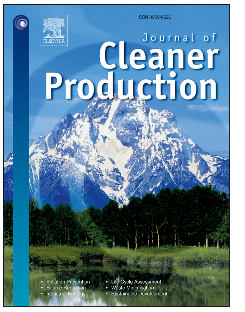

Re-examining the drive forces of China's industrial wastewater pollution based on GWR model at provincial level

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Author contributions

Pengyan Zhang: Conceptualization, Methodology, Software, Investigation, Writing - Original Draft.

Dan Yang: Validation, Formal analysis, Visualization, Software.

Yu Zhang: Validation, Formal analysis, Visualization.

Yu Liu: Resources, Writing - Review & Editing, Supervision.

Yanyan Li: Writing: Review & Editing.

Yunfeng Cen: Writing: Review & Editing.

Wei Zhang: Resources, Writing - Review & Editing, Supervision.

Wenliang Geng: Writing: Review & Editing.

Tianqi Rong: Writing: Review & Editing.

Ying Liu: Data Curation.

Jingwen Shao: Data Curation.

Re-examining the drive forces of China's industrial wastewater pollution based on GWR model at provincial level[1]

Pengyan Zhang[a,b], Dan Yang[a], Yu Zhang[a] , Yanyan Li[a], Yu Liu[c,d,*], Yunfeng Cen[a], Wei Zhang [e,f*], Wenliang Geng[a], Tianqi Rong[a], Ying Liu[a], Jingwen Shao[a]

[a] *Key Laboratory of Geospatial Technology for Middle and Lower Yellow River Region, Research Center of Regional Development and Planning, Institute of agriculture and rural sustainable development, Henan University, Kaifeng 475004, China*

[b] *Collaborative innovation center on Yellow River civilization of Henan Province, Henan University, Kaifeng, 475001, Chinas*

[c] *Institute of Science and Development, Chinese Academy of Sciences, Beijing, 100190, China.*

[d] *School of Public Policy and Management, University of Chinese Academy of Sciences, Beijing 100049, China*

[e] *State Environmental Protection Key Laboratory of Environmental Planning and Policy Simulation, Chinese Academy of Environmental Planning, Beijing, 100012, China*

[f] *The Center for Beijing-Tianjin-Hebei Regional Environment, Chinese Academy of Environmental Planning, Beijing 100012, China*

[1] *Corresponding author. E-mail addresses: Liuyu@casipm.ac.cn (Y. Liu); zhangwei4573@163.com (W. Zhang).

Re-examining the driving forces of China's industrial wastewater pollution based on GWR model at provincial level

Abstract: Quantitative analysis of the spatiotemporal changes in China's industrial wastewater and the hidden driving factors can provide important information for the overall process management of industrial wastewater. Taking China's 31 provincial-level administrative regions as research objects, this paper employed spatial econometric (OLS) model and geographically weighted regression (GWR) model to evaluate the spatial spillover effects and identify the drive forces of wastewater discharge between provinces during 2004-2015 period. The results show that industrial wastewater discharge at the national level showed a trend of first increasing to 24.7 billion tons in 2007 and then decreasing to 19.9 billion tons in 2015. There was a significant positive spatial autocorrelation of industrial wastewater discharge among China's provinces and the emission hotspots were mainly concentrated in central-western China. Moreover, the ① nationalization level of industry, ② industrial structure and ③ environmental protection measures were found to be major driving forces of the spatial changes of industrial wastewater discharge. Our findings indicated that strengthening industrial nationalization as well as encouraging cooperation between neighboring provinces may help to reduce the industrial wastewater discharge, which can pave the way for other developing countries that face similar water pollution problems.

研究目的 研究过程 结果 研究启示

Keywords: Industrial Wastewater Discharge, Spatial Patterns, Correlation Analysis, Spatial Econometric Analysis, Geographically Weighted Regression

1. Introduction

背景

Over the past century, the promotion of industrialization and urbanization has led to a constant increase in the consumption of global water resources (Dalin et al., 2012; Hoekstra et al., 2012; Kummu et al., 2016; Hoy 2017; Larsen et al., 2016), with a six-fold increase in global water usage, or twice the population growth rate (UNESCO, 2012; UNESCO, 2015; Veldkamp et al., 2017; Dalin et al., 2017). Between 1995 and 2025, areas affected by "severe water stress" have expanded and intensified and will continue to expand and intensify, with the global range of 36.4 million km^2 expanding to 38.6 million km^2 (Alcamo et al., 2000). By 2050, global water usage will have grown by 55% from 2000, and nearly 3.9 billion people will face severe water scarcity (Saritas et al., 2017). Furthermore, water quality has important functions across the water resource portfolio of all countries (Rice et al., 2017; Ludwig et al., 2014; Yue et al., 2017). A rapidly growing economy has changed the hydrological process, leading to severe water scarcity in approximately 400 Chinese cities (Larsen et al., 2016) and different degrees of water pollution in three-quarters of lakes. Moreover, the water scarcity in southern China is largely due to water pollution (Cai et al., 2017). At the end of 2015, China's industrial wastewater discharge amount to 181.6 billion tons (Ministry of environmental protection of the people's republic of China, 2018), posing a huge threat to households and the economic development of fisheries, agriculture and other sectors. Resource allocation and environmental pollution-related issues are gradually posing a threat to water resources, and there are increasing challenges in terms of global wastewater discharge (Morris et al., 2017). Water-related risks were identified as the most crucial factor influencing the global economy (Jensen and Wu, 2016), and water pollution was singled out as one of the issues that need to be addressed urgently (Ilyas et al., 2019; Cheng et al., 2016).

