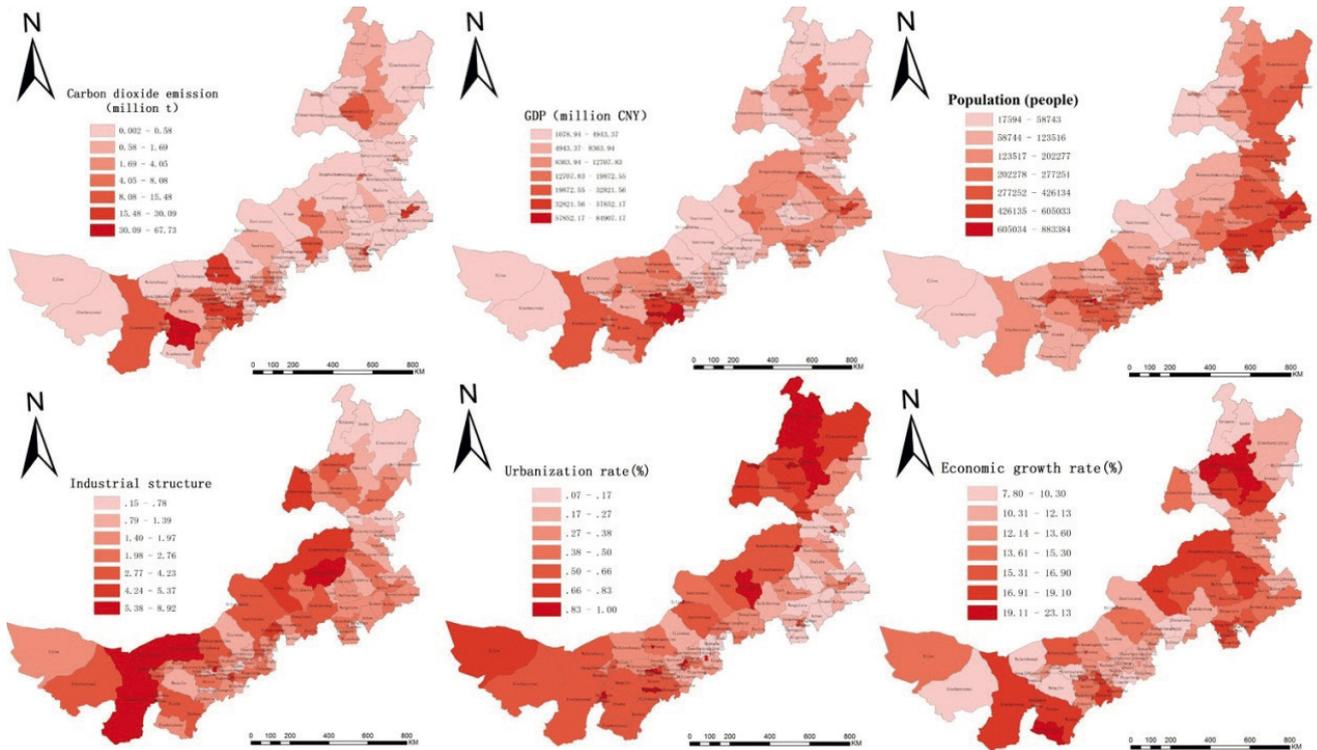
Fig. 2. The spatial distribution of each variable, namely CO_2 emissions, GDP, population, industrial structure, urbanization rate, and economic growth rate, respectively.

the provincial average, and increasing development should be promoted.

The Distribution of Urbanization Rate

From Table 2 and Fig. 2 we know that the average urbanization rate is 50% and the urbanization rate reaches up to 100% in Genhe city in Baiyunkuang and Wuda counties. The areas are characterized by low economic development, resulting in a high rate of urbanization. In contrast, the urbanization rate is low in Keyouqianqi because these areas are economically underdeveloped and urban development is rather backward. It also demonstrates that developing the economy is a necessity in the western region.

The Distribution of Economic Growth Rates

Fig. 2 shows that the average economic growth rate at county level is 13.96 and the spatial distribution of economic growth rate is relatively uniform throughout the province. The economic growth rates in the east and southeast are relatively high, such as in Huolinguole, which is more than 33 times the average. This has resulted in rapid economic development. However, economic growth in the central region is low, such as the economic growth rate of Liangcheng County at -9.7. There are great disparities in economic development throughout the province.

