The impact of heterogeneous environmental regulations on regional spatial differences in net carbon emissions

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Abstract

Effected by spatial difference and types of environmental regulation, enhanced environmental regulation does not necessarily lead to reduce net carbon emissions (NCE). Based on panel data of 30 province-level administrative regions in China from 2003 to 2018, this paper analyzed the impact of heterogeneous environmental regulations on NCE using geographically weighted regression (GWR). The results showed that (1) the total NCE of each province in China presented an increasing trend followed by fluctuation, with obvious spatial aggregation characteristics. (2) The intensity of four environmental regulations, command-and-control (CAC), market-incentive (MI), public-participation (PP), and voluntary environmental program of firm (VEPF) tended to increase slightly over the study period with decreasing spatial heterogeneity. (3) CAC environmental regulations had a "green paradox" effect on NCE, meaning an improving CAC environmental regulation would surprisingly increase its negative effects and contribute to NCE growth. The effect of MI environmental regulation on NCE shifted from overall promotion to partly promotion and even suppression. PP and VEPF environmental regulation would reduce NCE. The suppressive effect of PP environmental regulation grew over time, while VEPF did not. Finally, based on the research conclusion, some policy suggestion are proposed for differentiated management, diverse system of governance, and collaborative governance.

Keywords Net carbon emissions · Environmental regulation · Heterogeneous · Geographically weighted regression

Introduction

Carbon emission has typical negative externality and cannot be adjusted through the market mechanism, which requires the government to take some regulations. As the largest developing country in the world, China is in tough industrial upgrading times with sharp contradiction between carbon emission control and economic development. According to the International Energy Agency, China has been the world's largest carbon emission country since 2003 (Ma et al. 2019; Guo and Yan 2018). In 2018, China accounted for around 16% of the world's GDP, but 28% of world's carbon emissions (Udara Willhelm Abeydeera et al. 2019).

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In order to promote the positive change of global climate, the Chinese government has formulated a set of governance policies to deal with the extreme climate and ecological crisis caused by carbon emissions. Since 2010, the Chinese government investment in environmental governance has grown at an average rate of 10.9% by year, and a series of low-carbon development strategies, laws, and regulations have been implemented to reduce carbon emissions (Chen et al. 2018; Hao et al. 2018). However, there is a significant difference in the emission reduction effect of provincial environmental regulations on carbon emissions due to different resource endowment, economic level, as well as the different formulation and implementation of environmental regulations. Although the carbon emission of per unit GDP has declined, the total amount keeps rising, which brings great challenges for China to achieve the goal of carbon peak and carbon neutrality. As an atmospheric component, carbon dioxide can be transported to neighboring areas under the influence of natural factors; failure of governance in some regions may lead to failure of governance in the whole country. What are the characteristics of regional differences, and

how do local governments take effective regulatory measures according to these characteristics? In previous studies, most scholars did not clearly divide the types of environmental regulations, neither systematically consider the regional differences of the impact of different environmental regulations on total carbon emissions. Therefore, studying the relationship between the heterogeneity of environmental regulations and the spatial variation of regional carbon emissions is of great significance for a developing country to make differentiated carbon emission reduction policies in the future and realize the control of total carbon emission.

Literature review

The impact of environmental regulations on carbon emissions has three views. The first view is that environmental regulations will promote carbon emissions and produce the "green paradox" effect. According to the "green paradox," the increase of environmental regulation intensity will lead to the acceleration of fossil energy exploitation, which accelerates short-term energy consumption (Sinn 2008). Some scholars supported and complemented the conditions leading to the "green paradox" (Smulders et al. 2012; Van der Ploeg and Withagen 2012). They believed that, without considering the scarcity of fossil energy, if there is a time lag between the announcement and implementation of climate policies, early announcement of climate policies will drive energy owners to exploit energy in advance, resulting in energy consumption and carbon emissions increasing during the announcement and implementation of regulations.

The second view is that environmental regulation reduces carbon emissions. The effects of carbon emission reduction can be divided into direct effect and indirect effect. Direct effect refers to the direct reduction of carbon emission by environmental regulation. Early researches have studied the implementation of low-carbon city pilot policy (Dong and Li 2020; Zhang 2020), carbon trading policy (Wang et al. 2020; Zhang et al. 2021), and carbon tax policy (Lin and Li 2011) in China. The results showed that the carbon emission level in regions with environmental regulations was significantly reduced comparing with regions without regulations. Indirect effect refers to the impact of environmental regulation on carbon emission through technological innovation (Calel and Dechezlepretre 2016), industrial structure (Zhou and Luo 2021), and foreign investment (Muhammad et al. 2011; Zhang et al. 2020a, b). The most acknowledged views are "Porter hypothesis" and "pollution haven hypothesis." Porter hypothesis suggests that environmental regulation will provide incentives for regulated enterprises to reduce resource consumption and encourage them to update production mode to reduce carbon emission intensity. This incentive is more significant under market-incentive environmental regulation

(Berman and Bui 2001; Boyd et al. 2002). Pollution haven hypothesis refers to the fact that the environmental regulation intensity in developed countries is generally higher than developing countries, thus the high-polluting industries in developed countries prefer moving to developing countries through foreign investment in order to reduce pollution control costs. Some scholars tested pollution haven hypothesis using different developing countries as examples, the results showed that the pollution haven hypothesis is obvious in developing countries, but not in developed countries. (Hoffmann et al. 2005; Muhammad et al. 2011; Liu et al. 2021)

The third view is that due to the location difference of research samples, the effect of environmental regulation on carbon emissions presents a nonlinear relationship, including insignificant or threshold effect. Gao and Chen (2010) and Li (2015) used provincial-level data to verify the threshold effect of environmental regulations on carbon emissions in China. With the increasing of environmental regulation intensity, the influence of foreign investment on carbon emissions will change from promoting to significantly suppressing. Wang et al. (2019) used the threshold effect model to study the relationship between environmental regulations and carbon emissions in different regions of China and found that the significant differences existed in the response of carbon emission to environmental regulation in different regions of China. When the energy intensity of eastern China is in low threshold range, environmental regulations can effectively reduce carbon emissions. In central and western China, environmental regulations failed to reduce carbon emission effectively.

Through the review of existing literature, it can be found that with the continuous research on the effect of environmental regulations on carbon emission, some scholars tends to pay attention to the impact of spatial differences of environmental regulations on carbon emission. However, there is still gap for improvement in the existing researches. First, existing research results exploring the impact of environmental regulations on carbon emissions from spatial perspective mainly treated environmental regulation as a single variable, while few had focused on the examination the heterogeneity of environmental regulation. Second, existing studies about the impact of environmental regulations on carbon emission have ignored its impact on carbon sink function. Pollution damage to the ecological environment will lead to the degradation of the carbon sink function of the ecosystem. The pollution control of environmental regulation will not only reduce the degradation of the carbon sink function but also restore it (Maiti and Chowdhury 2013). Carbon neutrality means that the carbon emission amount is equal to the amount absorbed by the carbon sink in certain time and space. Therefore, the effect of the carbon sink function is an important part in the impact of environmental regulation on carbon emission. Third, the

existing research methods to correlate spatial factors with environmental regulation includes spatial lag model, spatial error model, and spatial Durbin model. Although these models have considered spatial factors, they focus more on the explanation of spatial correlation and adopt the spatial consistency hypothesis for all explanatory variables, while assuming that influential factors are spatially correlated or spatially independent in the sample interval and ignoring the investigation of spatial variation of influential factors in different samples from the perspective of spatial heterogeneity. Geographically weighted regression model (GWR) can reflect the difference of spatial correlation of explanatory variables simultaneously because it contains both global variables with no significant spatial correlation and local variables with significant spatial correlation. The first law of geography states that there is similarity between adjacent geographical entities (Tobler 1970). There are significant differences in the level of economic development and resource endowments between different provinces in China. Because of this, the regression parameters derived from the global regression model cannot correctly explain the situation of the individuals in the sample. Fotheringham et al. (2003) further proposed a GWR model based on the foster spatial variation regression using a local smoothing treatment, which uses geographic coordinates and core functions to estimate local regressions for each group of contiguous individuals. It has been demonstrated that the intensity of environmental regulation is influenced by regional economic and natural conditions, and there are certain regional differences and spatial and temporal distribution characteristics of the impact on carbon emissions. Thus, we use GWR method to investigate and analyze the spatio-temporal effects of heterogeneous environmental regulations on NCE.