综述

Academicians started taking heed of industrial pollution earlier and proposed that the "Kuznets curve" be used to study various types of environmental pollution (Grossman and Krueger, 1994; Grossman and. Krueger, 1995; Stem et al., 2001). Studies on industrial wastewater are mostly centered around the problems of a single sector or plant type, such as the wastewater discharge, industrial wastewater handling (Hashemi et al., 2019; Zakaria et al., 2017) and waste distribution (Qin et al., 2009) of the wine industry (Castex et al., 2015), steel industry (Gu et al., 2015) and certain processing industries (Popat et al, 2019). In such studies, the issue of metal pollution has become a pain point in the process of treating industrial wastewater (Guo et al., 2016; Wang and Yang, 2016). Because industrial wastewater can be reused more easily, governance studies on its characteristics are gradually becoming a focal point. However, due to the influence of various conditions, China's industrial wastewater are still discharged in a natural manner, and studies tend to revolve around the area-related differences of these discharge (Huang et al., 2019), the relationship between pollution and economic development (Ma et al., 2015; Zhang et al., 2019), and driving factors (Li et al., 2009; Li et al., 2013).

GAP

In summary, most studies tend to focus on spatiotemporal patterns based on statistical data and overlook the impact of various factors on discharge trends. In terms of analytical methods, the classical statistical methods find only an average or global estimation on the parameters, ignoring the spatially non-stationary characteristics of the parameters (Anselin, 1988; LeSage and Pace, 2008; Zhao et al., 2017). In terms of study scales, most of the existing research focused solely on the industrial wastewater discharge of a single sector in a local area or certain watersheds. Regional or large-scale studies are missing. Such as some scholars study the factors affecting Wastewater Discharge in China based on the LMDI model, from four aspects: resources, technology, economy and population. Such as Chen et al. (2016), conducted research on the discharge of wastewater (including domestic wastewater and industrial wastewater) and conducted research on 31 provincial administrative regions in China, while Geng et al. (2014) conducted research on industrial wastewater discharge, focusing on the analysis of four provinces and cities in Beijing, Jiangsu, Chongqing and Tibet. However, it is more constrained by subjective action, and limited by the model itself. On the one hand, it fails to obtain the degree of impact of specific sub-factors on wastewater discharge in several items after decomposition, on the other hand, the traditional factor decomposition model ignores the characteristics of parameters in space factors, so it may cause the results to have some deviation. Therefore, aiming at filling this gap, OLS and GWR model are used instead of the LMDI model, this paper extends the framework of the traditional model, combines spatial correlation with spatial differences, solves the spatial heterogeneity between the various factors, and satisfies that the relationship between the variables can change with the spatial position, and the calculation results are more in line with objective reality.

解决 GAP

2. Methods and data resources

2.1. Spatial correlation analysis

Based on the first law of geography, correlations exist between the spatial units or attributes that are distributed in a regulated, agglomerated or randomized manner, and there is an inverse relationship between correlation and distance (Tobler, 1970). This phenomenon is known as spatial autocorrelation (Moran, 1948; Geary, 1954). Spatial autocorrelation is the correlation among values on a two-dimensional surface, and it may be used to measure the distribution characteristics of a research area's correlated variables from a spatial perspective. Spatial correlation statistics can be used to measure whether interdependence exists among sample data within the same distribution area, and it is commonly used to analyze the geographical and factor spatial distribution characteristics to provide a basis for the exploration of spatiotemporal evolution characteristics (Lee and Wong, 2001; Wang et al., 2018). This model has been successfully used to analyze the industrial pollution spatial characteristics of all key cities (Hu et al., 2016) and regions (Cui et al., 2012) nationwide, with the results indicating that industrial pollution has significant spatial autocorrelations. As such, this model can be used to demonstrate the spatiotemporal evolution patterns of industrial wastewater discharge.

Global autocorrelation analysis. This paper selected global autocorrelation analysis to analyze the spatial agglomeration trends of the total quantity and intensity of industrial wastewater discharge to demonstrate the degree of spatial correlation or differences among areas. The most commonly used measurement index is Moran's I (Hu et al., 2016), which has the following formula:

$$I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(x_i-\bar{x}\right)\left(x_j-\bar{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}}\text{, in which }\quad S^2=\frac{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}{n} \qquad (1)$$

In the formula, I is Moran's I; n is the number of the observed area; x_i and x_j are the industrial wastewater discharge quantities of area i and area j, respectively; $\bar{x}$ is the average value of industrial wastewater discharge, and w_{ij} is the spatial adjacency weight matrix to defines the adjacency of a space unit. Generally, when area i and area j are adjacent, w_{ij}=1; when not adjacent,

w_{ij}= 0. The range of *Moran's I* is from -1 to 1. The statistical test was performed based on the *P* value and the *Z* score. A positive *Z* score represents a spatially clustered pattern; a negative *Z* score indicates a spatially dispersed pattern, which has the following formula (Pang et al, 2014):

$$Z(I) = \frac{I - E(I)}{\sqrt{\mathrm{Var}(I)}} \quad \text{,in which,} \quad E(I) = \frac{-1}{n-1} \tag{2}$$

In the formula, *E(I)* is the mathematical expectation under the assumption of spatial non-aggregation; *Var(I)* is the number of mutations.

