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A Heterogeneity Study of Carbon Emissions Driving Factors in Beijing-Tianjin-Hebei Region, China, Based on PGTWR Model

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Abstract: This paper introduced PGTWR model as the base model of the study and adopted thirteen prefecture-level cities as individuals of cross section and conducted spatial and temporal heterogeneity study of the converted influencing factors of carbon emissions in Beijing-Tianjin-Hebei region with the time period from the year 2013 to 2018 as panel data. From the perspective of time and space as a whole, the regression coefficient of each influencing factor of carbon emission in Hebei Province has obvious heterogeneity. Relatively speaking, the heterogeneity of influencing factors of carbon emission in Beijing-Tianjin-Hebei region is mainly reflected in time dimension. In the period of study, the impact of industrial structure, the level of urbanization, energy intensity and the level of economic development on carbon emission was on a decline curve while the impact of population size and the level of opening up on carbon emission was on the rise, which indicates that the former four factors that reflect the level of economy and technology are not the focus of consideration when making the policy of carbon emission reduction and that more attention should be paid to the latter two factors for the time to come. From the perspective of space, the differences in the impact of industrial structure and energy intensity on carbon emission vary significantly. As a result, these differences should be attached importance to when making the policy of carbon emission reduction.

Key words: Carbon emission; Beijing-Tianjin-Hebei region; PGTWR model; Heterogeneity; Driving factors; Prefecture-level city

1 Introduction

Global warming has become a serious issue of great concern to all countries in the world. Special Report on Global Warming of 1.5°C, issued on IPCC, pointed out that the space of global carbon emission has been very limited and that it is quite urgent to cope with climate change and achieve the goal of the temperature control of 1.5°C or 2°C (Xie et al. 2020). As the largest carbon emitter, China's greenhouse gas emissions accounted for 26.7% of the global total in 2019 (UNEP, 2020). Hence, great emphasis should be laid on carbon emission reduction. On September 22, 2020, President Xi Jinping stated for the first time that China will "strive to achieve carbon peaking by 2030 and carbon neutrality by 2060".

As an important economic growth pole in north China and a region with a high concentration of high-carbon-emission industries represented by steel and petrochemical industry, the Beijing-Tianjin-Hebei metropolitan Economic Circle withstands enormous pressure of the regional carbon emission reduction. Xi stressed that the coordinated development of the Beijing-Tianjin-Hebei region which serves as a major national strategy of China should persist in mutual benefit and solid advancement while accelerating in finding a scientific and sustainable path of coordinated development. Carbon emission and economic development are a complex and comprehensive system. Regional coordinated development should not only realize coordinated economic development, but also take into account ecological environment and achieve regional carbon emission reduction. The influencing factors of carbon emissions usually possess geographical-temporal heterogeneity (Wang et al. 2018; Dong et al. 2019; Zhang et al. 2020). Geographically, there are differences in economic development, industrial structure and other factors between regions. Temporally, there are also inevitably differences in degree of development of regions in the past and at present. Therefore, when we investigate carbon emissions driving factors, its spatial and temporal heterogeneity should be fully considered so as to obtain more accurate result. Hence, in-depth exploration of the spatial and temporal heterogeneity of driving factors of carbon emissions in the Beijing-Tianjin-Hebei region and accurate identification of driving factors of carbon emissions in different time and space is of great practical significance to the realization of the goals of carbon peaking and carbon emission reduction at the regional and national scale.

At present, domestic and foreign scholars' research on the influencing factors of carbon emissions can be divided into four categories. The first is based on factor decomposition method (Wang et al. 2005; Liu L C et al. 2007; Freitas and Kaneko, 2011). The second type is the STIRPAT model-based research (Fan et al. 2006; Shahbaz, 2016). Most of the above studies are the global models based on time series which did not consider the spatial-temporal correlation among the variables and the influence of temporal and spatial effects on various driving factors of carbon emissions. Spatial correlation is embodied in two aspects: geographic dependence and geographic heterogeneity. From the perspective of the former, scholars have carried out the third category of studies, which consider the spatial lag variables or lag error terms. The models adopted mainly include spatial lag model, spatial error model and spatial Durbin model (Li and Hong, 2017; Li and Fang, 2018), which still fall into global regression models. The fourth type of research, from the perspective of the heterogeneity, uses Geographically Weighted Regression (GWR) model, Geographically and Temporally Weighted Regression (GTWR) model and Panel Geographically and Temporally Weighted Regression (PGTWR) model to describe the variability of carbon emission driving factors on carbon impact coefficient in different time and space, thus reflecting the reality more scientifically, realistically and accurately (Wang et al. 2018; Dong et al. 2019). The research in this paper also belongs to the fourth category in which more detailed literature review is conducted.

The earliest model used to analyze the spatial heterogeneity of variable relations is GWR model which was applied by Brunsdon et al. (1996); Pavlov (2000) Fotheringham et al. (2002) to analyze the influence of spatial heterogeneity of various factors on housing price and most of the current GWR model-based applications also fall into the same category (Fotheringham, 2011; Geng et al. 2011). In addition, GWR model is widely used in the following research including regional economic development (Li et al. 2007; Chu and XU, 2011; Qian et al. 2021), spatial difference of Income Distribution and Influence Factors (Nemtoollah et al.2011; Hao and Li, 2017), spatial pattern of regional innovation(Bonnet et al. 2019; Wang et al. 2022), urban economy and ecology (Chen et al. 2022; Lin et al. 2022), ecological environment(Quan et al. 2010; Sun et al. 2021), spatial heterogeneity of carbon emissions(Wang et al.2014; Fan et al. 2021). The disadvantage of GWR model is that it is only applicable to large-sample cross-sectional data and can only analyze geographic heterogeneity and fail to reflect temporal heterogeneity of variable relationship. In view of the defects of GWR, Huang et al. (2010) extended GWR model to GTWR model by embedding time factor into spatial weight matrix which is based on the Gaussian kernel function and Euclidean distance while comparing the regression results of Temporally Weighted Regression (TWR) model. Thus, the conclusion that GTWR was better was drawn.

After that, GTWR has been widely used in research on spatial and temporal heterogeneity, e.g. influencing factors of housing price (Huang et al.2010; Liu et al. 2016), influencing factors of provincial economic development (Xuan et al. 2016), Temporal and spatial characteristics of hydrology (Zeng et al. 2020; Chu et al. 2018), atmospheric pollutant emission driving factors (Chu et al. 2015; Chen et al. 2021; Shi et al. 2020), driving forces of urban expansion (Wang et al.2020). Some scholars analyzed the spatial and temporal heterogeneity of different influencing factors of carbon emissions by means of GTWR model (Wang et al. 2018; Dong et al.2019). However, GTWR model did only a cross-section processing of panel data, which does not meet the need of local analysis and modeling of panel data. Meanwhile, these models also ignore the indirect path of the mapping process from the information of the sample region to the target analysis region and also ignore the temporal transfer and conducting effect of the spatial spillover effect of the sample region.