In summary, the main contributions of this study include three points. First, a comprehensive framework was constructed to characterize heterogeneous environmental regulations. Second, carbon sink was incorporated into the framework for assessing the impact of environmental regulations on carbon emission. Third, GWR model was used to better reflect the regional differences in the relationship between environmental regulations and carbon emission with local geographical variations.

Design of related research methods

Calculation of net carbon emission

Total NCE is expressed by the difference between total carbon emission and total carbon sink. Total carbon emission was calculated by multiplying energy consumption from fixed combustion sources by default emission factors in the "2006 IPCC Guidelines for National Greenhouse Gas Inventory." The energy consumption was based on the energy balance sheet of each province over the years, and the default factor wasderived from CEAD (CEADS 2017). The specific formula is as follow:

$$TCO_2 = \sum_{K=1}^{n} E_K \times SC_K \times CF_K \times \frac{44}{12} \tag{1}$$

where TCO_2 is the total carbon emission, K is the energy species, E is the energy consumption, SC is the standard coal conversion factor for the corresponding energy source, and CF is the carbon emission default factor for the corresponding consumption energy source, and 44/12 is a coefficient to transform total carbon weight into total carbon dioxide weight.

The total annual carbon sink (TCS) is estimated using the method of multiplying the carbon sink coefficient of each type of land use with its area, mainly concerning the carbon sinks of cultivated land, forest land, grass land, watershed, and unused land. Cultivated land, as a source of carbon, is not considered in this paper, while the rests, as typical carbon sinks, are mainly evaluated here.

$$TCS = \sum_{p=1}^{n} A_p \times \alpha_p \tag{2}$$

where TCS is the total carbon sink, p is the land-use type, A is the area of each land-use type, and α is the carbon sink coefficient of each land use type. The land-use data were obtained from the Resource and Environment Science Data Centre of the Chinese Academy of Sciences (http://www.resdc.cn), The resolution of land use data is 1 km × 1 km, based on LandsatTM/ETM, and the data on carbon sink coefficients were obtained from studies by related scholars (Table 1).

Evaluation index system of environmental regulation intensity

The strength of environmental regulation in each province was evaluated in four dimensions: command-and-control (CAC), market-incentive (MI), public-participation (PP), and voluntary environmental program of firm (VEPF).

CAC environmental regulation refers to the direct management and compulsory supervision of production activities through laws, regulations, and standards on environmental protection enacted by the state administration (Feng et al. 2020). Here, the number of local environmental laws and regulations enacted by each province, the proportion of staff in the environmental protection system (environmental protection agencies are adequately staffed to facilitate regular environmental monitoring of enterprises), and the ratio of administrative penalty cases to local industrial enterprises in the environmental protection agencies at this level were

Table 1 Carbon sink coefficient of land-use type

Land-use type			Coefficient	References
Forest land	Wood land		$0.87 \text{ t hm}^{-2} \text{ a}^{-1}$	Fang et al. (2018)
	Shrubbery		$0.23 \text{t hm}^{-2} \text{ a}^{-1}$	
	Open woodland		$0.58 \text{ t hm}^{-2} \text{ a}^{-1}$	
	Other forest land		$0.23 \text{ t hm}^{-2} \text{ a}^{-1}$	
Grass land	High coverage grassland		$0.138 \text{ t hm}^{-2} \text{ a}^{-1}$	Piao et al. (2009)
	Middle coverage grassland		$0.046 \text{ t hm}^{-2} \text{ a}^{-1}$	
	Low coverage grassland		$0.021 \text{ t hm}^{-2} \text{ a}^{-1}$	
Watershed	Canal		$0.671 \text{ t hm}^{-2} \text{ a}^{-1}$	Kong and Zhang (2015)
		Lake	$0.303 \text{ t hm}^{-2} \text{ a}^{-1}$	
		Mudflat	$0.567 \text{ t hm}^{-2} \text{ a}^{-1}$	
		Meadow	$0.567 \text{ t hm}^{-2} \text{ a}^{-1}$	
Unused land			$0.0005 \text{ t hm}^{-2} \text{ a}^{-1}$	Zhang et al. (2020a, b)

selected as proxy variables. Indicators above were used to measure the degree of management strictness, regulatory strictness, and review strictness of command-and-control environmental regulations in each province, respectively.

MI environmental regulation can be divided into subsidy type and punishment type. Subsidy type uses the ratio of total investment in environmental infrastructure and environmental pollution treatment to local GDP. Punishment type uses the ratio of sewage charge to the number of local enterprises.

PP environmental regulation refers mainly to the interaction between government and the public (Blackman et al. 2010). This paper uses the ratio of the number of environmental proposals from the two sessions to the local population as proxy variable to evaluate the legislative participation, and the ratio of environmental petition to local population was selected as proxy variable to evaluate the feedback participation.

VEPF refers to initiatives undertaken by manufacturing companies to reduce the consumption and waste of natural resources in their production activities out of their own perception of environmental protection (Bu

et al. 2019). The number of environmental label certifications and green patent applications was selected to be a good indicator of the self-driven and voluntary innovation of enterprises in environmental protection (Shen et al. 2018). Therefore, we use the ratio of the number of regional environmental label certifications and green patent applications to the number of industrial enterprises to evaluate the intensity of voluntary regulations by regional enterprises.

Entropy method was used to calculate the intensity of environmental regulation (Table 2).