Spatial Autocorrelation of Each Variable Based on GEODA

In this paper, global and local Moran I indices were used to evaluate the spatial patterns of each variable and CO_2 emissions in Inner Mongolia based on GEODA software. The global Moran I index mainly reflected the nationwide spatial correlation between different geographical regions, while the local Moran I index mainly reflected the local similarities and variations between neighboring regions.
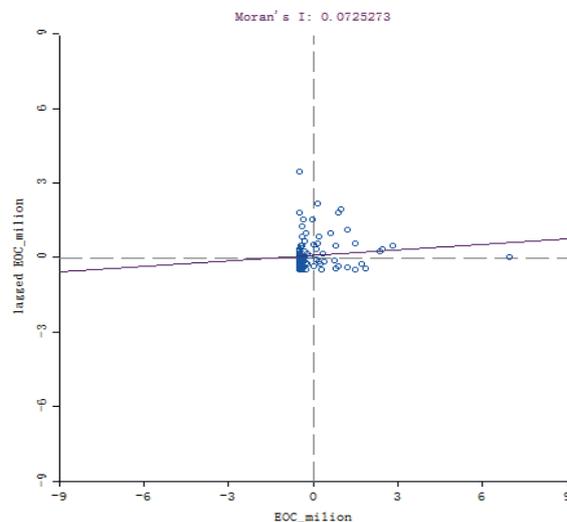
Fig. 3. Spatial autocorrelation testing for CO_2 emissions.
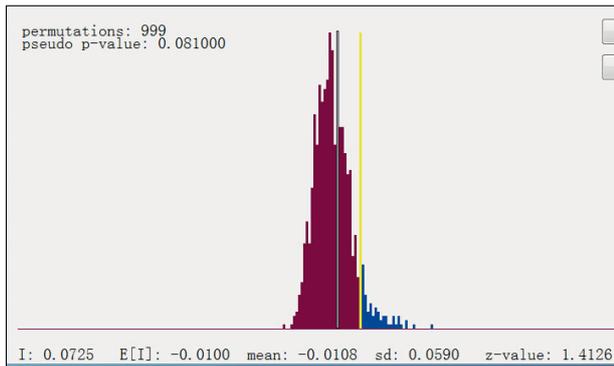
Fig. 4. The significant tests for CO_2 emissions using Moran I coefficients in Inner Mongolia.

The ranges of both global and local Moran indices were from 0 to 1. The positive values indicated the degree of similarities while negative values indicated the degree of differences. Zero values indicated no spatial correlation.

The spatial autocorrelation of the explanatory variables and CO_2 emissions was applied to GeoDA software and the results are shown in Figs 3-4 and Table 3. Fig. 4 reveals that the corresponding p value is 0.081, indicating that the CO_2 emissions do not exhibit positive correlation under the confidence level at 0.001 or 0.005. The spatial autocorrelation for the other explanatory variables use the same method. The result is shown in Table 3.

We found that there are positive relationships among GDP, industrial structure, economic growth rate, population, and urbanization rates. We use spatial econometric methods to analyze the spatial heterogeneity of these variables. Spatial correlation of CO_2 emissions is not significant, indicating that the county's CO_2 emissions do not exist as significantly positively correlated over space.

Test for Multi-Collinearity

The strong multi-collinearity among variables may produce biased parameter estimates and generate too much standard error of the regression coefficients, which makes the model unstable and statistical inference invalid [25]. The OLS regression (ordinary least square, OLS) model can exclude the dependent variable itself by the correlation coefficient matrix, which has little contribution and strong multi-collinearity on independent variable, according to tolerance coefficient and the variance inflation factor (VIF) test [26]. In this paper we use the OLS regression model based on ARCGIS software to test the multi-

Table 4. VIF value of variables.

Variables	VIF value
GDP	1.795
Industrial structure	1.336
Population	2.065
Urbanization rate	1.612
Economic structure	1.116

collinearity and exclude multiple potential collinearity using GWR model regression. Generally, severe collinearity exists when VIF>10, moderate collinearity exists when 5<VIF<10, and mild collinearity exists when 2<VIF<5 [26]. Table 4 shows that the VIF values of all explanatory variables are less than 5, indicating that there is lower collinearity among these variables, which could be incorporated into spatial econometric analysis of geographically weighted regression models.