Given the defects of GTWR model, Fan and Guo (2021) proposed the holographic mapping-based approach, which structures the unified framework and analytical paradigm of the panel geographic-temporal weighted regression model adapted to the local analysis of panel data space. The model not only reflects the characteristics of the panel data model, but also comprehensively analyzes the direct path and indirect path of influence between local points in space. Thus, the GTWR model is fundamentally improved by including optimal spatial bandwidth and optimal temporal bandwidth into the effective nearest neighbor local points, which makes the analysis of regularity and heterogeneity of spatial dependence of local points more accurate.

To sum up, this paper focuses on PGTWR model to analyze the spatial and temporal heterogeneity of influencing factors of carbon emissions in Beijing-Tianjin-Hebei region and puts forward policy suggestions for regional transition development of low carbon and the attainment of carbon neutrality.

2 Material and methods

2.1 PGTWR model

This article adopted PGTWR model proposed by Fan and Guo (2021) as benchmark model in which expression is displayed as in Equation 1:

$$y_{\{i,t\}} = \beta_0(i,t) + \beta_1(i,t)X_{1,\{i,t\}} + \beta_2(i,t)X_{2,\{i,t\}} + \cdots + \beta_k(i,t)X_{k,\{i,t\}} + \mu_{\{i,t\}} \quad (1)$$

Y is the explained variable, X is explanatory variable, β is the regression coefficient, i is individual of cross section, t is time, μ is stochastic disturbance term to satisfy the classical assumption.

The modeling steps are as follows:

1.Select samples, arrange the data according to certain rules, thus form the matrix of variable explained and of explanatory variable;

2.Based on the location information of the sample region's time-space dimension and by means of the kernel function, the paper converted the information of the sample region's temporal and spatial location to spatial effect level which finally serves as the element of the spatial and temporal weighted matrix. As is shown in Equation 2:

$$STW_{\{\in l\}} = STW_{l,direct} + \left[STW_{l,spillover} diag\left(STW_{l,direct}\right)\right].* I_{Num_{\{\in l\}}} \quad (2)$$

$STW_{l,direct}$ is spatial and temporal weighted matrix of direct impact of sample area on target area.

$\left[STW_{l,spillover} diag\left(STW_{l,direct}\right)\right].* I_{Num_{\{\in l\}}}$ is spatial and temporal weighted matrix of indirect impact of sample area on target area. Among them,$STW_{l,spillover}$ is spatial and temporal weighted matrix of spillover effects of time and space in the sample area; $diag$ $(STW_{l,direct})$ is the new vector formed by extracting the main diagonal elements from the matrix in brackets; $I_{Num_{\{\in l\}}}$ is the phase identity matrix of $Num_{\{\in l\}}$, the symbol.$*$ denotes the dot product between matrix.

(1) The calculating method of indirect effect of spatial and temporal weighted matrix is shown in Equations 3,4,5,6

$$STW_{l,spillover} = TW_{l,spillover} \otimes SW_{l,spillover} \quad (3)$$

In Equation 3,$TW_{l,spillover}$、$SW_{l,spillover}$ are the initial spatial and temporal weight matrices of the spatial spillover effect relationship between two sample areas after standardization, the values of the matrix elements are from Equation 4 and Equation 6 respectively,$\otimes$ is the Kronecker product.

$$sw_{l,spillover} = \begin{cases} f\left(d_{n_o \to n_d}, h_d\right), n_o \neq n_d \\ 0, n_o = n_d \end{cases} \quad (4)$$

$$f(.) = exp[-\frac{1}{2} \times \left(\frac{d_{ij}}{h}\right)^2] \quad (5)$$

In Equation 4,$sw_{l,spillover}$ is the element value of the initial spatial weight matrix of the sample region and the spatial weight matrix is formed after standardized processing to represent the spatial distance between the starting region n_o and the destination region n_d; h_d represents the adaptive space bandwidth corresponding to the destination region n_d;in Equation 5,$f(.)$ is the kernel function.

$$tw_{l,spillover} \begin{cases} \frac{MI_{t_d}}{MI_{t_o}}, t_d - t_o \\ 0, t_d - t_o < 0 \end{cases} \quad (6)$$

In Equation 6,$tw_{l,spillover}$ is the element value of the initial time weight matrix of the sample region and it is formed to $TW_{l,spillover}$ after a standardized processing,t_d、t_o represent the period numbers corresponding to the starting and destination regions respectively,MI_{t_d}、MI_{t_o} represent the global

Moran's I which is calculated on the basis of all the region cross sections with the period numbers corresponding to the starting region and the destination region respectively.

(2) The calculating equation of spatial and temporal weighted matrix of direct impact is shown in Equations 7 and 8.

$$STW_{l,direct} = \{diag(TW_{l,spillover}).* I_{T_{\{\in l\}}}\} \otimes \mathrm{SW}_{l,direct} \tag{7}$$

In Equation 7,$STW_{l,direct}$ is the spatial weight matrix of sample region's direct spatial effect on target region, and the value of matrix element comes from Equation 8;

$$sw_{l,direct} = f(d_{n\{\in l\}\to l,}h_l) \tag{8}$$

In Equation 8,h_l is the adaptive spatial bandwidth corresponding to target region l; $d_{n\{\in l\}\to l}$ is the spatial distance between the area cross section $n\{\in l\}$ and target region l. The kernel $f(.)$ is shown in Equation 5.

(3) The bandwidth h_d and h_l are adjusted and the adjusted adaptive space bandwidth is finally obtained which is shown in Equation 9.

$$h = Max(d_{\{\in l\}\to l}, d_{n_o\to n_d})/\sqrt{-\frac{1}{n}ln(sevc)} \tag{9}$$

In Equation 9, the empirical constant n is 0.5, and the critical value of spatial effect is 0.05

3.Based on the spatial and temporal weighted matrix and multiplication criterion, the data information of the sample region is mapped to the target analysis region so as to analyze the data information of the region, that is: $y_l \to STW_{\{\in l\}y\{\in l\}}, X_l \to STW_{\{\in l\}}X_{\{\in l\}}$

4.Finally, in combination with the Ordinary Least Square, the paper completed the parameter estimation process.