Global space autocorrelation method

The global Moran's index

Spatial correlation means that variables show certain regularity instead of random distribution in space. The global Moran's index is generally used to test for spatial correlation relationships, and the formulas are expressed as follows:

Table 2 Environmental regulation indicators

Form of regulation	Index	Calculation
Command-and-control (CAC)	Management strictness	Cumulative number of laws and regulations
	Regulatory strictness	Public officials of environmental protection system/local public officials
	Review strictness	Annual environmental administrative punishment cases/local enterprises
Market-incentive (MI)	Subsidy type	Total investment in environmental infrastructure and environmental pollution control/local GDP
	Punishment type	Pollutant discharge fee/local enterprises
Public participation (PP)	Legislative participation	Environmental proposals of the two sessions/local population
	Feedback participation	Number of environmental petitions/local population
Voluntary environmental program of firm (VEPF)	Autonomous driving force	Local environmental labeling certification/local enterprises
	Voluntary innovation force	Green patents/local enterprises

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{j} \omega_{ij}} \tag{3}$$

where:

$$S^2 = \sum_{i=1}^{n} (x_i - \bar{x})^2 / n \tag{4}$$

The global Moran's index is I, which takes values between -1 and 1. $I > 0$ is the spatial aggregation of carbon emission values between provinces and neighbouring provinces, indicating positive autocorrelation. $I < 0$ is the spatial dispersion of carbon emission values between contiguous provinces, and $I = 0$ represents complete random dispersion. W_{ij} is the spatial weight matrix, and the k-nerest nearest contiguous spatial weight matrix is used in this research. The global Moran's index is calculated subject to a Z-value significance test, the formula for which is given below:

$$z = \frac{I - E(I)}{\sqrt{\text{Var}(I)}} \tag{5}$$

Hotspot analysis

Hotspot analysis was used to describe whether the net carbon emissions of Chinese provinces are autocorrelated in local space. It is also possible to distinguish between hotspot areas (high-high value agglomerations) and cold spot areas (low-low value agglomerations). The formula is as follows:

$$G_i = \frac{\sum_{j \neq i}^{n} \omega_{ij}(d) x_j}{\sum_{j \neq i}^{n} x_j} \tag{6}$$

where G_i is the hotspot, d is the designated radius, n is the number of prefectures, ω_{ij} is the spatial weight matrix, i and j are the municipalities, and x is the carbon emissions.

Geographically weighted regression model

GWR is a widely used spatial analysis model in the field of energy economics in recent years. Compared with the global regression model, its main advantages are as follows: (1) Global ordinary least squares regression (OLS) would lead to a loss of information about spatial heterogeneity and usually only yields an average state for the whole study area. In contrast, the GWR model can incorporate the geographical location of the sample into the regression parameters, and the regression estimate can be made locally based on information from sub-sample data of adjacent observations, which can reflect the relationship between variables as the local geographical location varies (Fotheringham et al. 1996). (2) In terms of modelling methodology, the GWR model can set multiple variables and perform rigorous econometric tests, improving the

applicability and scientific validity of the model. Therefore, the GWR model was chosen for this study, with the following functions:

$$y_i = \beta_0(\mu_i, \vartheta_i) + \sum_k \beta_k(\mu_i, \vartheta_i) x_{ij} + \varepsilon_i \tag{7}$$

where y_i is the $n \times 1$ dimensional explanatory variable; x_{ij} is the matrix of $n \times j$ dimensional explanatory variables; $\beta_0(\mu_i, \vartheta_i)$ is the regression coefficient of factor k at the regression point i; (μ_i, ϑ_i) represents the longitude and dimensional coordinates of the i observation point; and ε_i is the random and error terms of the independent identical distribution.

The GWR model applies the weighted least squares (WLS) method to estimate the parameters for each observation, and the i-point regression parameters $\beta(\mu_i, \vartheta_i)$ are as follows:

$$\beta(\mu_i, \vartheta_i) = (X^T W_{ij} X^{-1}) X^T W_{ij} Y \tag{8}$$

In order to overcome the disadvantage of discontinuous spatial weight functions, Gaussian function was used to determine the weight function, with the following formula:

$$\omega_{ij} = \exp\left[-\left(\frac{c_{ij}}{b}\right)^2\right] \tag{9}$$

c_{ij} is the direct distance between i and j in the sample. b is the bandwidth, a parameter of the size of the spatial region in which the sample data is located; the larger the value of b, the larger the spatial extent in which the sample is located.

In this paper, the akaike information criteron (AIC) proposed by Fotheringham et al. was used to calculate the bandwidth, with the following equation:

$$AIC_c = 2i \ln(\sigma) + i \ln(2\Pi) + i \frac{i + tr(s)}{i - 2 - tr(s)} \tag{10}$$

where σ is the standard error of the error term estimate, $tr(s)$ is a function of bandwidth, and i is the trace of the matrix s. The bandwidth with the smallest AIC value is the optimal bandwidth.

With NCE as the explanatory variable, we use ER1 (CAC), ER2 (MI), ER3(PP), and ER4 (VEPF) as the core explanatory variables (FER), respectively, and the level of economic development (UED) and energy structure (ESTR) was selected as explanatory variables, and the specific form of the GWR model constructed is as follows:

$$\begin{aligned} NCE = \beta_0(\mu_i, \vartheta_i) + \beta_1(\mu_i, \vartheta_i)(FER)_i \\ + \beta_2(\mu_i, \vartheta_i)(UED)_i + \beta_3(\mu_i, \vartheta_i)(ESTR)_i + \varepsilon_i \end{aligned} \tag{11}$$

where UED is expressed in terms of GDP per unit and the ESTR is expressed in terms of the share of coal consumption in total energy consumption. Real GDP for each year is calculated in constant 2003 prices; ε_i is the residual term.

Data source

The data this paper used are obtained from the China Statistical Yearbook (2004–2019), the China Environmental Statistics Annual Report (2004–2019), the China Environmental Statistics Yearbook (2004–2019), the China Energy Statistics Yearbook (2004–2019), and the website of the National Bureau of Statistics and the environmental statistics bulletins of provinces and municipalities (Table 3).

In this paper, 30 provinces, municipalities directly under the Central Government and autonomous regions in China were selected as the research subjects, among which (excluding Tibet, Taiwan, Hong Kong and Macao due to the lack of data) panel data were selected as the research samples and the research period was 2003–2018 (Table 4).

Results and discussion

Net carbon emission measurement results

The total NCE of province in China from 2003 to 2018 are shown in Fig. 1. The total NCE in China increased from 4146.01 Mt in 2003 to 11,142.61 Mt in 2018, and the total NCE continued rising, but the average annual growth rate showed a decreasing trend, and the NCE increased at a high rate from 2003 to 2013, with an average annual growth rate of 6.8%; NCE show a fluctuating increase after 2013, but the total increase is decreasing. After the Copenhagen Conference in 2009, carbon emission reduction targets were included in the 5-year plan for the first time, and the growth rate of NCE began to decrease gradually during the 12th Five-Year Plan period. It is worth noting that the increase in NCE is mainly due to the increase in total carbon emissions. In terms of growth rate, the growth

Table 4 Descriptive statistics

| Variable	Obs	Mean	Std. dev.	Min	Max
NCE	480	28,921.134	24,767.232	610.819	154,917.425
ER1 (CAC)	480	0.470	0.268	0.064	1.869
ER2 (MI)	480	0.297	0.194	0.016	1.527
ER3 (PP)	480	0.451	0.243	0.064	1.773
ER4 (VEPF)	480	0.141	0.268	0	1.734
UED	480	37,183.143	25,775.816	3701.142	153,095.647
ESTR	480	0.445	0.155	0.016	0.802

of NCE has slowed down significantly since 2013, and the implementation of carbon emission reduction policies has had a significant effect.

Fig. 2 compares TCE and TCS of each province in 2003 and 2018. TCE varies greatly by region, with Shandong, Hebei, and Jiangsu having higher carbon emissions and Qinghai and Hainan having the lowest carbon emissions. Since China's entry into WTO in 2001, energy consumption has started to grow rapidly. However, China's energy resource characteristics of "rich coal, poor oil and little gas" have formed the energy consumption structure dominated by coal, which also determined the rapid increase of carbon emissions. Compared with TCE, the TCS of all provinces in China is relatively weak. The highest ratio of TCS and TCE was found in Qinghai, which was 19.3% in 2003, but this ratio dipped to 7.3% in 2018. Meanwhile, the ratio in most provinces was less than 1%. Compared with the TCS in 2003 and 2018, the TCS of most provinces has decreased slightly. From 2003 to 2018, China's urbanization rate increased from 40.53 to 57.35%. The conversion of forest land and grassland into industrial land was the key reason for the reduction of carbon sequestration.