Local autocorrelation analysis. Moran's I is an overall statistical index that reflects only the degree of differences in the spatial distribution of industrial wastewater discharge quantities among provinces; it does not identify the cluster locations or spatial autocorrelation types (Anselin, 1988). Local indices of spatial autocorrelations (scatter diagram) are required to explain the interactive relationships among the spatially proximate units. Presented in the form of four quadrants, the H-H model and L-L model represent the high-value zone with geometrically proximate zones of high values and the low-value zone with geometrically proximate zones of low values, respectively, with positive spatial autocorrelations for both models. The H-L model and L-H model represent the high-value zone with geometrically proximate zones of low values and the low-value zone with geometrically proximate zones of high values, respectively, with negative spatial autocorrelations for both models.

2.2. Spatial econometric analysis

The spatial autocorrelation analysis shows that there was a significant spatial clustering relationship among the industrial wastewater discharge of the provinces in China. However, we were unable to qualitatively analyze the driving factors and mechanisms resulting in the agglomeration effects of industrial wastewater discharge among provinces in China. To conduct an in-depth analysis of the factors influencing industrial wastewater discharge, the impact of the various indexes under the spatial spillover effect on the spatial agglomeration of industrial wastewater discharge in China was investigated. Based on the classical ordinary least squares (OLS) estimation model, the spatial econometric model was selected to study industrial wastewater discharge (Zhao et al., 2017). It mainly comprised the Spatial Lag Model (SLM) and Spatial Error Model (SEM) (Anselin, 1988) to further demonstrate the spatial correlations of industrial wastewater discharge nationwide and select the most optimum spatial model.

Variable selection. Industrial wastewater pollution is a product of human activity. As such, the driving factors are multi-faceted. Previous studies have analyzed the driving factors of industrial pollution from the perspectives of industrial structures, economic conditions, technological standards, and the degree of opening-up (Jin et al., 2019; Xu, 2010; Zhao et al., 2017). Based on previous studies, this paper carried out an analysis of the driving factors of industrial wastewater pollution in terms of six aspects based on the principles of abiding by scientific, complete, and accessible data (Table 1).

Table 1. Evaluation index system.

Target	Criterion layer	Index layer	Description
Dependent variable	Y	industrial wastewater discharge	Discharge quantity of industrial wastewater (10^4 t)
Independent variable	X_1	Population size	The total population in the region (10^4 people)
	X_2	Urbanization level	Urban population/ total population (%)
	X_3	industrial structure	Regional industrial output/ Local GDP (%)
	X_4	Industrial welfare level	Industrial output per capita in the region/ Industrial output per capita in China (%)
	X_5	The nationalization level of industry	Total assets of state-owned industry / Total assets of non-state-owned industrial industry (%)
	X_6	Environmental protection measures	Industrial pollution control completed investment /GDP (%)

Spatial Lag Model (SLM). Drawing reference from Anselin (1996)'s guidelines on selecting spatial models, we determined the existence or non-existence of spatial dependence based on the OLS model, and then selected the appropriate spatial econometric model according to the findings. The SLM model was mainly used to explore whether geometrically proximate areas had a diffusion effect on the research areas (spillover effect) with the following formula (Zhao et al., 2017):

$$\mathrm{y} = \rho W_y + X\beta + \varepsilon \tag{3}$$

In the formula, y is the dependent variable; ρ is the regression coefficient of the y spatial lag value, reflecting the spatial dependence of the data; W is the spatial weight matrix (This paper chooses the commonly used binary adjacency matrix. Based on the rook standard, which is 1 when the space units are adjacent and 0 is not adjacent.); X is the measurement matrix of the independent variable; β is the correlated parameter vector of independent variable X; and ε is the random error.

Spatial Error Model (SEM). The SEM model is mainly used to analyze the spatial dependence among possibly neglected factors. The spatial correlation functions in the interference errors are used to measure the impact of dependent variable errors of geometrically proximate areas on the observed value of local areas. The formula used is shown below (Zhao et al., 2017; Hu et al., 2016):

$$y = X\beta + \varepsilon \text{, whereby } \varepsilon = \lambda W\varepsilon + \mu \tag{4}$$

In the formula, ε is the random error, λ is the spatial error parameter, and μ is the random error vector of normal distribution. The other values are the same as that of Formula (2).

This paper used the spatial discrimination guidelines by Anselin and Floraz (1995), such as the Lagrange multiplier (LM)-LAG model and the LM-error (LM-ERR) model, which both produced insignificant diagnostic results, showing that the estimated results of the OLS model better demonstrated the spatial correlation of the industrial wastewater discharge among provinces. If one of the two demonstrated obvious significance, this would imply an existence of bias in the OLS estimation results, and the appropriate spatial econometric models would be selected for analysis (Zhu et al., 2017; Lin et al., 2014). The basic principles applied were: LM-LAG is statistically more significant than LM-ERR, and when Robust LM-LAG is significant and Robust LM-ERR is insignificant, the Spatial Lag Model should be used. Otherwise, the Spatial Error Model should be applied (Griffith, 1988; Li et al., 2014).

2.3. Geographically Weighted Regression (GWR) Model

The classical OLS estimation model is spatial, neglecting the spatial non-stationary characteristics of the underlying processes (Gao, 2016). According to Tobler's first law of geography, the condition that spatial units are independent of each other and homogeneous is virtually non-existent. As such, the findings of classical estimation models are bound to have certain degrees of bias (Tobler, 1970; Cheng et al., 2013). In contrast, the Geographically Weighted Regression (GWR) model is an expansion of the classical regression framework that effectively addressing issues of spatial heterogeneity by enabling the variable coefficients to change with the spatial locations (Fotheringham et al., 1998; Sun et al., 2016). To examine and eliminate the multiple collinearity problems among variables, this paper first performed the OLS model estimation on the variables and eliminated variables with significance levels above 5%. After, GWR modeling was performed on the adjusted variables using the GWR tool of the ArcGIS10.2 software.