2.2 Construction of the empirical model

Based on modeling theory of STIRPAT model established by Dietz and Rosa (1994), this paper expanded the STIRPAT model and conducted an empirical study by consulting the reference literature.

The full name of STIRPAT is Stochastic Impacts by Regression on Population, Affluence and Technology which is used to analyze the impact of the three independent variables of population, affluence and technology on the dependent variable of environmental stress. Its basic model is demonstrated in Equation (10). When building the econometric model, the paper transformed the models by using the logarithms of both sides of the Equation (10), as is shown in Equation (11):

$$I_i = a * p_i^b * A_i^c * T_i^d * e_i \tag{10}$$

$$LnI_i = a + b(lnp_i) + c(lnA_i) + d(lnA_i) + e_i \tag{11}$$

Equation (10) is the basic form of STIRPAT model in which I stands for variable of environmental stress,p is variable of population, A is variable of affluence, T is variable of technology, i is individual of cross section, a is constant term, b, c, d represent respectively the coefficient of the three variables of population, affluence, technology, e is stochastic disturbance which meets the classic assumption.

In this paper, carbon emission is used to represent the variable of environmental stress and the original variables b, c, d are defined as population, economic development level and energy intensity. In terms of the studies on influencing factors of carbon emissions, most scholars believe that populations size, industrial structure and foreign trade are important influencing factors of carbon emissions. (York et al. 2003; Fang et al.2019), so the above three factors are introduced into the model.

According Equation (1) and (11), the empirical model of this paper is constructed in the Equation (12)

$$lnc_{\{i,t\}} = ln\beta_0(i,t) + \beta_1(i,t)lnX_{1,\{i,t\}} + \beta_2(i,t)lnX_{2,\{i,t\}} + \beta_3(i,t)lnX_{3,\{i,t\}} + \beta_4(i,t)lnX_{4,\{i,t\}} + \beta_5(i,t)lnX_{5,\{i,t\}} + \beta_6(i,t)lnX_{6,\{i,t\}} + \mu_{\{i,t\}} \quad (12)$$

In Equation (12), C is the total amount of regional carbon emissions, X_1, X_2, X_3, X_4, X_5 and X_6 are industrial structure, land area of urban construction, energy intensity, per capita GDP, population size and the amount of foreign investment actually utilized respectively.

Table 1 Definition and sources of relevant variables

variable	Variable meaning	Unit	Data source
Carbon emissions		10,000 ton	See 2.3
Industrial structure	Proportion of output value of secondary industry	%	Local Statistical Yearbook
Urbanization level	Land area of urban construction	Square kilometers	China City Statistical Yearbook
Energy intensity	Energy consumption per unit of GDP	Tons of standard/100 million yuan	Local Statistical Yearbook
Level of economic development	GDP	One hundred million yuan	Chinese Statistical yearbook
Population size	Population of permanent residents	Ten thousand people	Local Statistical Yearbook
Opening up	Amount of foreign investment actually utilized	Thousands of dollars	Local Statistical Yearbook

2.3 Methods of carbon accounting

The carbon emission level of a region can be generally represented by the carbon emission generated by combustion of fossil energy (Xu et al. 2014). Based on the guidance of IPCC (2006), the paper calculated the carbon emissions in Beijing and Tianjin by using coefficient of carbon emission (Yu et al. 2014). As is shown in Equation 13

$$\mathrm{Qco2} = \sum_{i=1}^{10} \mathrm{Ki} \cdot \mathrm{Ei} \quad (13)$$

$$\mathrm{Ki} = NCV_i \times CEF_i \times COF_i \times {}^{44}/_{12} \quad (14)$$

Among them, Ei is the energy consumption of energy type i, which can be converted into standard coal according to some criterion. The coefficient Ki is the specific net calorific value of energy type i. CEF is the content of carbon of each fossil fuel per calorific value and COF is carbon oxidation rate of each fossil fuel. The reference coefficient by which various energy is converted into standard coal and the emission coefficient of CO_2 are shown in Table 1. Among them, the average low calorific value and conversion coefficient of standard coal are mainly derived from The General Rules for Calculation of Comprehensive Energy Consumption (GB/2589-2008); the content of carbon of each fossil fuel per

calorific value and carbon oxidation rate are derived from The Preparation Guide for Provincial Greenhouse Gas List (Office of NDRC: Climate Volume 1041, 2011). Considering that most parts of China use coal-generated power and a few areas are based on hydro power, natural gas power and wind power and that CO_2 generated by such clean energy as hydro power, wind power and natural gas power can be omitted, the specific net calorific value consumed by electricity (Zhang et al. 2019), carbon content per calorific value and carbon oxidation rate are therefore believed to be the same as those of coal.

Table 2 Calculation of CO_2 Emission Coefficient

energy	Average low emission	Standard coal coefficient	carbon content per calorific value	Carbon oxidation rate	CO_2 emission coefficient
Coke	28435KJ/kg	0.7143kgce/kg	26.37 tons of carbon/TJ	0.93%	1.9003kg-co2/kg
Natural gas of oil field	38.931kg/m^3	1.3300kgce/m^3	15.3 tons of carbon/TJ	0.99%	2.1622kg-co2/m^3
Raw coal	20908KJ/kg	0.7143kgce/kg	26.37 tons of carbon/TJ	0.94%	1.9003kg-co2/kg
Crude oil	41816KJ/kg	1.4286kgce/kg	20.1 tons of carbon/TJ	0.98%	3.0202kg-co2/kg
Fuel oil	41816KJ/kg	1.4286kgce/kg	21.1 tons of carbon/TJ	0.98%	3.1705kg-co2/kg
petroleum	43070KJ/kg	1.4714kgce/kg	18.9 tons of carbon /TJ	0.98%	2.9251kg-co2/kg
kerosene	43070KJ/kg	1.4714kgce/kg	19.5 tons of carbon/TJ	0.98%	3.0179kg-co2/kg
diesel	42652KJ/kg	1.4571kgce/kg	20.2 tons of carbon/TJ	0.98%	3.0959kg-co2/kg
Liquefied petroleum gas	50179KJ/kg	1.7143kgce/kg	17.2 tons of carbon/TJ	0.98%	3.1013kg-co2/kg

