Spatio-Temporal Analysis of CO_2 Emission Driving Force in Various Provinces in China Using the Extended STIRPAT-GWR Model

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Abstract. To fill the shortcomings of traditional research that ignores the driver's own spatial characteristics and provide a theoretical support to formulate suitable emission reduction policies in different regions across China. In this pursuit, based on the panel data of provincial CO_2 emission in 2007, 2012, and 2017, the present study employed the extended environmental impact assessment model (STIRPAT-GWR model) to study the effect of population, energy intensity, energy structure, urbanization and industrial structure on the CO_2 emissions in 29 provinces across China. The empirical results show that the effect of drivers on the CO_2 emissions exhibited significant variations among the different provinces. The effect of population in the southwest region was significantly lower than that of the central and eastern regions. Provinces with stronger energy intensity effects were concentrated in the central and western regions. The effect of energy structure in the eastern and northern regions was relatively strong, and gradually weakened towards the southeast region. The areas with high urbanization effect were concentrated in the central and the eastern regions. Furthermore, significant changes were observed in the high-effect regions of the industrial structure in 2017. The high-effect area showed a migration from the northwest and northeast regions in 2007 and 2012, respectively, to the southwest and southeast regions in 2017. Urbanization showed the strongest effect on the CO_2 emissions, followed by population and energy intensity, and the weakest effect was exhibited by the energy and industrial structure. Thus, the effects of population and energy structure showed a downward trend, in contrary to the effect of urbanization on the CO_2 emissions in China.

Keywords. CO_2 emissions, STIRPAT-GWR model, spatial analysis drivers, China

1. Introduction

China has proposed the goal of reaching its peak CO_2 emissions by 2030. However, China's accelerating industrialization, urbanization and growing population have continuously increased the total energy consumption. Fossil energy consumption generates huge amounts of CO_2.

Many scholars have done a lot of relevant research on the CO_2 emissions, and they have also achieved fruitful results. The driving factors of the CO_2 emissions have been

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studied based on the factor decomposition methods and environmental impact assessment models [1], [2], [3], which mainly included population, energy, industry, urbanization, and economy. Many scholars have also studied the spatial differences of the CO_2 emissions based on the traditional regression models [4], and studied the spatial autocorrelation of CO_2 emissions based on the Moran index [5]. The results of the study indicate that there were significant spatial differences and autocorrelation in the CO_2 emissions. Despite the fruitful results, the existing research still faces certain shortcomings as follows: (1) Traditional models have shortcomings in space research. When it comes to space research, most scholars conduct analysis and research based on the traditional Ordinary Least Square model, but the OLS model does not involve the geographic location of the region. Traditional estimation models could have possibly presented biased results or even unreliable considering the spatial analysis[6]. (2) The traditional research ignored the spatial characteristics of the drivers themselves. Studies have shown that in spatial analysis, geographically weighted model was better than the traditional OLS regression [7]; and the environmental impact assessment model (STIRPAT) is not only relatively simple, but also can determine the impact of multiple human activities on the environment [8]. Therefore, the present study combined the traditional environmental impact assessment model with the geographically weighted model along with the spatial autocorrelation to build an integrated model, in order to study the spatial and temporal characteristics of the impact of the driving factors on CO_2 emissions, which overcomes the shortcomings of the traditional models in spatial research.

2. Data

The data of total population, urban population, gross domestic product, gross output value of secondary industry, gross output value of tertiary industry in this study were obtained from the China Statistical Yearbook. The data on coal, oil, and natural gas consumption was obtained from the China Energy Statistical Yearbook. The data of CO_2 was calculated from the three primary energy consumption using the method recommended by IPCC 2006. Since the data of Taiwan Province, Hong Kong Special Administrative Region, Macau Special Administrative Region, and Tibet National Autonomous Region were difficult to obtain, they were not included in the data set in this study. There were no provinces around Hainan that share the same border and points. In the conceptualization of spatial relationship, adjacent elements need to meet the characteristics of common edge and common point. Therefore, the data of Hainan Province was discarded.

3. Research methods

Our data shows that there was a serious multicollinearity between the urbanization and per capita GDP. Considering that urbanization can reflect more problems, and the model fits well after removing per capita GDP, we mainly studied the demographic factors: total Population (PEO, expressed by the total population of the province); Economic factor: Urbanization (URB, expressed by the ratio of urban population to the total population of the province); Technical factor: Industrial structure (INST, expressed by the total output value of the secondary industry and the third The proportion of industry); the impact of

energy intensity (ENIN, total energy consumption compared with the regional GDP) and energy structure (ENST, the proportion of coal consumption to total consumption) on CO_2 emissions.