Geographically Weighted Regression Analysis

In this study, CO_2 emissions were regarded as the dependent variable, and certain influencing factors – namely GDP, economic growth rate, industrial structure, urbanization rate, and population – were designated as the independent variable on the basis of the 101 county units of Inner Mongolia in 2012.

Because of the low correlation coefficient between these five elements, they can be analyzed by geographically weighted regression models. The GWR local estimation coefficient reveals the complex relationships between influencing factors and CO_2 emissions in the region. The impact of each of these factors on CO_2 emissions changes with location and whether the regression coefficient is negative or positive. In order to complement the drive mechanism more efficiently, the model calculates the influencing factor regression coefficients of three years and uses the ArcGIS 10.2 software spatial visualization module to analyze the effects of influence factors on CO_2 emissions in Inner Mongolia and its spatial difference.

Spatial Variability of GDP Impact on CO_2 Emissions

In this paper, we choose GDP as an important indicator of economic development. As shown in Fig. 5,

Table 3. Moran coefficients of each variable.

	CO_2 emissions	GDP	Economic growth rate	Industrial structure	Urbanization rate	Population
Moran's coefficient	0.0725	0.4133	0.328	0.2118	0.4427	0.4214
Confidence level (%)	91.9%	99.90%	99.9%	99.8%	99.9%	99.9%
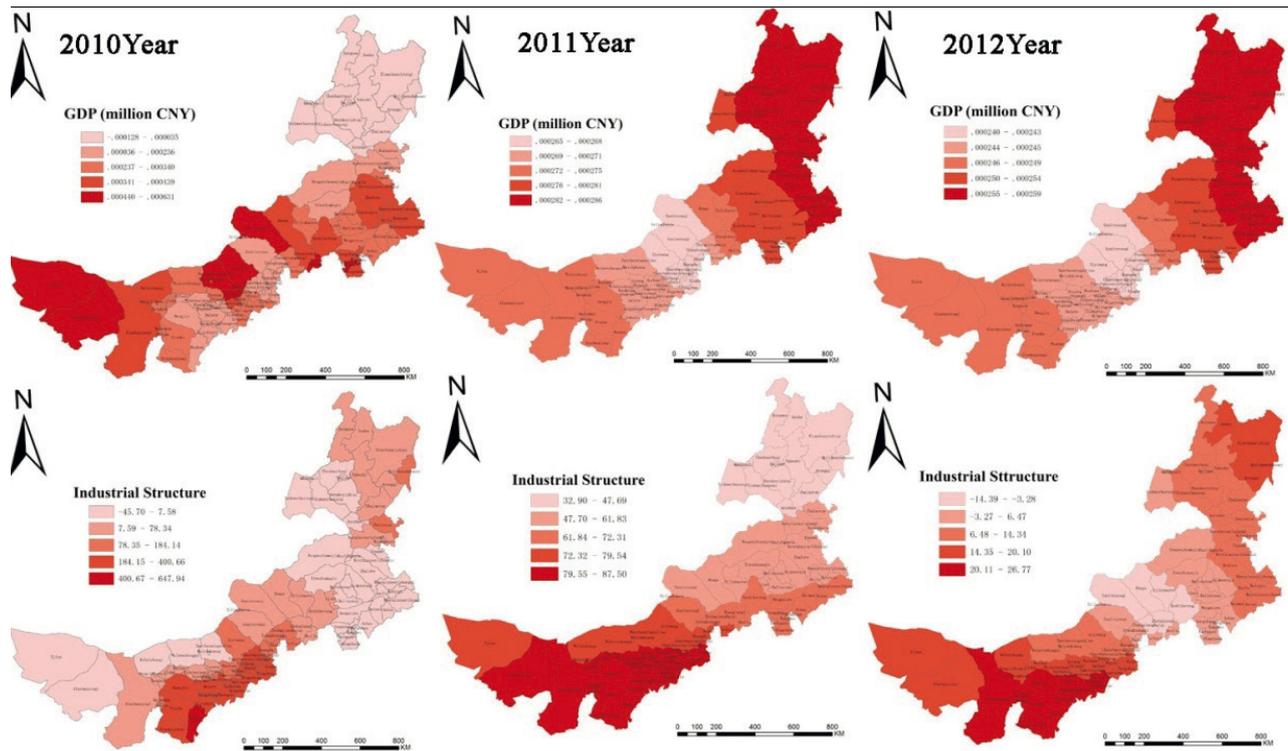
Fig. 5. Spatial distribution of regression coefficients of GDP and industrial structure based on GWR models in 2010, 2011, and 2012.