Due to incomplete disclosure of energy consumption data of prefecture-level cities in Hebei Province, the above method cannot be used for carbon conversion. The paper borrowed Li 's (2010) and Yang's (2016) principles of calculating the total amount of urban energy consumption (as is seen in Equations 15 and 16), that is, the proportion of consumption of each energy in the total energy consumption of prefecture-level cities is the same as that of provinces. Assuming that the proportion of carbon emission of each energy consumption in carbon emission of the total energy consumption of prefecture-level city is the same as that of provincial level, the paper used Equations 16-18 to calculate the total carbon emission of each prefecture-level city. The specific calculation steps are as follows: Step 1: calculate the carbon emission of provincial energy type i (Equation 15) Step 2: calculate the conversion coefficient of provincial carbon emission (Equation 16) and take it as the conversion coefficient of municipal carbon emission (Equation 17) Step 3: calculate the total carbon emission of each prefecture-level city. (Equation 18)

$$\mathrm{Qco2}_i = \mathrm{Ki} \cdot \mathrm{Ei} \tag{15}$$

$$CEEI_{it} = \frac{PE_{it} + PG_{it} + PL_{it}}{CO_{it} + CK_{it} + PE_{it} + PG_{it} + PL_{it} + PT_{it} + KR_{it} + DS_{it} + FO_{it} + CQ_{it}} \tag{16}$$

$$CEEI_{it} = CEEK_{it} \tag{17}$$

$$COE_{it} = \frac{CE_{it} + CG_{it} + CL_{it}}{CEEK_{it}} \tag{18}$$

In the equation, i is city, t is year, $\mathrm{Qco2}_i$ is the carbon emission of energy consumption of type i, $CEEK_{it}$ is conversion coefficient of carbon emission of Province i, COE_{it} is the total carbon emission of prefecture-level city i, CO_{it} is coal consumption of Province i, CK_{it} is coke consumption of Province i, PT_{it} is petroleum consumption of Province i, KR_{it} is kerosene consumption of Province i, DS_{it} for diesel consumption of Province i, FO_{it} is fuel oil consumption of Province i, CQ_{it} is crude oil consumption of Province i, CE_{it} is consumption of electricity of city i, CG_{it} for consumption of natural gas of city i, CL_{it} is consumption of liquefied petroleum gas of city i. Energy carbon emissions of each province is from China's Energy Yearbook and energy carbon emissions of each city from China City Statistical Yearbook.

3 Results

3.1 PGTWR estimation of results

By using the standardized program complied in MATLABR 2020a by Fan and Guo (2021), the paper estimated the regression equation of Equation 6, and the optimal spatial and temporal bandwidths based on AICc criteria are 13 and 6 respectively, which means that carbon emissions of a prefecture city in the Beijing-Tianjin-Hebei region are affected by the spatial influence from other 13 prefecture cities and the temporal influence of carbon emissions values of 6 years. The optimal spatial and temporal bandwidths based on the GCV criterion and RSS criterion are 7 and 6 respectively, which means that the spatial influence from the other seven prefecture-level cities and the temporal influence of the carbon emission values of 6 year have had an impact on the carbon emissions of one prefecture city in the Beijing-Tianjin-Hebei region. Since the selection result of optimal bandwidth based on GCV criterion is basically equivalent in value to optimal bandwidth based on CV criterion, the optimization of optimal spatial or temporal bandwidth based on CV criterion is not considered in this paper. The inconsistent optimal spatial and temporal bandwidths derived from AICc, GCC and RSS criterion led to two different panel data which are produced by the effective neighboring local points included in the two optimal bandwidth dimensions, consequently, based on the two optimal spatial and temporal bandwidths respectively, this paper conducted an estimation on the PGTWR model including the mixing effect, individual fixed effect, period fixed effect and individual-period fixed effect. The results are shown in Table 3.

Table 3 Overall statistical properties of the example model under the two bandwidth dimension and four kinds of effect

	AICc criterion (optimal spatial bandwidth=13, optimal temporal bandwidth=6)				**GCV\RSS criterion (optimal spatial bandwidth=7, optimal temporal bandwidth=6)**			
	Mixing effect	**Individual fixed effect**	**Period fixed effect**	**Individual-period fixed effect**	**Mixing effect**	**Individual fixed effect**	**Period fixed effect**	**Individual-period fixed effect**
significance ratio of the	0.8919	0.3397	0.9679	0.4423	0.6703	0.2885	0.6688	0.3376

estimate of local coefficient								
Sample size	78	78	78	78	78	78	78	78
Degree of freedom	31	32	31	32	15	15	15	15
Estimate of Variance of stochastic disturbance	13.835	0.538	1.928	16.832	28.157	1.087	2.956	32.830
Value of CV criterion	428.9	17.2	59.8	538.6	422.4	16.3	44.3	492.4
Value of GCV criterion	0.0851	0.0034	0.0119	0.1069	0.0838	0.0032	0.0088	0.0977
Value of AICc criterion	448.1	192.2	291.7	461.2	501.7	245.2	323.5	511.3
Modified goodness of fit	0.9996	0.9814	0.9952	0.9999	0.9998	0.9319	0.9880	0.9999
F statistical value	48378	1035	4521	3822745	80040	264	1581	244461
F probability of statistics	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Modified critical value of probability（α=0.01、0.05,0.1）	0.0169 0.0844 0.1688	0.0171 0.0853 0.1706	0.0202 0.1012 0.2024	0.0185 0.0924 0.1849	0.0149 0.0745 0.1489	0.0159 0.0796 0.1592	0.0178 0.0888 0.1775	0.0166 0.0829 0.1658
logarithmic likelihood values	-213.1	-86.5	-136.3	-220.8	-240.9	-113.9	-152.9	-246.8

It can be seen from Table 3 that F statistics estimated in the eight models all passed the hypothesis test of significance level of 0.01, and the goodness of fit was greater than 90%. Based on significance ratio of the estimated value of local coefficient, CV, GCV, AIC, logarithmic likelihood value and the estimate of variance of stochastic disturbance, the paper made a comprehensive evaluation on the result of models with the following judging criteria: the bigger the significance ratio of the estimate of local coefficient and the logarithmic likelihood ratio, the better; the smaller CV, GCV, AIC and the estimate of variance of stochastic disturbance, the better.

The significance ratio of the regression coefficients of the individual fixed effect and the individual-period double fixed effect under the two bandwidths were lower than 50%. The significance ratio of the regression coefficients of mixed effect and period fixed effect under bandwidth determined by GCV/RSS criterion is about 65%, and the significance ratio of the regression coefficients of period fixed effect and mixed effect under bandwidth determined by AICC criterion is 90%. After making a further analysis and comparison of the statistical property of model results of the mixed effect and the period fixed effect under AICC criterion, the paper found (1) that significance ratio of the estimate of local coefficient of the period fixed effect was 0.9679, higher than 89.19% of the mixed effect and (2) that estimated value of variance of stochastic disturbance, value of CV criterion, value of GCV criterion and value of AICC

criterion of the model as a whole were all lower than the mixed effect and (3) that the logarithmic likelihood value is closer to 1 than the mixed effect. In conclusion, when the optimal spatial and temporal bandwidths were 13 and 6 respectively, the period fixed effect showed superior overall statistical properties. Table 4 and Fig. 1 give the descriptive statistics of the estimated results of PGTWR parameters from which we can see there are different degree of variation in regression coefficients of each influencing factor of carbon emissions.