Table 3 Data sources

Indicate	Data sources
Cumulative number of laws and regulations	The China Environmental Statistical Yearbook (2004–2019)
Public officials of environmental protection system	
Annual environmental administrative punishment cases	
Total investment in environmental infrastructure and environmental pollution control	
Environmental proposals of the two sessions	
Number of environmental petitions	
Local environmental labeling certification	Directory of environmental labeling Enterprises (2004–2019)
Green patents	Chinese Research Data Services
Local enterprises	The National Bureau of Statistics of provinces and municipalities.(2004–2019)
Local GDP	The China Statistical Yearbook (2004–2019)
Energy consumption	The China Energy Statistical Yearbook (2004–2019)

Fig. 1 Annual net carbon emissions of provinces in China from 2003 to 2018
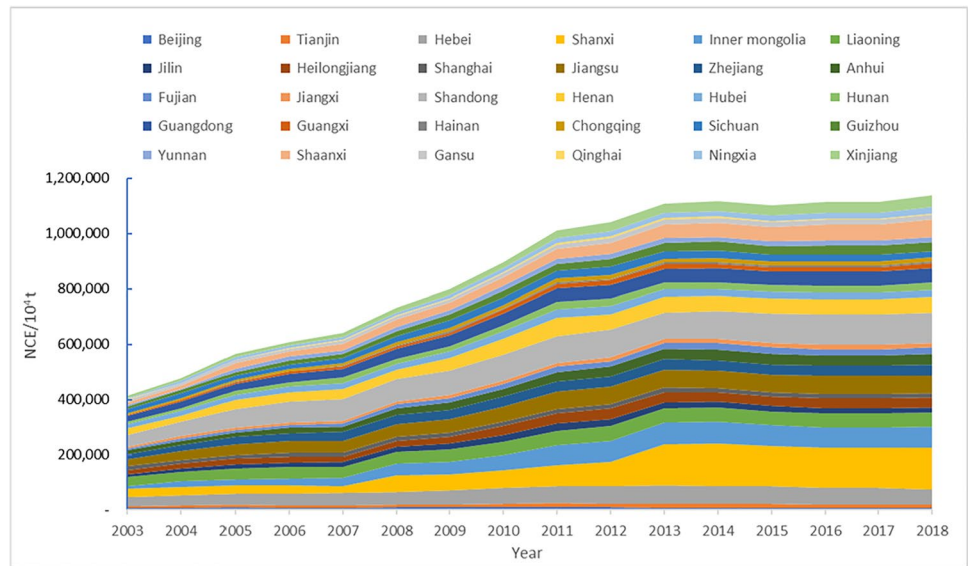
Fig. 2 TCE and TCS comparison in China's provinces in 2003 and 2018
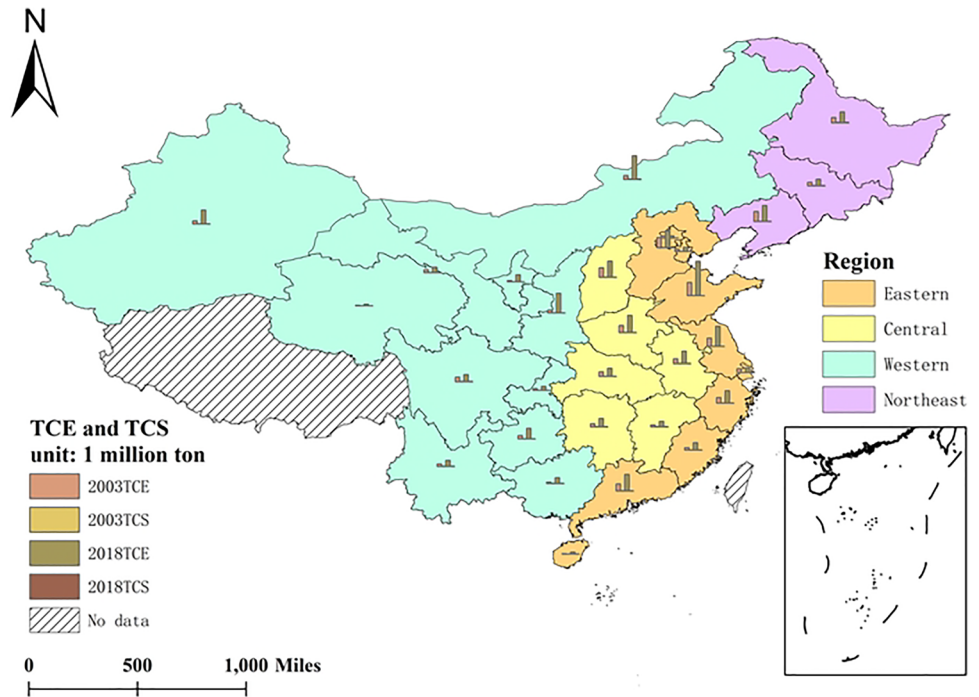
Spatial association characteristics

The results of the global spatial autocorrelation analysis of NCE of 30 provinces and urban areas in China from 2003 to 2018 are shown in Table 5. The global Moran's I of NCE in China from 2003 to 2018 is greater than 0, and there is a significant positive autocorrelation of NCE in all provinces and cities, which shows a low-low or high-high concentration in space. The global Moran's I of NCE shows a trend of increasing and then decreasing, and the spatially concentrated distribution of provinces and municipalities

with similar NCE has been increasing from 2003 to 2011, which reaches its maximum in 2011. From 2012 onwards, the global Moran's index for the provinces began to gradually decline; this is probably due to the fact that since the 12th Five-Year Plan, China has started to attach importance to energy saving and emission reduction; especially after the 18th National Congress, the construction of ecological civilization has been incorporated into the overall layout, and various environmental regulatory policies such as the new Environmental Protection Law, the most strict air pollution policies, and the carbon emission trading pilot have

Table 5 Moran's *I* of province level in China from 2003 to 2018

Variables	Moran's *I*	*z*	*p*-value*	Variables	Moran's *I*	*z*	*p*-value*
nce2003	0.292	2.986	0.001	nce2011	0.338	3.396	0.000
nce2004	0.299	3.088	0.001	nce2012	0.324	3.285	0.001
nce2005	0.319	3.355	0.000	nce2013	0.311	3.421	0.000
nce2006	0.285	3.091	0.001	nce2014	0.283	3.170	0.001
nce2007	0.271	2.938	0.002	nce2015	0.287	3.157	0.001
nce2008	0.280	2.965	0.002	nce2016	0.273	2.973	0.001
nce2009	0.308	3.203	0.001	nce2017	0.273	2.973	0.001
nce2010	0.328	3.340	0.000	nce2018	0.251	2.793	0.003

been launched one after another. As a result, the growth rate of carbon emission slowed down and the total amount of carbon sinks began to rise. In general, the NCE of each province are not randomly distributed, but have a significant spatial autocorrelation. The GWR model can be used to investigate the spatial and temporal heterogeneity of the influencing factors.