The parameter estimation model can be expressed as:

$$lnC = ln\alpha_0(u_i, v_i) + \alpha(u_i, v_i)\ln(x_i(PEO)) + \beta(u_i, v_i)\ln(x_i(URB))$$
$$+ \gamma1(u_i, v_i)\ln(x_i(INST)) + \gamma2(u_i, v_i)\ln(x_i(ENIN))$$
$$+ \gamma3(u_i, v_i)\ln(x_i(ENST)) + ln\mu_i$$

In this study, we proposed a new integrated model that combines the traditional OLS model and the GWR model to explore the direction and extent of the impact of social factors such as population, economy and energy on the CO_2 emissions.

4. Empirical results

4.1 Spatial correlation analysis

In 2007, 2012, and 2017, the Moran Index was 0.220, 0.186, and 0.166, respectively, which were all positive numbers, indicating that there was a positive correlation between the CO_2 emissions of the provinces, and geographic weighted regression models were available. However, the Moran index gradually declined, indicating that the degree of spatial autocorrelation of CO_2 emissions between the provinces was gradually weakening.
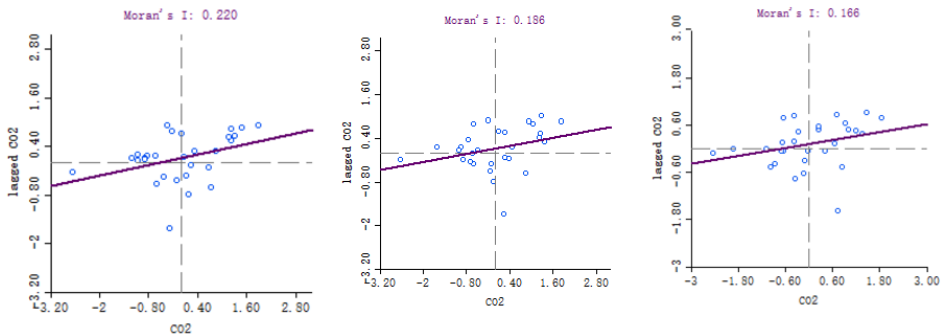

Figure 1. Moran index in 2007, 2012 and 2017

4.2 Detection of variable multicollinearity

The GWR model requires no multicollinearity between the variables. The multicollinearity of test is shown in Table 1. The VIF value can reflect, whether there is multicollinearity between variables. When the VIF value is greater than 7.5, it indicates that there are redundant variables. The results of the multicollinearity test of the variables showed in Table 1. The VIF value of each variable in 2007, 2012, and 2017 was less than 7.5, indicating that there was no problem of multicollinearity among the variables in the model.

Table 1 Test results of multicollinearity of variables

Variable	2007	2012	2017
Population	1.92	2.13	1.78
Energy intensity	2.22	2.57	2.24
Energy structure	1.65	2.50	3.35
Urbanization	1.89	1.98	1.78
Industrial structure	1.38	1.71	2.47

4.3 Results

The summary statistics of the STIRPAT-GWR coefficients show that the adjusted R^2 values in 2007, 2012, and 2017 were all greater than 0.95, indicating that the integrated model exhibited a good degree of fit. In addition, there were significant differences between the minimum and maximum values of the explanatory variables among the 29 provinces in each year, further indicating that it is necessary to consider the geographic location information.

Table 2 Summary of the statistics of model coefficients

Variable	2007		2012		2017	
	Mean	Max-Min	Mean	Max-Min	Mean	Max-Min
Population	1.162320	0.305388	1.142193	0.386277	1.084614	0.332365
Energy intensity	0.857523	0.210014	0.883835	0.313516	0.849800	0.283530
Energy structure	0.578695	2.335581	0.320238	0.805641	0.247680	0.849750
Urbanization	1.941086	2.030032	2.054936	1.501717	2.377061	1.762383
Industrial structure	0.270392	0.238898	0.282393	0.577279	0.218559	0.770032
Adj R^2	0.958723		0.952656		0.957677	