Table 4 PGTWR Model's Descriptive Statistics of Regression Coefficient of Various Explanatory Variable

variable	minimum	maximum	average	upper quartile	lower quartile	quartile range	standard deviation
X1	1.07	1.90	1.51	1.38	1.62	0.23	0.18
X2	0.76	1.12	0.90	0.84	0.94	0.10	0.09
X3	1.65	2.47	1.90	1.78	1.98	0.19	0.16
X4	0.35	0.62	0.50	0.43	0.55	0.12	0.07
X5	-0.81	-0.42	-0.63	-0.71	-0.52	0.19	0.11
X6	0.08	0.15	0.11	0.09	0.13	0.04	0.02

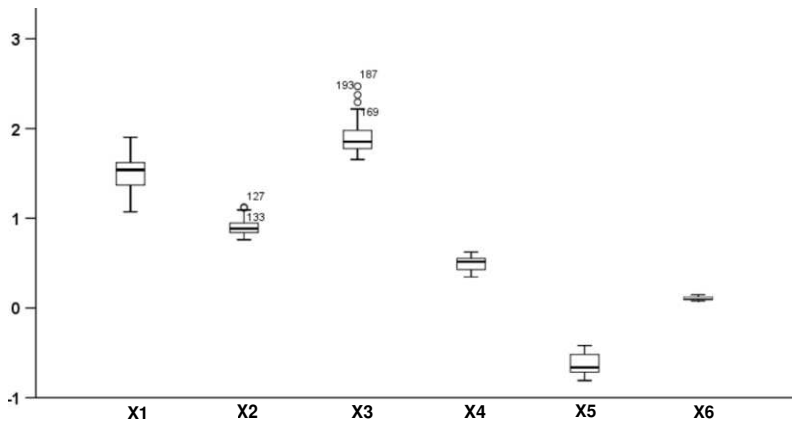


Fig.1 Box plot of Regression Coefficient of Various Explanatory Variable of PGTWR Model

3.2 Temporal Heterogeneity Analysis of the Regression Coefficient of Influencing Factors of Carbon Emission

The paper did box plots of regression coefficient of various influencing factors of carbon emission in the prefecture-level cities of Beijing-Tianjin-Hebei according to years respectively (Fig. 2).

3.2.1 Temporal Heterogeneity Analysis of the Influence of Industrial Structure on Carbon Emission

During the period of study, the industrial structure had a forward impact on carbon emissions. The degree of influence rose after falling first with a general downward trend, which is closely related to Beijing-Tianjin-Hebei Region's efforts in elevating traditional manufacturing level, promoting the added value of second industry product, controlling strictly the capacity of highly energy-consuming and high emission industries and developing low-carbon industries by means of high technology. The trend also suggests that the economy of Beijing-Tianjin-Hebei region is moving toward quality development. Meanwhile, the dispersion degree of the box plot tends to converge, indicating that the difference in economic development between the Beijing- Tianjin Hebei region is gradually decreasing.

3.2.2 Temporal Heterogeneity Analysis of the Impact of Urbanization Level on Carbon Emission

The direct and indirect demand of city life for energy is considered to be a major contributor to the adverse environmental impact of urbanization (Cole and Neumayer, 2004). During the period of study, the impact of urbanization on carbon emissions in Beijing-Tianjin-Hebei region decreased year by year, mainly because the rise of urbanization rate and the agglomeration of population in cities have promoted scientific and technological progress, facilitated the transformation and upgrades of the industrial structure and improved the efficiency of industry through sharing, matching, and learning effect. At the same time, it has contributed to a more intensive use of infrastructure, facilitated the agglomeration of economic activities and production behavior and improved the efficiency of resources and energy use, thus effectively reducing the carbon emissions. From the perspective of policy, in recent years, China has vigorously implemented new urbanization development strategy of economy and intensiveness, ecological and suitable living and harmonious development and advocated the idea of low-carbon living of urban residents as well, therefore, the impact of level of urbanization on carbon emission has gradually weakened.

3.2.3 Temporal Heterogeneity Analysis of the Impact of Energy Intensity on Carbon Emission

During the period of study, the influence of the energy intensity on carbon emissions has been relatively high, which is consistent with the fact that fossil energy is the main source of carbon emissions. The slow decline in the impact of energy intensity on carbon emissions indicates that the implementation of the strategy of Beijing-Tianjin-Hebei coordinated development has promoted intensive regional development as well as the progress of low-carbon technologies, thus improving efficiency of energy utilization and reducing energy consumption per GDP. It also suggests that the economic structure of the Beijing-Tianjin-Hebei region has been constantly optimized and the proportion of tertiary industry has been increased. The high economic benefits and low energy consumption of the tertiary industry has led to the decline in the impact of energy intensity on carbon emission.

3.2.4 Temporal Heterogeneity Analysis of the Impact of Level of Economic Development on Carbon Emission

During the study period, the overall impact of GDP on carbon emissions showed an inverted U-shape. During 2013-2015, the impact gradually increased but it began to decline after 2016. In 2018, the impact was much lower than that in 2013, which shows that the economic aggregate increased the demand of various economic sectors for energy such as electricity and oil. The use of these fossil energy produced a large amount of carbon emissions. With the innovation of economic structure and improvement of the efficiency of input and output, the economy has gradually decoupled from carbon emissions and GDP growth has mainly been fueled by consumption and scientific and technological innovation. In addition, the formulation of low-carbon economic strategy has controlled and counteracted carbon emissions that is caused by economic development. Therefore, the impact of economic development on carbon emissions has been decreasing.