Ordinary Least Squares (OLS). OLS linear regression was performed beforehand for variable selection purpose. Factors influencing wastewater discharge were filtered through gradual regression using the following formula (Dempster et al., 1977; Gong et al., 2016):

$$y = \beta_0 + \sum_{k=1}^{p} \beta_k \alpha_k + \varepsilon \tag{5}$$

In the formula, y is the dependent variable, β_0 is the intercept constant, p is the total number of independent variables, k is the numerical order of the independent variable, β_k is the regression coefficient, α_k is the k-th independent variable, and ε is the error term.

GWR Model. Because the filter the results of the OLS model could neglect spatial heterogeneity among factors, the GWR model, which was expanded from the OLS model, was employed. The geographical locations of sample data were used to further reflect the spatially non-stationary characteristics among factors (Lin et al., 2014). After doing so, the goodness of fit of the two findings was compared. The formula below was used (Brunsdon et al., 1998):

$$y_i = \beta_0 (u_i, v_i) + \sum_k \beta_k (u_i, v_i) x_{ik} + \varepsilon_i \tag{6}$$

In the formula, i represents the ith province, y_i is the fitting value, (u_i,v_i) are the coordinates of the geographical center of the ith province, β_0 (u_i,v_i) is a constant term, k is the numerical order of the independent variable, β_k (u_i,v_i) is the regression coefficient of the kth variable of the ith province, x_{ik} is the value of the kth independent variable in the ith province, and ε_i is the error term.

In order to avoid the estimation error caused by the less spatial unit data, the weight is determined by the Gaussian function in the calculation, which is calculated as follows (Xu, 2017):

$$W_{\mathrm{ij}} = \begin{cases} \exp^{-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2} \\ 0 \end{cases} \tag{7}$$

In the formula, d_{ij} represents the distance between points i and j; b represents the bandwidth. When $d_{ij}<b$ is the above formula, when $d_{ij}> b$ is the bottom formula.

Model evaluation. For the comparison of the OLS model and GWR model, where the adjusted fitted results of R^2 and Moran's I were used as a basis for evaluation, the corrected Akaike information criterion (AIC) was used as an evaluation index to strengthen the accuracy of the fitted results. Generally, the smaller the AIC_c value, the better the model fitting degree (Akaike, 1981; Akaike, 1998). The formula used to calculate AIC_c is listed below:

$$AIC_c = 2n\ln(\sigma) + n\ln(2\pi) + n\left(\frac{n+tr(S)}{n-2-tr(S)}\right) \tag{8}$$

In the formula, n is the observed index number, σ is the error estimation/ standard deviation, and $tr(S)$ is the trace of the S Matrix of the GWR model, which represents the bandwidth function.

2.4. Data resources

This paper studied 31 provincial-level administrative regions in China from 2004 to 2015. The data on industrial wastewater discharge and economic and social development were collected from the *China Statistical Yearbook* (2005-2016)(National bureau of statistics of the people's republic of China, 2006-2017), the *China Statistical Yearbook on the Environment* (2005-2016) (Ministry of environmental protection of the people's republic of China, 2016), the *China Statistical Yearbook for Regional Economy* (National bureau of statistics of the people's republic of China, 2005-2016), the 2005-2016 statistical yearbooks of relevant provinces (autonomous regions and municipalities), and the annual statistics from the National Bureau of Statistics of China. In consideration of the accessibility of the data, the study did not cover regions such as Hong Kong, Macau and Taiwan.

3. Results

3.1. Spatiotemporal distribution of national industrial wastewater discharge

The discharge quantity reflects changes in the national industrial wastewater discharge quantity to a certain degree, and it directly demonstrates the actual changes in quantity. Meanwhile, industrial production, which is one of the key pillars 支柱 of China's economy, is also a key contributor to pollution, with 47% of pollutants being emitted from the industrial sector (Zhang et al., 2010). As such, discharge intensity was selected to reflect the impact of industrialization on wastewater pollution, which is the wastewater discharge quantity per unit industrial output value.

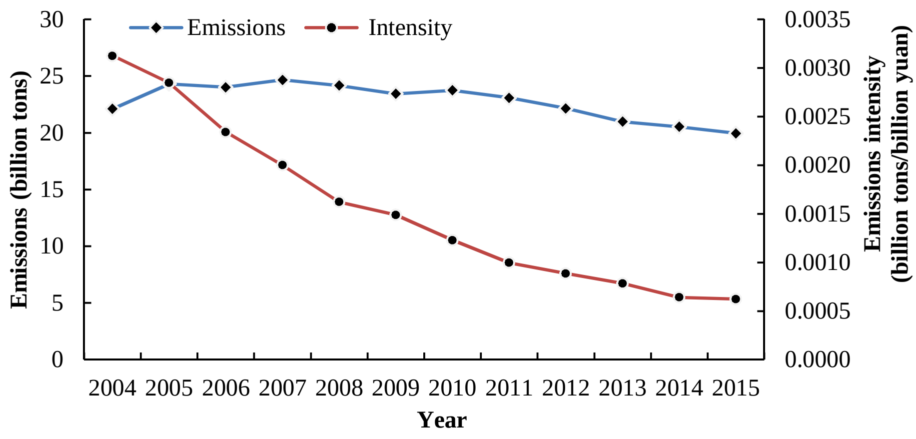

Fig. 1 The change trends of the industrial wastewater discharge quantity and discharge intensity in China from 2004 to 2015.