The NCE hotspot analysis uses the natural interruption point grading method to classify the $ZG(i)^*$ values calculated by Eq. 6) for each year into high clustering region, sub-high clustering region, sub-lowest-value clustering region, and low value clustering region in descending order, and the clustering results for 2003 and 2018 are used for the analysis. This is shown in Fig. 3.

The evolution of the clustering of high and low values of NCE in China's provinces shows a decreasing spatial trend from northeast to southwest. In terms of temporal change, the high-value clustering reigon gradually expands. The high value clustering region shows an increasing trend along the clustering area from China's eastern coastal areas gradually moving northwestward, forming a region centered on the Beijing-Tianjin-Hebei region, including Inner Mongolia, Shandong, Shanxi, Liaoning, and Shaanxi. These provinces are the regions where China's heavy industry is most

concentrated, and they are also the main fossil energy producing and using regions in China, and the Inner Mongolia is also the main province for coal power transmission out of the North China Power Grid. In addition, the gradual shift of traditional high-energy-consuming industries from the eastern coastal region to the northwest after 2005 was also one of the main factors triggering the movement of high-value clusters to the northwest. The secondary high-value clusters are concentrated in Jiangxi, Hubei, Shaanxi, and Zhejiang provinces, which were once dominated by high-energy-consuming industries and began to upgrade their industries during the 12th Five-Year Plan period, gradually forming high-end manufacturing and service industries that are mainly capital-intensive and less dependent on fossil energy. Sub-low-value clusters and low-value clusters are concentrated in Xinjiang, Qinghai, Sichuan, and Gansu are less economically developed, which are vast and rich in ecological resources, and have not only low carbon emissions but also large carbon sinks.

Trends in the intensity of environmental regulation

Figure 4 shows the spatial distribution of environmental regulation intensity of CAC, MI, PP, and VEPF in 2003 and
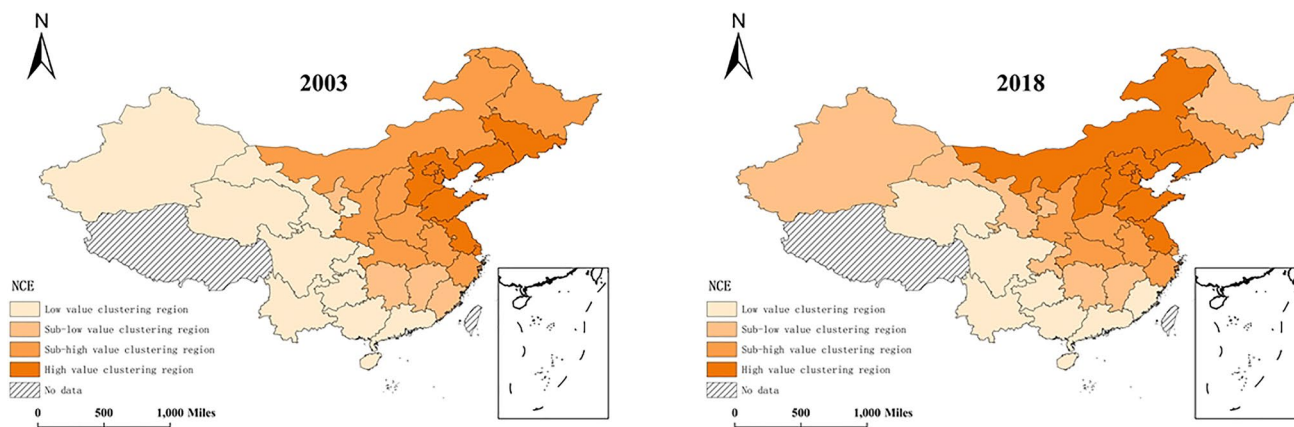
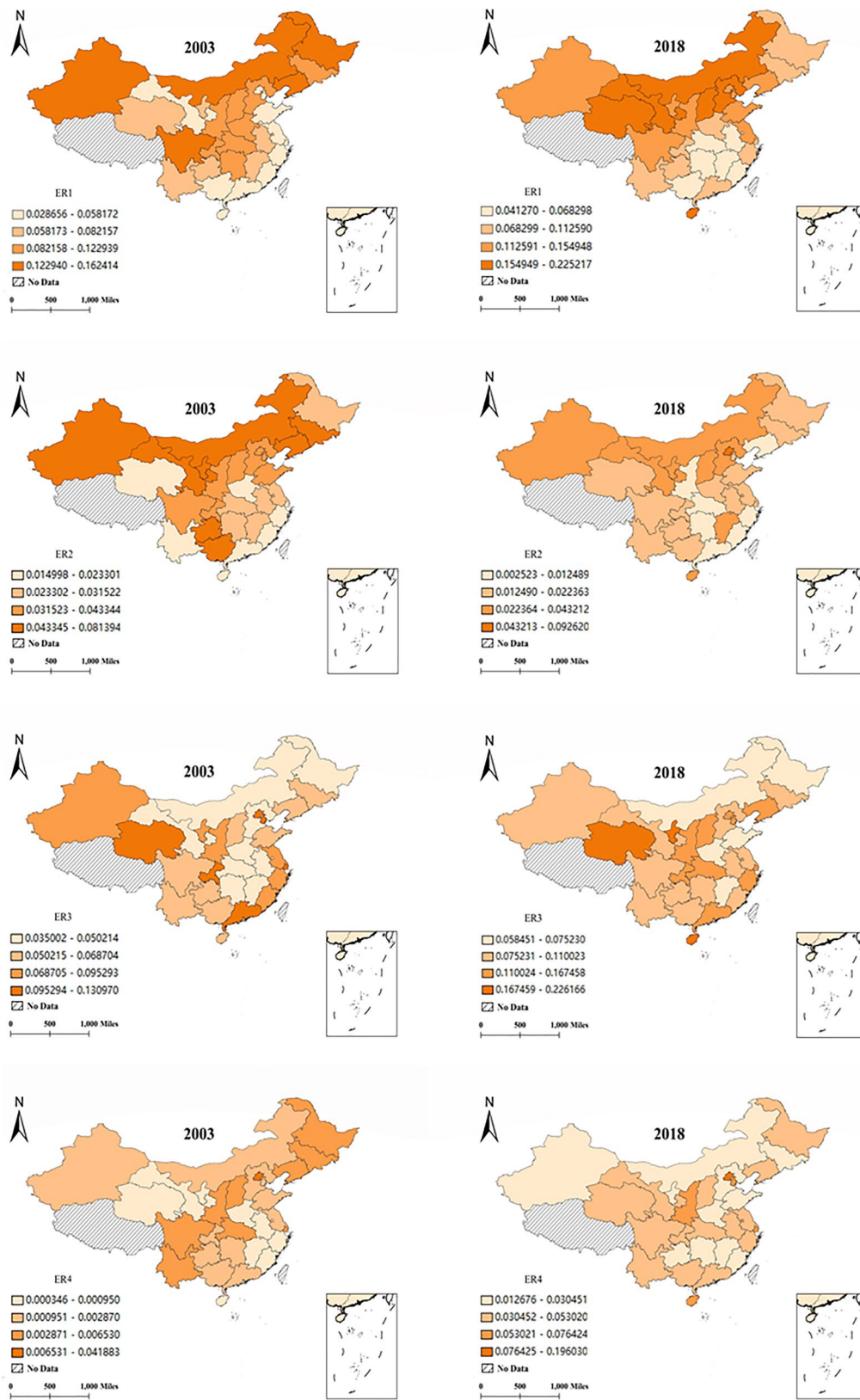**Fig. 3** NCE hotspots in province level of China from 2003 and 2018