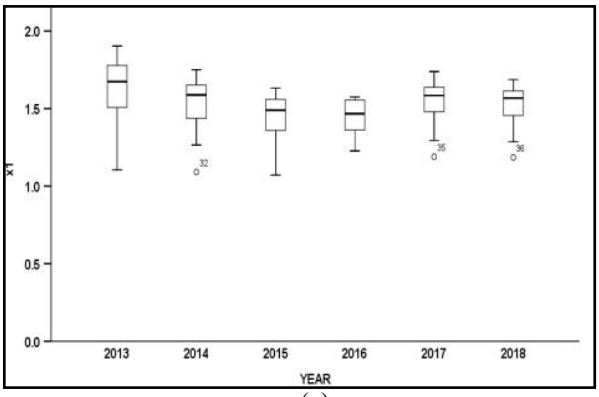
3.2.5 Temporal Heterogeneity Analysis of the Impact of Population Size on Carbon Emission

The regression coefficient between population size and carbon emission was a negative during the study period mainly because population size has stimulated industry to grow rapidly and promoted the technological innovation and popularity of education as well as intensive development and application of energy-conserving technology. Meanwhile, population size contributes to providing personnel and technical support. The data reveal, however, that the advantage of carbon emission reduction brought by population size has been gradually disappearing.

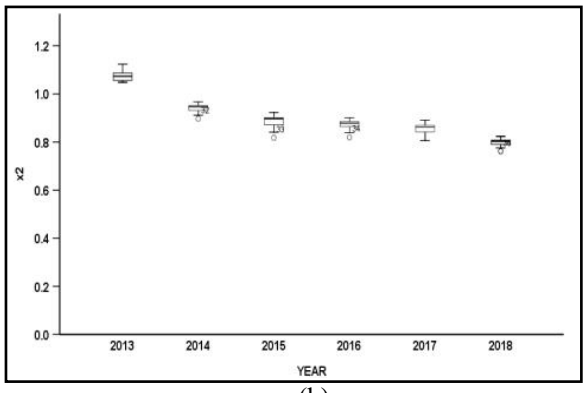
3.2.6 Temporal Heterogeneity Analysis of the Impact of Opening-up on Carbon Emission

The influence of the level of opening-up on carbon emission was positive during the study period. With the deepening of opening up and the increase in utilization of the foreign investment, building factories with investment and expanding the scale of production will inevitably aggravate carbon emission.

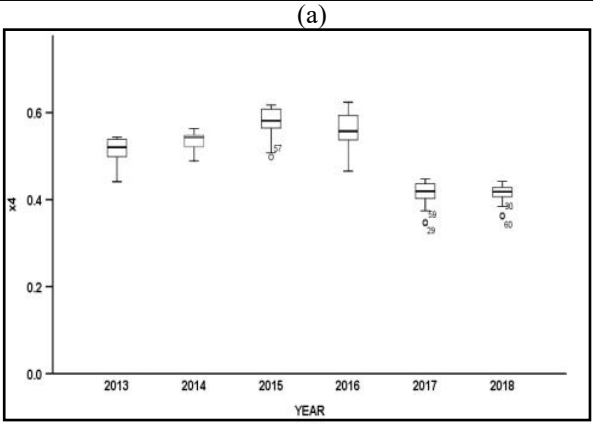
To sum up, the impact of industrial structure, urbanization level, energy intensity on carbon emissions generally showed a downward trend while the impact of population size and opening-up on carbon emissions showed an upward trend during the study period. And the level of economic development increased first and then decreased. During the study period, population size had a negative impact on carbon emissions while the other five factors presented a stable positive impact, which was basically in line with the empirical expectation. The study also found that the status of some influencing factors was rising, while that of others was weakening. The overall numerical change has a certain guiding effect on policy making.



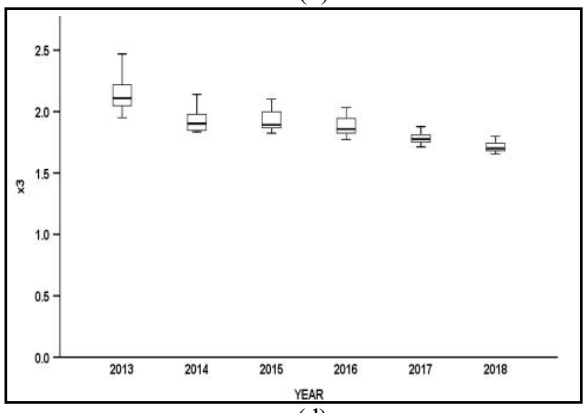
(a)



(b)



(c)



(d)

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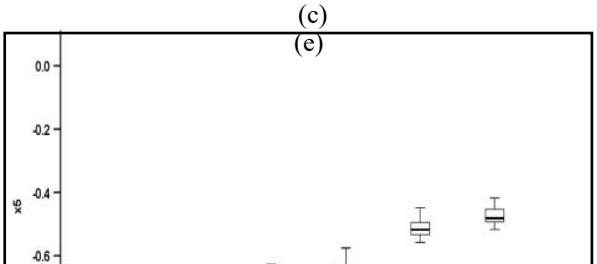


(f)

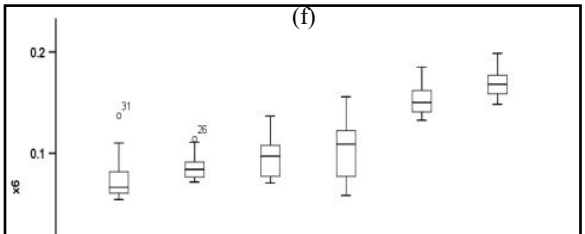
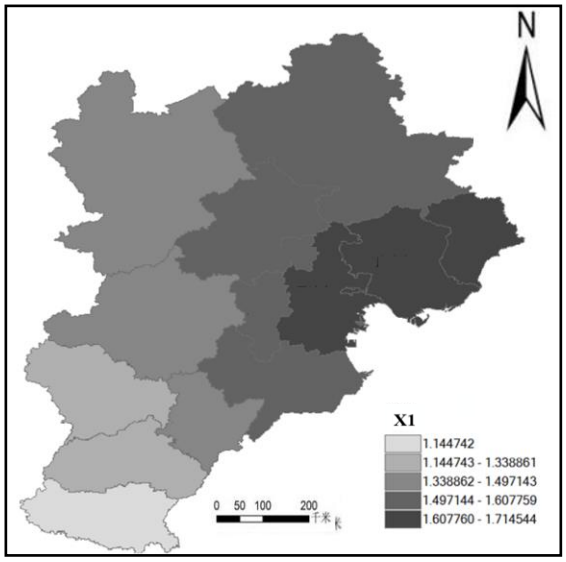


Fig.2 a Temporal heterogeneity of PGTWR regression coefficients of Industrial structure; **b** Temporal heterogeneity of PGTWR regression coefficients of Urbanization level; **c** Temporal heterogeneity of PGTWR regression coefficients of Energy intensity; **d** Temporal heterogeneity of PGTWR regression coefficients of Level of economic development; **e** Temporal heterogeneity of PGTWR regression coefficients of Population size; **f** Temporal heterogeneity of PGTWR regression coefficients of Opening up