Fig.1 shows that between 2004 and 2015, the industrial wastewater discharge quantity decreased after an initial increase, increasing from 22.1 billion tons in 2004 to 24.7 billion tons and falling gradually to 19.9 billion tons in 2015. From 2004-2005 (during the Tenth Five-Year Plan), the discharge quantity rose by a growth rate of 12%, before dropping by 20% from 2006-2015 due to the "energy conservation and discharge reduction" policy. During this period, there was a slight increase in 2009-2010 due to the industrial output growth, which was then followed by a decreasing trend. Compared with the discharge quantity, there was a rather huge change in the discharge intensity with a persistent declining trend (up to 417% decrement).

The above analysis only revealed the temporal trends in industrial wastewater discharge quantity and intensity in China from 2004 to 2015. It did not uncover the spatial evolution patterns of the industrial wastewater discharge for the stated duration. To directly demonstrate the spatial variation trends of industrial wastewater discharge quantity and intensity, discharges of the year 2004 and 2015 were selected for comparison in Fig. 2.

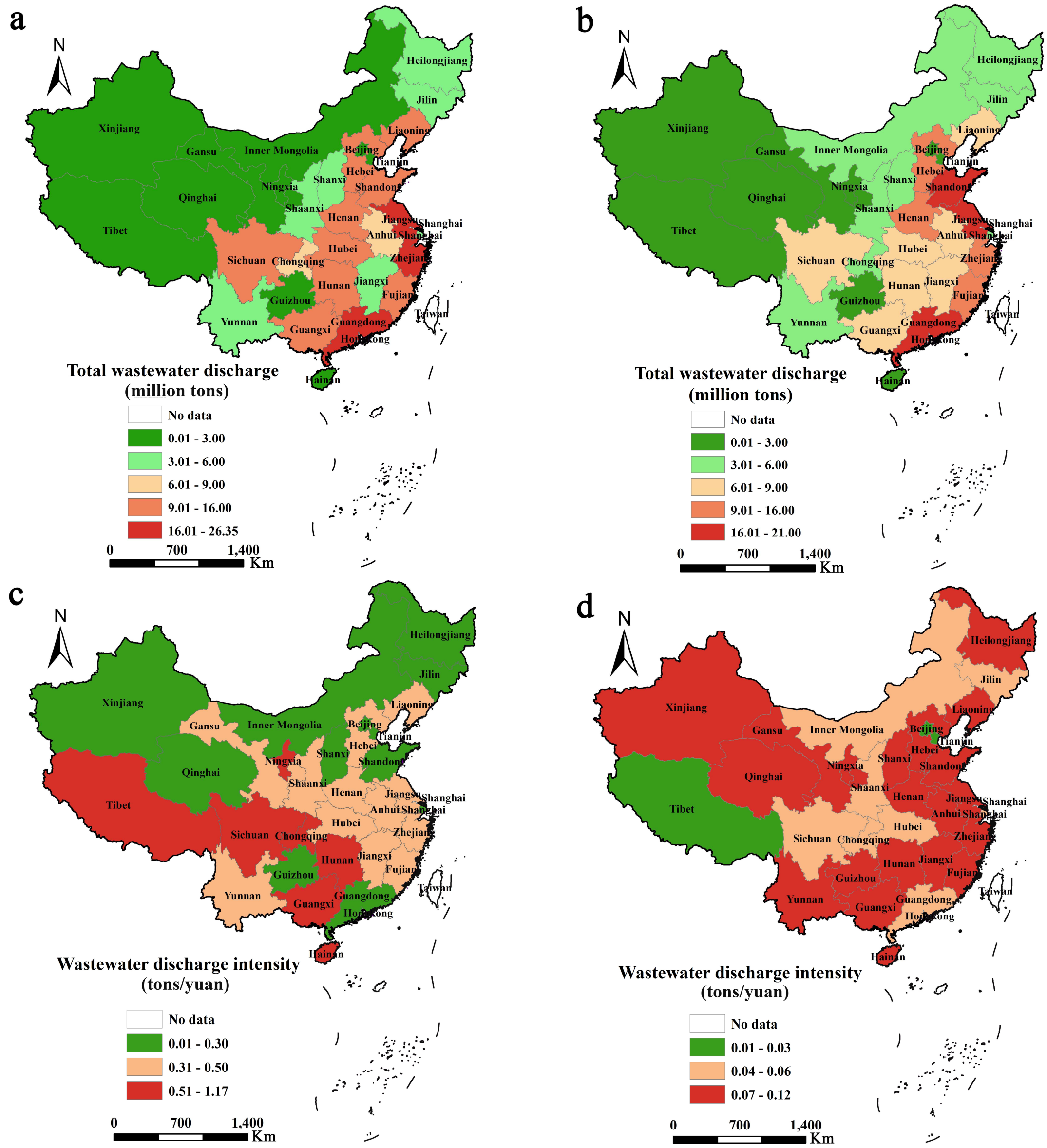

Fig. 2 The spatial variation patterns of industrial wastewater discharge quantity and the discharge intensity in 2004, 2015. (a. industrial wastewater discharge in 2004, b. industrial wastewater discharge in 2015, c. the discharge intensity in 2004, d. the discharge intensity in 2015)