Fig. 4 Changes of environmental regulation intensity in provincial level of China in 2003 and 2018

2018, as calculated by the entropy weight method. From Fig. 4, we can clearly see that the geographical distribution of each type of environmental regulation varies, and the implementation intensity of different types of environmental regulation is not uniform in the same region, which further indicates that it is unscientific to analyze the impact of environmental regulation on regional NCE in an aggregate manner by unifying different types of environmental regulation. Specifically, we find that the medium to high values of the intensity of CAC are mainly found in Heilongjiang, Liaoning, Inner Mongolia, Hebei, and the central regions such as Hunan, Henan, Jiangxi, Anhui, Hubei, and Shanxi. For MI, the high values are concentrated in the northern regions of Inner Mongolia, Tibet, and Liaoning, while the low values are concentrated in the southeast coastal area of Zhejiang, Fujian, and Guangdong, which indicates a higher absolute but insufficient relative investment in environmental management in the eastern regions and corrects the stereotype of insufficient investment in environmental management in the central and western regions. For PP, the high values are concentrated in the central-eastern region, while the low values are mainly found in the northeastern region. The VEPF shows a unique situation in Beijing and Shanghai. It can be seen that Beijing and Shanghai, which are home to China's top high-tech enterprises, have indeed played a leading role in promoting green development of enterprises.

Comparing 2003 with 2018, it can be found that the intensity of all four types of environmental regulation has increased to varying degrees, but generally tends to move in a more balanced direction. The growth rate of regulation intensity in regions with weak environmental regulation (e.g., Guangxi, Guizhou) was significantly higher than that in regions with strong regulations (e.g., Beijing, Shanghai). This may be due to the spatial spillover effect of environmental regulations, as local governments adjust their local environmental protection policies through learning and exchange among themselves in order to achieve the goal of energy conservation and emission reduction. The result of this interaction was that environmental regulation tends to be more balanced. In order to verify the spatial effect of environmental regulations on NCE, further step in the empirical analysis is necessary.

Geographically weighted regression analysis

Multicollinearity testing

The GWR model must be applied based on variables with low correlations, and multicollinearity should be diagnosed before the GWR is performed. Herein, the most commonly used measurement of multicollinearity, the variance inflation factor (*VIF*), was used to ensure low correlations among variables. The *VIF* value of the regression variable should be no greater than 7.5 ($VIF \leq 7.5$), which ensures that no multicollinearity or redundant independent variables were used in the regression model (Sheng et al. 2017). The results are shown in Table 6.

Estimation results of the GWR model

In order to avoid the correlation between the variables from affecting the model analysis results, the least squares (OLS) method was applied to analyze the impact environmental regulation on NCE before using GWR, and the results are shown in Table 7. The difference between the AIC_C values of OLS and GWR and the AIC_C values of OLS is greater than 3, which indicates that the fitting results using the GWR are more accurate than OLS (Tasyurek and Celik 2020).

CAC environmental regulation As shown in Fig. 5, the regression coefficient of CAC environmental regulation from 2003 to 2018 is positive, indicating that CAC environmental regulations in China played a promoting role on NCE. The regression coefficients for each year show that the elasticity coefficients of neighboring provinces are less different; thus, the spatial dependence effect of CAC environmental regulation on NCE was clear. Between 2003 and 2018, the average elasticity coefficient in each province increased from 0.348 to 2.497, with an increasing trend of promoting effects, and the spatial aggregation characteristics showed a spatial shift from the west to the northeast in a clockwise direction, and the pattern of influence also changed with the year. Heilongjiang, Jilin, Liaoning, Beijing, Hebei, and Inner Mongolia had the largest elasticity coefficients of CAC environmental regulation in 2018, and the size of the elasticity coefficients of CAC environmental regulation did not differ significantly across provinces. On the whole, the degree of influence of CAC environmental regulation on NCE gradually tends to be consistent.

The main reasons for the increase of NCE due to the improved CAC environmental regulation can be divided into two levels: macro and micro. At the macrolevel, the interval (2003–2018) was a period with high growth in fossil energy use in China, with coal-dominated fossil energy being the key driver of carbon emissions growth. Ma et al. pointed out that the form of intensity constraint based on tightening emission standards was unable to limit the growth rate of energy consumption and led to simultaneously increase of total fossil energy use and total NCE (Ma et al. 2019). At the microlevel, CAC environmental regulation primarily aims at polluting companies, and the higher intensity of regulation, the less likely that companies will violate it, which means that polluters must use larger number of treatment technologies to avoid non-compliance. However, the operation of treatment projects is accompanied by the use of

large amounts of fossil energy, resulting in the reduction in pollution and the increase in carbon emissions.

MI environmental regulation

There is considerable spatial and temporal variability in the impact of MI environmental regulation on NCE (Fig. 6). From 2003 to 2018, the contribution of MI environmental regulation to NCE shifted from an overall positive to a partial negative correlation, with a decreasing average elasticity coefficient. The contribution of MI environmental regulation to NCE gradually declines. In terms of spatial patterns, the spatial aggregation of MI environmental regulations on NCE shifted from the northwest to the northeast, with the regression of the high value area and the second highest value area located in northern China, showing a gradually decrease in facilitation from north to south in 2018, and the southern provinces showing a suppressive effect.

The increasing inhibiting effect of MI environmental regulation on NCE may be explained by the fact that early investments (before 2010) in environmental infrastructure and environmental management in China were mainly in urban landscaping, amenities, sanitation, and sewage treatment, which focused on pollution treatment rather than carbon emission reduction. The daily operation of these facilities would increase local energy consumption to significantly promote NCE. Since announcing the targets of controlling greenhouse emissions at the Copenhagen Climate Change Conference in 2009, China started to work on the construction of facilities related to carbon emission reduction. In 2010, carbon intensity was included as a binding target for the first time in China's 12th Five-Year Plan, and local governments began to respond to the national policy by investing in carbon dioxide control as well, such as carbon trading pilot and low-carbon city investment. Among all researched provinces, the role of MI environmental regulation has gradually diminished in promoting NCE, while some regions even suppressed. At the same time, pollution control investments have a certain effect on ecological restoration and carbon sinks, which may also be one of the reasons why MI regulation in southern provinces has a dampening effect on NCE.