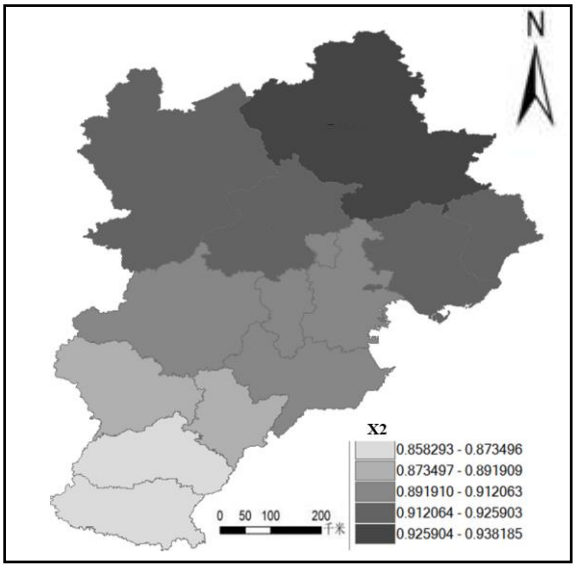
3.3 Spatial Heterogeneity Analysis of Regression Coefficient of Influencing Factors of Carbon Emission

In order to explore the spatial heterogeneity of regression coefficient of influencing factors of carbon emissions, the PGTWR model regression coefficients of influencing factors in indifferent regions and periods were averaged. With the use of ArcGIS10.2, the mean value was classified into five levels according to the rule of natural cutoff points and presented in the form of geographical map (Fig.3) so as to express more directly and analyze the spatial heterogeneity of regression coefficients.

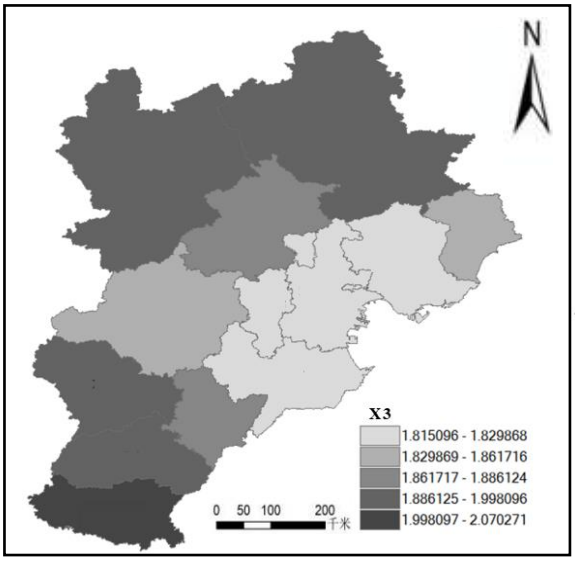
The influence of industrial structure on carbon emission decreases from the east to the west. Tianjin, Tangshan and Qinhuangdao are the most affected cities, followed by Cangzhou, Chengde and Langfang, and with Handan the least influenced city. The influence of urbanization level on carbon emission weakens from the north to the south with Chengde being the most affected city, followed by Zhangjiakou, Beijing, Tangshan and Qinhuangdao, and with Handan the least influenced city. The impact of energy intensity on carbon emission declines progressively from the north-south to the middle regions, and Handan is the most influenced city, followed by Zhangjiakou, Chengde, Shijiazhuang and Xingtai. The impact of economic development on carbon emission decreases from southwest to northeast, and Shijiazhuang and Baoding are the most affected cities and Chengde and Qinhuangdao the least affected. The absolute value of regression coefficient of population size increases progressively from north- south to the middle regions and Handan, Chengde and Qinhuangdao have the highest absolute value and the lowest value is in Baoding. When it comes to the impact of the level of opening up on carbon emission, Qinhuangdao, Tangshan and Chengde are the most affected cities, followed by Beijing and Tianjin. Among them, Qinhuangdao, Tangshan and Tianjin are the major ports in the Beijing-Tianjin-Hebei region, among which Tianjin port is the largest port in north China, while Beijing, as the capital, has the capital airport with the most comprehensive functions, thus enjoys the remarkable geographical advantage of aviation and a high level of opening-up.


N
X1
1.144742
1.144743 - 1.338861
1.338862 - 1.497143
1.497144 - 1.607759
1.607760 - 1.714544
0 50 100 200
千米

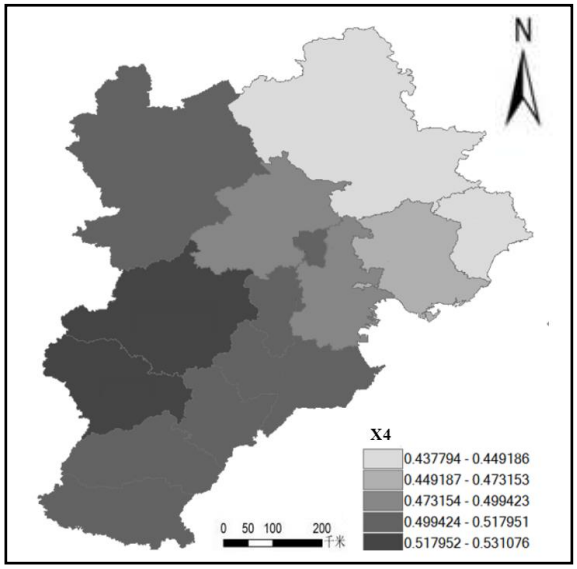
(a)


N
X2
0.858293 - 0.873496
0.873497 - 0.891909
0.891910 - 0.912063
0.912064 - 0.925903
0.925904 - 0.938185
0 50 100 200
千米

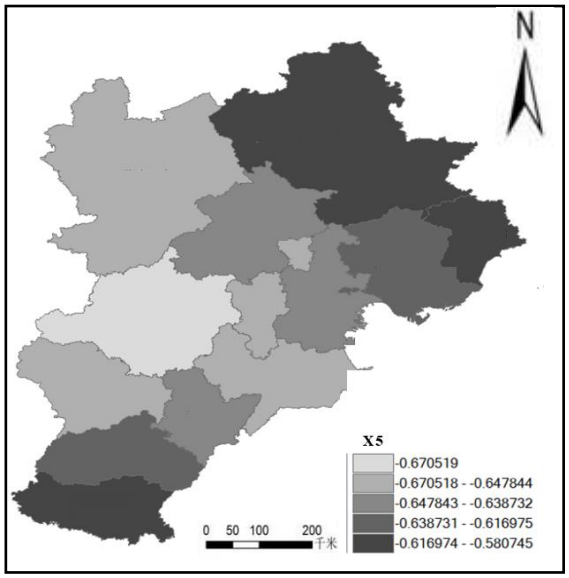
(b)