there exists a positive correlation between GDP and CO_2 emissions. GDP is representative of wealth (specifically at the economic development level) and is one of the most important factors affecting carbon emissions. The higher the GDP, the greater the amount of CO_2 emissions. The degree of influence is the highest in the east and west, and the weakest in the central part of Inner Mongolia. It is conceivable that rapid economic development signifies high rates of economic growth at the expense of elevated levels of CO_2 emissions. If the economic development is sustained by such means, it will inevitably lead to a vicious economic circle. Therefore, the eastern and western regions should develop regional economies according to local characteristics and advantages in order to obtain a favorable benefit-to-cost ratio. We should adopt the scientific "green GDP" indicator to change the type of economic development in the eastern regions.

Spatial Variability of Industrial Structure Impact on CO_2 Emissions

Fig. 5 shows that there is a negative correlation between industrial structure and CO_2 emissions of 21 counties in the Xilingol League and Chifeng, which indicates that the ratio of secondary industry to tertiary industry is low, and specifically that the industrial structure is mainly dominated by primary and tertiary industries. The economic development of these regions is rather backwards and the dominance of traditional pastoral life implicates a low demand for energy as well as the landscape being in its natural condition, resulting in

a strong limiting effect on CO_2 levels. There is a positive correlation between industrial structure and CO_2 emissions in the other 80 counties, including Huhhot and Baotou. These county-level economic development types that are dominated by secondary and tertiary industrial structures have a significant positive impact on CO_2 emissions, suggesting that a large proportion of secondary and the tertiary industry were not fundamentally developed according to the extensive economic development type, resulting in higher CO_2 emissions. Therefore, the province should improve energy efficiency by altering the economic development type from the extensive economic growth type to intensive economic development type – the inevitable option for our province.

Spatial Variability of Economic Growth Rate Impact on CO_2 Emissions

As shown in Fig. 6, there exists a negative correlation between economic growth rate and CO_2 emissions in the Xinan, Zhelimu, Hulunbeier, Xilinguole, and Chifeng leagues. In all other leagues there is a positive correlation between economic growth rate and CO_2 emissions. From spatial distribution of regression coefficients in each year, we know that regression coefficients increase from northeast to southwest, where the highest value is located. This mainly delineates the industrial area of our province where economic development is faster. As a result of economic development, the demand for energy is higher than other regions and the resulting CO_2 emissions in that region will be greater.
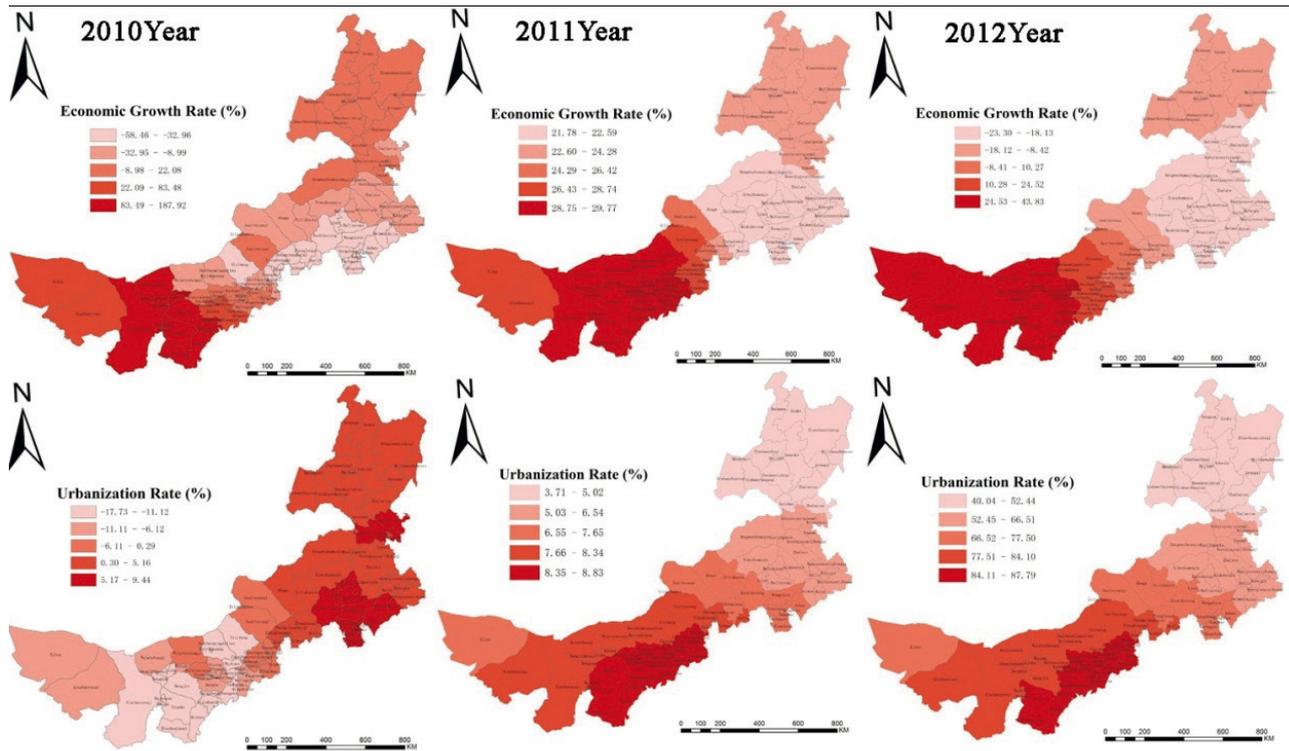
Fig. 6. Spatial distribution of regression coefficients of economic growth rate and urbanization rate based on GWR models in 2010, 2011, and 2012.