PP environmental regulation The spatial variation in the impact of PP environment regulation on NCE in China's provinces varied insignificantly, with a negative correlation (Fig. 7), which indicates that an increase in the intensity of PP environmental regulation contributes to a reduction in total NCE. From 2003 to 2018, the three northeastern provinces, Beijing, Hebei, and Inner Mongolia, had the smallest elasticity coefficients and the most significant suppressive effect on NCE. The distribution of regression coefficients for the effect of PP environmental regulation on NCE

follows a pattern of spatial gradients, gradually weakening from the northeast to the southwest. The increasing elasticity coefficient reflects its increasing suppressive effect of PP environmental regulation on NCE. From the perspective of legislative participation, the number of proposals on environmental protection at the two sessions (the National People's Congress and the Chinese Political Consultative Conference) has been increasing year by year in all provinces and regions of China, reflecting an overall increase in public concern and participation in environmental protection issues. However, from the perspective of feedback participation, the northern regions of China are more involved than the southern regions, probably due to the fact that China's major heavy industrial provinces are concentrated in the northeastern and northern regions of China (Ouyang et al. 2020). Environmental pollution is more serious in the north than in the south, especially in terms of air pollution, with all the top 10 cities suffering severest particulate matter pollution in China being in the north. $PM_{2.5}$ would cause haze pollution, which is the key public environmental issue in the last 10 years. To address the problem of haze pollution, a large number of heavily polluting enterprises have been shut down, which objectively contributed to the reduction of carbon emissions. The natural environment and climate in the southern regions of China are generally better than those in the north, and the southern regions have higher level of economic development, with a more robust mechanism for petitioning environmental protection in the south and more remarkable public opinion formed by the disclosure of environmental pollution incidents, especially in areas with a developed tourism industry such as Guangxi and Yunnan, where the government attaches more importance to environmental pollution controlling, The more environmental problems promptly solved, the less frequent of public pollution concern received.

VEPF environmental regulation The VEPF environmental regulation has the most significant suppressive effect on provincial NCE (Fig. 8). From 2003 to 2018, the mean value of the regression coefficient of VEPF environmental regulation on provincial NCE changed from −2.50 to −1.47, with a gradually decreasing suppressive effect. The regression high value region and the second highest value region of the impact of VEPF environmental regulation on NCE in 2003 are located in northeast and north and the eastern coast of China, which are the most technologically and economically developed regions and have applied large number of clean and pollution control technologies. The spatial aggregation characteristics from 2003 to 2018 show a spatial shift from the northwest to the southern region clockwisely, and the pattern of impact also shows changes with the year. The possible reason for the gradually decline in the suppressive effect of VEPF environmental regulation on NCE is

Table 6 Results of variance inflation factor

VIF	2003	2018
ER1 (CAC)	1.03	2.34
ER2 (MI)	1.09	1.15
ER3 (PP)	1.72	3.06
ER4 (VEPF)	2.32	2.92
UED	2.28	6.25
ESTR	1.28	1.91

Table 7 Comparison of GWR model and OLS model fitting results

Year	Model	R^2	Adjusted R^2	AIC_C
2003	OLS	0.4762	0.3374	−54.1378
	GWR	0.5063	0.3773	−66.9476
2018	OLS	0.6171	0.2917	−1.4582
	GWR	0.6477	0.3402	−6.9698

that, as the enterprise's green innovation develops, it will reach a stage of decreasing returns to scale, which would reduce the willingness of green innovation. In addition, Yuan et al. point that the government's standards for enterprises to obtain green subsidies keep increasing in recent years and growing number of enterprises are unable to meet the government's subsidy standards, which also objectively increases the cost and reduces the willingness of enterprises to green innovation (Yuan and Xie 2016).

Conclusion

Based on the panel data of 30 provinces in China from 2003 to 2018, this paper empirically tests the impact of heterogeneous environmental regulations and spatial differences on NCE by using a geographically weighted regression model. The conclusions are mainly as follows:
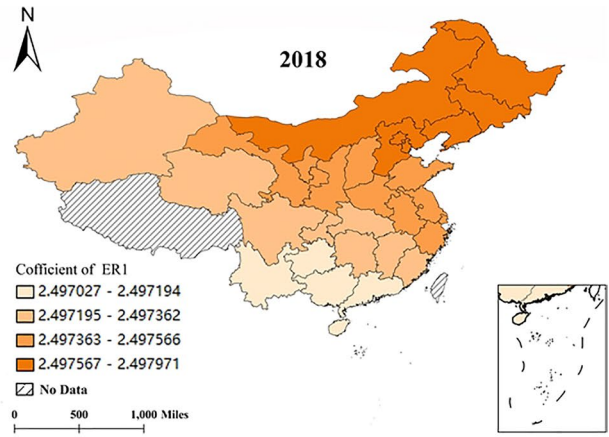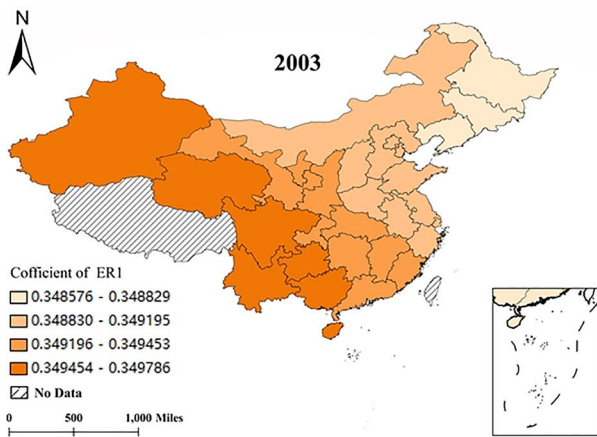
Fig. 5 Regression coefficient of CAC environmental regulation
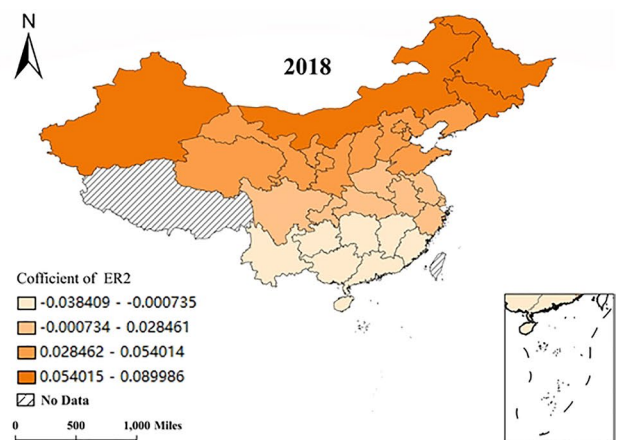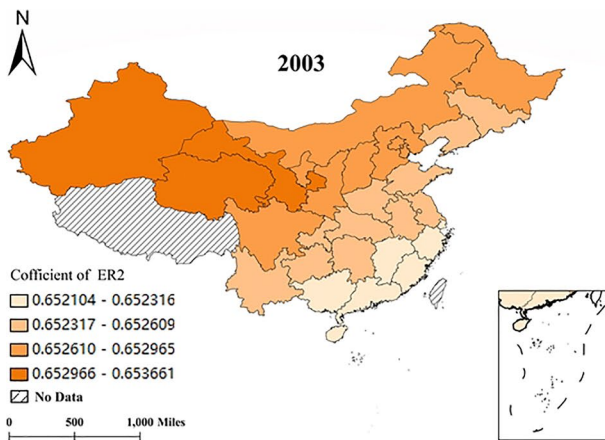
Fig. 6 Regression coefficient of MI environmental regulation
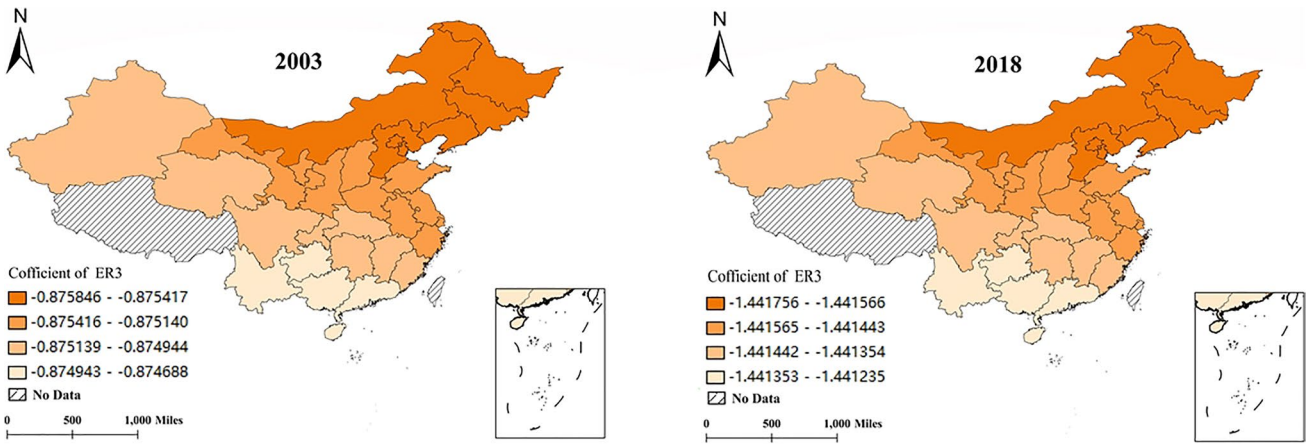
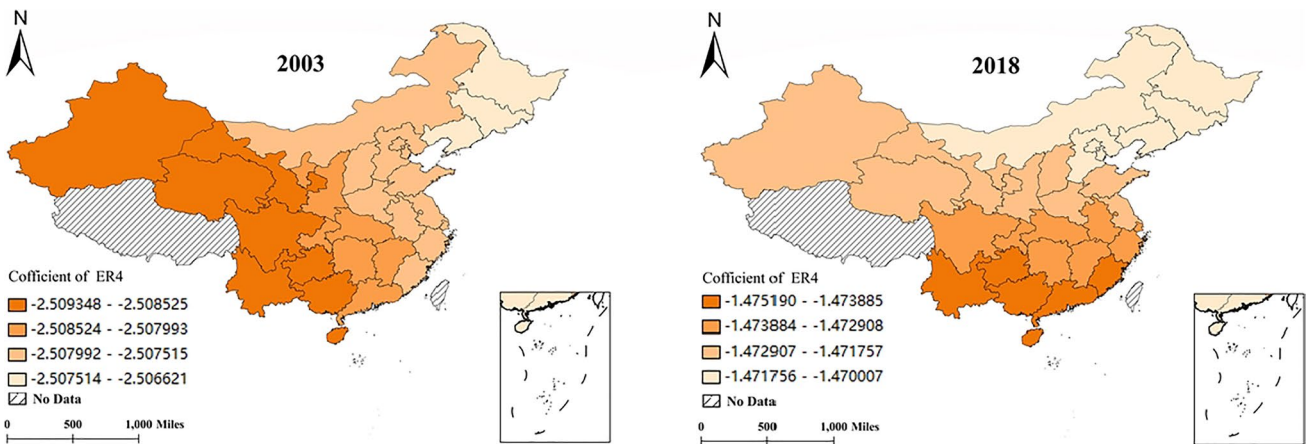**Fig. 7** Regression coefficient of PP environmental regulation