From 2004 to 2015, there was a rather huge difference in the industrial wastewater discharge quantity in China: In 2004, the industrial wastewater discharge quantity in Jiangsu, Zhejiang and Guangdong each exceeded 1.5 billion tons (Fig. 2a), with Jiangsu's industrial wastewater discharge being the highest, at 2.635 billion tons. In 2015, the wastewater discharge in Zhejiang dropped to 1.474 billion tons, whereas that of Shandong rose to 1.864 tons. Jiangsu's industrial wastewater discharge, which was the highest at 2.064 tons, decreased by 27.67% from 2004 (Fig. 2b). The number of cities with industrial wastewater discharge quantities amounting to 1-1.5 billion tons reduced from 7 cities in 2004 to 2 cities in 2015. The number of cities with industrial wastewater discharge quantities amounting to 500 million-1 billion tons rose from 6 cities in 2004 to 9 cities in 2015. The number of cities with industrial wastewater discharge quantities amounting to 100 million to 500 million tons increased slightly. These changes demonstrate two characteristics: Firstly, the industrial wastewater discharge quantities in most provinces generally dropped within the 12-year period. Secondly, cities with rather high industrial wastewater quantities were mostly concentrated geographically in the eastern coastal region.

Likewise, there was also a very large difference in the industrial wastewater discharge intensity among provinces. The discharge intensity showed different spatial patterns from that of discharge quantity. Due to the overly rapid growth of the industrial output value, the overall wastewater discharge intensity in China from 2004 to 2015 fell around ten-fold. As such, the classification principles of the categories in Fig. 2c and 2d are different. Furthermore, due to the index units, the discharge intensity values obtained were rather low. To highlight the regional characteristics (under the condition that it does not impact the outcome), all the values were doubled over the original values. In terms of the discharge intensity in 2004 (Fig. 2c), the industrial wastewater intensity of the central-western regions (such as Guangxi, Chongqing and Hunan) was significantly higher than that of the eastern coastal regions. Although certain provinces in the eastern regions were high-value areas, the overall values in the eastern regions were significantly low. The discharge intensity in 2015 was significantly higher than that of 2004 (Fig. 2d), with the high-value areas mainly distributed across the railway routes (the Beijing-Guangzhou Line and Longhai Line). Among these findings, the key reason for the rather huge discharge intensity changes in Tibet was due to the rather minimal changes in the local industrial output value.

3.2. Spatial correlation analysis of national industrial wastewater emissions

To further demonstrate the spatial correlations and agglomeration of industrial wastewater at the provincial level, a spatial autocorrelation model that embedded in ArcGIS10.2 and GeoDa software was used.

3.2.1. Global spatial correlation analysis for industrial wastewater discharge quantities

The Global Moran's I index of industrial wastewater discharge quantity was derived based on Formula (1) (Refer to Table 2). The Moran's I of the industrial wastewater discharge quantity was positive. Meanwhile, after 2010, there was a gradual increase in the significance level of spatial agglomeration of industrial wastewater discharge. Due to the contribution of the energy conservation and discharge reduction policy proposed in 2006 (Li et al., 2009), the Z-score values were all higher than 2.58 and all exceeded 1% in the significance level test except for those since 2005. The findings show that there were significant positive spatial autocorrelations (high-high agglomeration or low-low agglomeration) the industrial wastewater discharge of various provinces in China.

In the above-mentioned spatiotemporal evolution trends of industrial wastewater discharge (Fig. 1), there was a fluctuating increasing trend in the discharge quantity levels from 2004-2010 and a uniform declining trend after 2010. Meanwhile, the spatial correlation test (Table 2) indicated that after 2010, there was an increase in the significance of spatial agglomeration of the industrial wastewater discharge quantity. As such, this paper identified 2010 as the turning point and selected 2010 as the first year and the last year of the research period to conduct spatial statistical analysis and driving factor analysis.

Table 2. Spatial correlation index of industrial wastewater discharge in various provinces of China in 2004-2015.

Year	Moran's I	E(I)	Variance	Z-score	P-value
2004	0.266	-0.033	0.013	2.622	0.009
2005	0.246	-0.033	0.013	2.456	0.014
2006	0.267	-0.033	0.013	2.634	0.008
2007	0.302	-0.033	0.013	2.900	0.004
2008	0.291	-0.033	0.014	2.780	0.005
2009	0.331	-0.033	0.014	3.130	0.002
2010	0.324	-0.033	0.013	3.083	0.002
2011	0.377	-0.033	0.014	3.529	0.000
2012	0.349	-0.033	0.013	3.300	0.001
2013	0.380	-0.033	0.013	3.580	0.000
2014	0.366	-0.033	0.013	3.450	0.000
2015	0.392	-0.033	0.013	3.696	0.000

3.2.2. Local spatial correlation analysis for industrial wastewater discharge quantities

Moran's I is an overall statistical index that reflects only the average degree of spatial differences of industrial wastewater discharge and does not evaluate the area structure of spatial autocorrelation, neglecting the local spatial characteristics (Chen, et al., 2008). As such, to further ascertain the key control area, the spatiotemporal evolutions were analyzed through a scatter diagram of industrial wastewater discharge of various provinces nationwide produced by the GeoDa software (Refer to Fig. 3).