Spatial Variability of Urbanization Rate Impact on CO_2 Emissions

There is a positive correlation between urbanization rate and CO_2 emissions. Fig. 6 deduces the impact of urbanization rate on CO_2 emissions given the fact that the spatial distribution of urbanization rate becomes stronger moving from the eastern region to the western region. The impact of urbanization rate on CO_2 emissions is the strongest in the western region, mainly because this area is the province's major industrial zone; in addition, the economic development model still retains the extensive economic growth pattern, and economic development is mainly characterized by secondary industries with high energy consumption and pollution. The impact of urbanization rate on CO_2 emissions is the weakest in the eastern region, which shows that the economic development pattern of eastern area is gradually changing from extensive development type into intensive development type, and that economic development features of these areas mainly consist of primary and tertiary industries that have low energy consumption. With the improvement of urbanization rate continually, the CO_2 emissions of these areas does not increase and actually may exhibit a decrease due to improvements in energy efficiency.

Spatial Variability of Population Impact on CO_2 Emissions

There is a positive correlation between population and CO_2 emissions. Populations in all regions have a significant
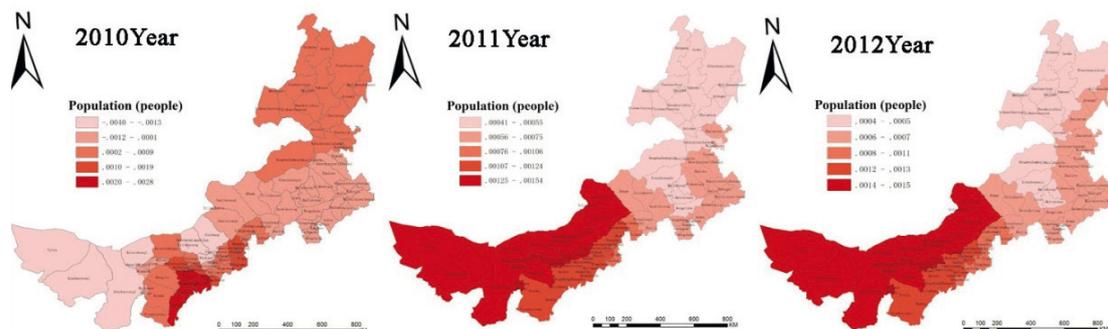
Fig. 7. Spatial distributions of regression coefficients of population based on the GWR model in 2010, 2011, and 2012.

positive impact on CO_2 emissions, and fast population growth results in increased emissions. Currently, with the rapid increase of the province's population and the improvement of quality of life, the demands for energy have increased substantially. We need to meet the demand for energy caused by an increasing population, which can lead to increased CO_2 emissions. Inner Mongolia should decrease the CO_2 emissions caused by population growth by improving energy efficiency. From the perspective of spatial variation of the regression coefficients, the population has a greater influence on CO_2 emissions in the central and western regions of Inner Mongolia than the eastern region. The population impact on CO_2 emissions extending from the northeast to the southwest has the same spatial distribution in the years 2010, 2011, and 2012 (as shown Fig. 7).