Fig. 8 Regression coefficient of VEPF environmental regulation

(1) China's NCE grew from 4146.01 Mt in 2003 to 11,142.61 Mt in 2018. Although NCE continuing to rise, the average annual growth rate is falling. The increase of NCE was caused by TCE growth and the TCS reductions, and the absorption ratio of TCS to TCE gradually decreased. Considering that China's economic growth rate is expected to remain strong in the future, this trend will not change before the carbon peak in 2030.

(2) The NCE of provinces shows positive spatial autocorrelation, with a divergence of high values in northeast and north China and low values in southwest China. There is no large-scale regional shift in high-value clustering areas, which are concentrated in the Beijing-Tianjin-Hebei region, including Inner Mongolia, Shandong, Shanxi, Liaoning, and Shaanxi, but there is an increasing trend in high-value clustering areas, with shifts occurring along clustering areas in adjacent regions. Sub-low value clustering areas and low value clustering areas are primarily concentrated in Xinjiang, Qinghai, Sichuan, Gansu, and other provinces with less developed economies but abundant biological resources and carbon sink resources.

(3) The four types of environmental regulation strengths tend to develop in a more balanced direction in space, with weaker regions showing a tendency to increase (such as the southwest and central regions) and stronger regions showing a trend to weaken (such as northeast China, central China), resulting in a gradual weakening of the spatial performance differentiation.

(4) During the study period, the impact of CAC environmental regulations on NCE is a "green paradox," with an increase in intensity leaded to an increase in NCE; the impact of MI environmental regulations on NCE is

first promoted, then partially suppressed; both PP and VEPF environmental regulations have a suppressive effect on NCE.

The results of the research can also help local governments develop environmental regulation that promote carbon peaking and carbon neutralization, as follows:

(1) Carbon sink function is critical in China's "carbon neutral" strategy. However, the absorption of carbon sink has received little attention. According to the study, China's carbon sink has been declining. Governments should build a long-term environmental regulation, raise environmental protection investment, and maintain and extend the carbon-absorbing system's service time.

(2) Environmental regulations should be implemented by the government in accordance with local conditions. Rather than adopting a "one-size-fits-all" regulatory approach, design specific environmental regulating rules and intensities based on geographical heterogeneity. For example, provinces in China's eastern region, such as Guangdong, Fujian, and Zhejiang, have developed economies with a high degree of marketization, and many private enterprises can implement MI and VEPF environmental regulations, decrease the intensity of CAC environmental regulation, and strengthen local regulation by defining appropriate environmental tax and hastening the development of carbon trading.

(3) The homology between air pollution and carbon emissions should be paid attention to in the process of promoting carbon neutralization, and the advantages of collaborative pollution control of CAC environmental regulation should be brought into play. This study found that increasing the intensity of CAC environmental regulation promotes carbon emissions, because the existing CAC environmental regulation is "end of pipe governance" with accountability and punishment, not only results in high marginal emission reduction costs, but also in insufficient emission reduction effects and sustainability. CAC environmental regulation should pay attention to "source governance," such as controlling the use and quality of fossil energy, which is the primary source of carbon emissions and air pollutants. Controlling total fossil energy consumption through CAC environmental regulation, which includes optimizing industrial structure, actively developing clean energy, and promoting environmentally friendly technological progress, should be the key direction of formulating CAC environmental regulation. Eventually, attain the goal of coordinated carbon emission and air pollution control.

(4) Establishing a diverse environmental regulation system for carbon emission reduction. The results found that PP and VEPF environmental regulation have a significant impact on reducing carbon emissions. Therefore, give full play to the independent contributions of enterprises and the public in carbon emission governance, build a carbon emission governance system with the government as the leading role, enterprises as the main body, and social organizations and the public as the common participants, to form an "environmental interest community" with "government-enterprise-social organization/public" tripartite governance. Make full use of the mobile Internet, mobilize the enthusiasm of all sectors of society, broaden the channels for the public to appeal for environmental protection, publicly feed back the handling results, and cultivate the public's enthusiasm for participating in environmental management. Stimulate enterprises' awareness of environmental responsibility, guide enterprises' low-carbon behavior, and enable enterprises to voluntarily participate in the action of carbon emission reduction.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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