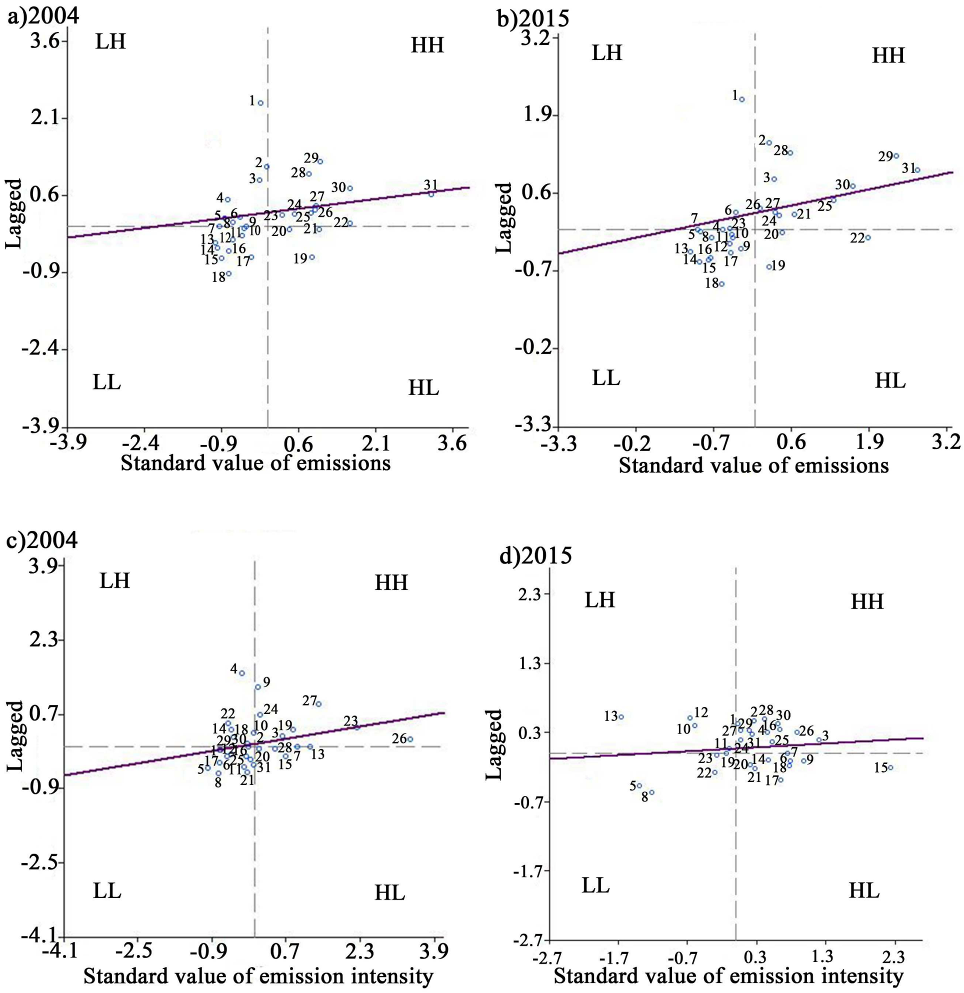

Fig.3 Scatter diagram of the industrial wastewater discharge quantity (a, b) and discharge intensity (c, d) of various provinces in 2004, 2015.

Annotation: 1,Shanghai; 2,Anhui; 3,Jiangxi; 4,Guizhou; 5,Beijing; 6,Shanxi; 7,Hainan; 8,Tianjin; 9,Yunnan; 10,Shaanxi; 11,Jilin; 12,Inner Mongolia; 13,Tibet; 14,Qinghai; 15,Ningxia; 16,Gansu; 17,Heilongjiang; 18,Xinjiang; 19,Sichuan; 20,Liaoning; 21,Hebei; 22,Guangdong; 23,Chongqing; 24,Hubei; 25,Henan; 26,Guangxi; 27,Hunan; 28,Fujian; 29,Shandong; 30,Zhejiang; 31,Jiangsu.

The distribution of the industrial wastewater discharge intensity in the east and west regions was the inversion of that of the discharge quantity (Fig. 3); that is, the spatial pattern of the industrial wastewater discharge intensity is different from that of the discharge quantity. This result was consistent with the conclusion drawn from Fig. 2. From the distributed numbers of regions in the four quadrants in the scatter diagram, the HH zone and LL zone had absolute dominance and were a significant agglomeration characteristic. In terms of changes in the number of regions, the number of regions increased from 10 in 2004 to 11 in 2015 in the HH zone of discharge quantity and from 9 in 2004 to 12 in 2015 in the LL zone of discharge quantity; the number of regions increased from 7 in 2004 to 13 in 2015 in the HH zone of discharge intensity and dropped from 13 in 2004 to 5 in 2015 in the LL zone of discharge intensity. The results show that the different patterns of industrial wastewater discharge in China, the trend of slowdown in the high discharge area, and the measures of energy saving and emission reduction have achieved good results. On the spatial distribution of discharge quantity (Fig. 3a, 3b), the central and eastern regions were the hot spots of high value and sub-high value concentration areas, such as Shandong, Jiangsu, Zhejiang, Fujian, etc. Moreover, the western regions were the low-value concentration areas, mainly including Inner Mongolia, Tibet, Xinjiang, Qinghai, Ningxia, etc. From the perspective of discharge intensity (Fig. 3c, 3d), contrary to the distribution of discharge quantity, the high-value areas were concentrated in central-western China, and the low-value areas were concentrated in central-eastern China and certain eastern coastal regions. On the time scale, there is a certain spatial spillover effect in both discharge quantity and discharge intensity. The discharge quantity areas showed a gradual spreading trend towards the west, and the discharge intensity showed a transferring trend from low-value areas to high-value areas.