Conclusions

We applied the geographically weighted regression (GWR) model calibrated to explore the spatially varying relationships between CO_2 emissions and explanatory variables in 2010, 2011, and 2012.

The general spatial pattern shows that CO_2 emissions and the five influencing factors of 101 counties in Inner Mongolia have a strong positive correlation and significant spatial heterogeneity. The areas with high CO_2 emissions are concentrated in industrial and economically developed regions such as Hohhot and Baotou, while emissions are low in areas such as the northeastern prairie and forest areas. The Moran I tests showed that the spatial autocorrelation of CO_2 emissions and explanatory variables are positive over counties. The results also showed that the GWR successfully captured the spatially non-stationary relationships between CO_2 emissions and influencing factors at the county level in Inner Mongolia. The parameters of variables in the GWR varied spatially, suggesting that the effects of influencing factors on CO_2 emissions were different between counties. Overall, population, GDP, and urbanization rate have a positive effect on CO_2 emissions while the industrial structure and economic growth rate has both positive and negative effects on emissions. We characterized the fact that varying industrial structures and economic growth rates result in different effects on the emissions of various regions.

The GWR model in current research attempts to investigate the influencing factors and CO_2 emissions as a complement to global regression models. The estimated parameters by GWR can depict more realistic spatial relationships between CO_2 emissions and influencing factors at different locations with higher confidence. One of the deficiencies of the GWR model is that it assumes spatial non-stationarity for all variables, when in reality some natural processes may exhibit spatial stationarity, especially in homogeneous regions [27]. In the future, some improvements have been proposed to further enhance the explanatory power and generalization of the GWR model. At present, most research for panel data empirical analysis

assumes this for each set. The panel data of sectional units are homogeneous, namely there is no difference between the regions. Additionally, conventional global statistics assume one relationship for the entire study extent, and are not designed to consider whether a relationship varies across space. In fact, there is instability and heterogeneity among most panel data.

The geographically weighted regression model mainly applies to the existence of spatial heterogeneity of panel data and empirical analysis results explain the spatial heterogeneity problem by a geographically weighted regression model. One advantage of this alternative technique is that it is based on the traditional regression framework with which most readers will be familiar. Another advantage is that it incorporates local spatial relationships into the regression framework in an intuitive and explicit manner [13]. The other advantages of the GWR model is the convenience of the technique that has been built into the ''GWRx3.0'' software package. In addition, limited data availability has restricted the long-term analysis of CO_2 emissions of the 101 counties in Inner Mongolia. For future studies, we can obtain more accurate data by visiting statistics or relevant administrative departments. The calculation of CO_2 emissions uses the formula and CO_2 emission coefficients, which are provided by the 2006 IPCC guidelines for national greenhouse gas inventories, which fails to consider the differences of CO_2 emission coefficients caused by regional differences.

Although this method is simple and easy to operate, it is extensive and does not take into account the regional differences in energy consumption and energy technology. The planned analysis of the impact of 11 influencing factors on final energy use for CO_2 emissions had to be reduced to five factors because of a lack of annual data. Therefore, due to the resolution limit of currently used geological and stream sediment geochemical datasets, only general and regional influencing factors of CO_2 emissions (i.e., GDP, industrial structure, and population) are discussed. For individual deposits, other factors that may specifically contribute to the emissions of CO_2 (e.g., CO_2 intensity, energy structure, etc.) should be investigated as well.

Therefore, in order to further facilitate analysis, more detailed influencing factors identified from other sources of geo-datasets will be included in our future research. In spite of this, this study is the first attempt to analyze the spatial heterogeneity between CO_2 emissions and other explanatory variables such as industrial structure, GDP, population, and the economic structure of 101 counties in Inner Mongolia. According to the discussion above, the results obtained from this study reasonably assess and meaningfully support efforts to control CO_2 emissions in the industrial sector of Inner Mongolia Province.

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