We visualized the regression coefficient of the model in ArcGIS, and the results are shown in Fig 5. According to the natural discontinuity method, the 29 provinces were divided into three categories, namely, the high impact factor area (dark), medium impact factor area (medium), and low impact factor area (light). The red map, blue map and purple map show the results of 2007, 2012 and 2017 respectively. A blank area in the map indicated that there was no data in the area. The results of the drivers are as follows:The impact of population on the CO_2 emissions showed a positive correlation trend (Liu et al. 2021), and the influence of the southwest region was significantly lower than that of the central and eastern regions. In 2007, high-impact areas were concentrated in the central and northeastern regions, and in 2012 and 2017, it was reduced to six central provinces. Energy intensity exhibited a positive impact on the CO_2 emissions, the average impact was about 0.8, and the high impact areas were concentrated in the central and western regions. The energy structure showed a positive effect on the CO_2 emissions. High-impact areas were concentrated in the eastern and northern regions, while the influence of the southeast was gradually decreasing. Urbanization showed a positive driving effect on the CO_2 emissions, and the intensity of the impact was very strong. High-impact areas were concentrated in the central and eastern regions. It can be seen that the high-impact areas of the industrial structure have undergone a major change in 2017. The high-impact areas have moved from the northwest and northeast regions in 2007 and 2012, respectively, to the southwest and southeast regions in 2017. The final quantitative change caused a qualitative change, and the industrial structure changed significantly during the 13th Five-Year Plan.
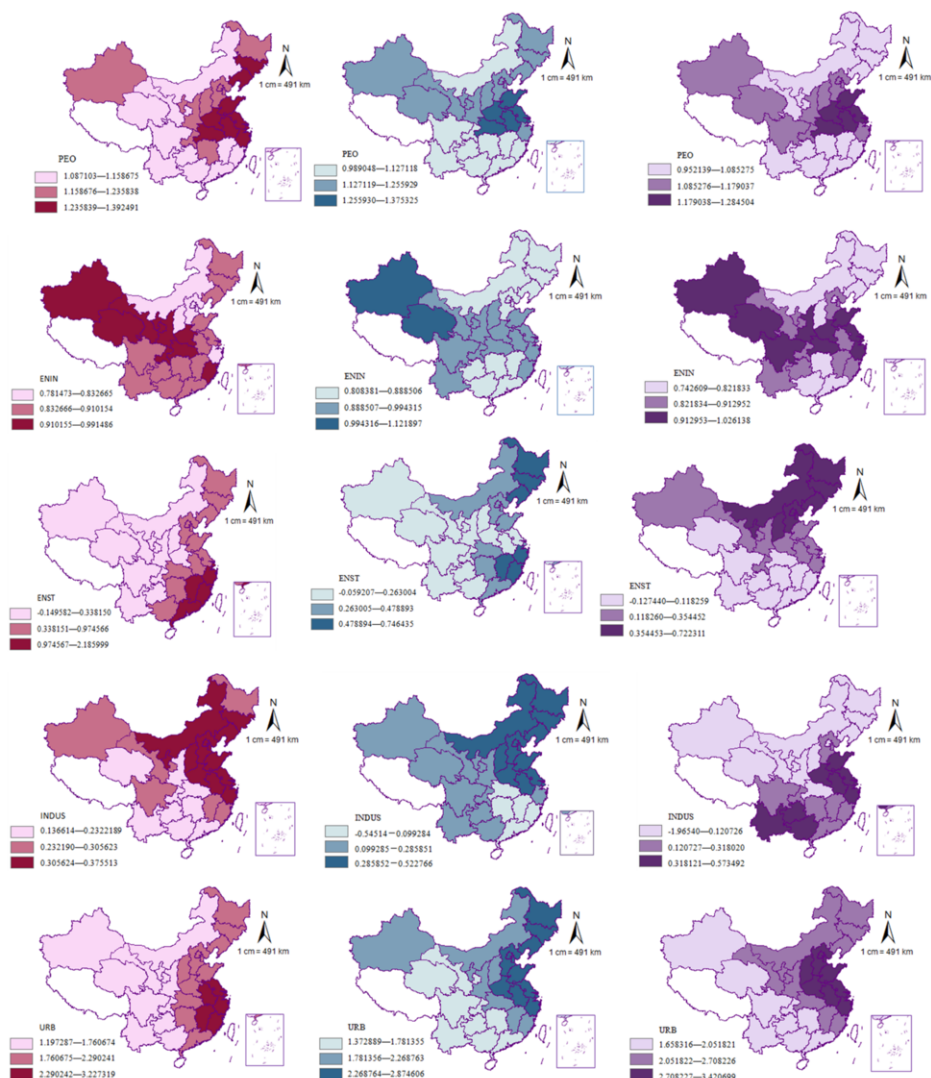
Figure 2. STIRPAT-GWR results in 2007, 2012 and 2017

5. Conclusions

In the present study, we employed the extended environmental impact assessment model to study the effect of population, energy intensity, energy structure, urbanization and industrial structure on the CO$_2$ emissions in 29 provinces across China. Our empirical results showed that: (1) There was a positive correlation and high concentration between the CO$_2$ emissions in various provinces across China. (2) Among the five factors, urbanization exhibited a highest impact on the CO$_2$ emissions, followed by population and energy intensity, while energy and industrial structure showed the weakest impact. (3) The five drivers had obvious spatial differences and regional concentration

characteristics on the intensity of CO_2 emissions. (5) The influence showed an upward or downward trend with time. Therefore, in areas where population, energy intensity, energy structure, urbanization and industrial structure influence gather, multi-provincial linkage will achieve good emission reduction effects. In the process of urbanization, more environmentally friendly and green building materials and more advanced energy-saving technology products are introduced will help urban pollution control. Increase the ratio of tertiary industry will improve energy efficiency.

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