N
X3
1.815096 - 1.829868
1.829869 - 1.861716
1.861717 - 1.886124
1.886125 - 1.998096
1.998097 - 2.070271
0 50 100 200
千米

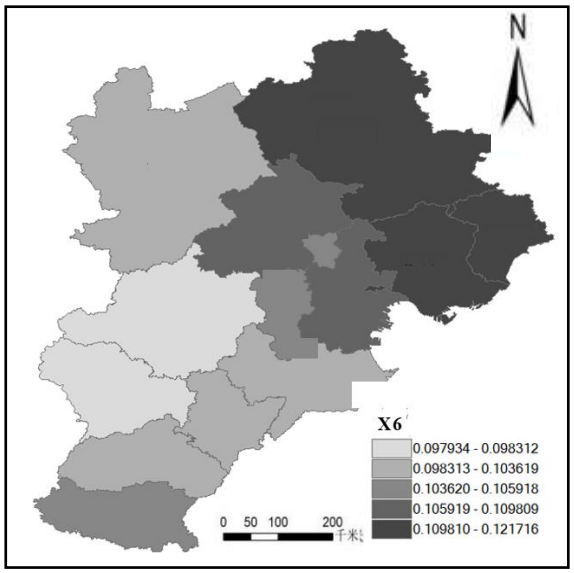
(c)


N
X4
0.437794 - 0.449186
0.449187 - 0.473153
0.473154 - 0.499423
0.499424 - 0.517951
0.517952 - 0.531076
0 50 100 200
千米

(d)


N
X5
-0.670519
-0.670518 - -0.647844
-0.647843 - -0.638732
-0.638731 - -0.616975
-0.616974 - -0.580745
0 50 100 200
千米

(e)


N
X6
0.097934 - 0.098312
0.098313 - 0.103619
0.103620 - 0.105918
0.105919 - 0.109809
0.109810 - 0.121716
0 50 100 200
千米

(f)

Fig. 3 a Spatial Heterogeneity of PGTWR regression coefficient of Industrial structure; **b** Spatial heterogeneity of PGTWR regression coefficients of Urbanization level; **c** Spatial heterogeneity of PGTWR regression coefficients of Energy intensity; **d** Spatial heterogeneity of PGTWR regression coefficients of Level of economic development; **e** Spatial heterogeneity of PGTWR regression coefficients of Population size; **f** Spatial heterogeneity of PGTWR

4 Conclusions and policy recommendations

4.1 Conclusion

This paper introduced PGTWR model as the base model of the study and adopted thirteen prefecture-level cities as individuals of cross section and conducted spatial and temporal heterogeneity study of the converted influencing factors of carbon emissions in Beijing-Tianjin-Hebei region with the time period from the year 2013 to 2018 as panel data. From the perspective of time and space as a whole, the regression coefficient of each influencing factor of carbon emission in Hebei Province has obvious heterogeneity. From the perspective of space, the differences in the impact of industrial structure and energy intensity on carbon emission vary significantly. As a result, these differences should be attached importance to when making the policy of carbon emission reduction. Relatively speaking, the heterogeneity of influencing factors of carbon emission in Beijing-Tianjin-Hebei region is mainly reflected in time dimension. In the period of study, the impact of industrial structure, the level of urbanization, energy intensity and the level of economic development on carbon emission was on a decline curve while the impact of population size and the level of opening up on carbon emission was on the rise, which indicates that the former four factors that reflect the level of economy and technology are not the focus of consideration when making the policy of carbon emission reduction, which is consistent with the conclusion that the most cities in Beijing-Tianjin-Hebei region are in a strong decoupled state(Li et al. 2019), hence, more attention should be paid to the latter two factors for the time to come.

4.2 Policy recommendations

The paper put forward the following recommendations. First, we should adjust the industrial structure and reduce the proportion of secondary industries. Among the cities in the Beijing-Tianjin-Hebei region, Tangshan's secondary industry accounts for the highest proportion, with an average of nearly 60% during the study period. Its main industries have always been coal, oil and natural gas extraction and other traditional fossil energy industries. The secondary industries of Cangzhou, Tianjin, Qinhuangdao accounted for nearly 50%, also at a high level. Among the three industries, the secondary industry consumes mainly fossil energy and produces the most carbon emissions. Therefore, it is necessary to accelerate the transformation of economic development mode, reduce the proportion of heavy industry, and develop the tertiary industry with low energy consumption and high output level.

Second, energy intensity is one of the most important factors affecting carbon emissions. We should strengthen technological innovation, develop new energy technologies, eliminate high energy consumption and high pollution technologies, and increase the role of science and technology in empowering industrial development. We will concentrate on developing advanced manufacturing, new and high technology industries, and low-carbon and low energy-consuming industries so as to reduce energy consumption per GDP and promote high-quality economic development.

Third, we should steadily promote the development of urbanization, pay attention to ecological protection in the process of urbanization, and put an end to the expansion of urban scale by extensive development mode. This requires reasonable planning and layout according to the environmental self-

purification capacity of different cities and towns as well as controlling the urban size below the ecological critical scale. Meanwhile, we should give play to the advantages of population scale to enhance infrastructure construction and keep improving efficiency of resource allocation.

Finally, while strengthening the introduction of foreign investment, we should pay attention to environmental protection, carry out environmental impact assessment on imported projects, and strictly control the introduction of projects with high carbon emissions. The Beijing-Tianjin-Hebei government should also learn from the successful experience of harmonious coexistence between foreign investment and environmental protection, and formulate scientific and reasonable local policies in order to reduce the carbon emissions caused by foreign investment.

Data availability

1.https://v.hbu.cn/https/77726476706e697374686562657374 21f4f6559d6933665b774687a98c/yearbook/Single/N2019110026

2.https://v.hbu.cn/https/77726476706e697374686562657374 21f4f6559d6933665b774687a98c/Yearbook/Single/N2020110103

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7.https://v.hbu.cn/https/77726476706e697374686562657374 21f4f6559d6933665b774687a98c/yearbook/Single/N2020120303

Statements & Declarations

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Competing interests The authors declare no competing interests.

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Authors' contributions Lou T: thesis writing. Ma JH: providing ideas and methods, revise the article. Yu L, Guo ZP: data collection and collation. He Y: data visualization. Sun QR: review and editing. All authors read and approved the final manuscript.

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