3.3. Spatial statistical test

The above-mentioned global and local spatial autocorrelation analysis shows that there was a significant spatial clustering phenomenon in the industrial wastewater discharge among various provinces. As there is a need to further analyze the driving factors that generated the said phenomenon to provide a targeted basis for effectively alleviating wastewater pollution, this paper used a spatial econometric model.

3.3.1. The factors influencing the industrial wastewater discharge variations

As shown in Table 3, LM-ERR was more significant than LM-LAG for the industrial wastewater discharge of 2004 and 2010, implying that the Spatial Error Model is more appropriate for analyzing the industrial wastewater discharge quantities of 2004 and 2010. Meanwhile, the LM-LAG and LM-ERR for the industrial wastewater discharge quantity of 2015 were both insignificant, implying that the spatial effects for that year had a rather minimal impact on the discharge quantity. The OLS model could explain the correlations between dependent variables and independent variables. The estimation results show that X_1, X_2, X_3, X_5 and X_6 all passed the 1% significance test, and X_4 passed the 5% significance test. X_1, X_2 and X_3 had a promotive effect on industrial wastewater discharge quantity, whereas X_4, X_5 and X_6 had an inhibitory effect on the said discharge. The estimation results above are in line with the actual situation, suggesting that the model is overall effective.

Table 3. OLS estimations for the industrial wastewater discharge in 2004, 2010 and 2015.

Variable	2004	2010	2015
CONSTANT	-0.003	0.013	-0.010
$\ln X_1$	1.058***	0.871***	0.977***
$\ln X_2$	0.683**	1.366***	1.391***
$\ln X_3$	0.640	1.817***	1.138***
$\ln X_4$	-0.121	-0.636**	-0.397**
$\ln X_5$	-0.642**	-0.935***	-0.629***
$\ln X_6$	0.034	0.118*	0.355***
R^2	0.989	0.990	0.996

LM-LAG	0.076	0.670	0.619
Robust LM-LAG	0.201	1.077	0.709
LM-ERR	2.948*	5.049**	0.767
Robust LM-ERR	3.074*	5.455**	0.858
LM-SARMA	3.149	6.126**	1.477

Note: "***", "**" and "*" in the table represent values that have passed the 1%, 5% and 10% significance tests, respectively. To facilitate the analysis, the logarithm operation has been performed on the data for each index.

3.3.2. Spatial econometric model test

Table 4 shows the Spatial Error Model results for the quantity of industrial wastewater discharge in 2004 and 2010. The R^2 values of the Spatial Error Model (0.991 and 0.993, respectively) were both higher than those of the OLS model (0.989 and 0.990, respectively), further proving that the Spatial Error Model is superior to the OLS model estimations. According to the results, there was a significant spillover effect for the spatial errors of industrial wastewater discharge, and the most significant driving factors for industrial wastewater discharge in 2004 were population size (promotive effect), urbanization level (promotive effect), the nationalization level of industry (inhibitory effect) and the industrial structure (promotive effect). On another note, the influences of economic development, industrial welfare standards and environmental protection measures were negligible. Meanwhile, the industrial structure was added to the list of the most significant driving factors in 2010 compared with 2004, with other driving factors all passing the 1% significance test. Industrial welfare levels and nationalization levels of industry both had a controlling effect on the increase in industrial wastewater discharge, whereas the strength of environmental protection measures had a facilitating effect on wastewater discharge. Thus, the governance of industrial pollution in 2010 was not able to fulfill the requirements of the rapid growth in industrial output value.

Table 4. Spatial regression results of industrial wastewater discharge quantity.

Variable	SEM-2004		SEM-2010		OLS-2015	
	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error
Independent variable	-0.071	0.076	-0.076	0.065	-0.010	0.058
X_1	1.073***	0.074	0.915***	0.065	0.977***	0.066
X_2	0.620***	0.225	1.458***	0.194	1.391***	0.179
X_3	0.639*	0.359	1.898***	0.276	1.138***	0.287
X_4	-0.173	0.206	-0.652***	0.155	-0.397**	0.162
X_5	-0.753***	0.164	-0.887***	0.105	-0.629***	0.141
X_6	-0.036	0.074	0.177***	0.050	0.355***	0.069
λ	-0.694***	0.244	-0.929***	0.215	-	-
R^2	0.991		0.993		0.996	
AIC	-24.654		-33.346		-53.473	
SC	-13.970		-22.661		-42.788	

Note: The "***", "**", "*" in the table represent values that have passed the 1%, 5% and 10% significance tests, respectively; "-" means that no items are involved.

3.4. The driving factors of national industrial wastewater discharge

3.4.1. OLS model results

For 2004, 2010 and 2015, Y was used as the dependent variable for national provinces, and X_1, X_2, X_3, X_4, X_5 and X_6 were used as the independent variables (Please refer to the definitions in Table 1) in the construction of the OLS model. In order to eliminate the dimensional difference between the indicators and avoid the distribution of independent variables affecting the accuracy of the regression model, the log-processed data of each indicator is used for analysis (Table 5).

Table 5. Parameter estimation and test results of the OLS model.

Variables	2004	2010	2015
X_1	1.087***	-	-
X_2	0.550***	-	-
X_3	0.440**	-4.969	-4.983***
X_4	-	-0.503	-0.012
X_5	-0.591***	-1.825**	-4.075***
X_6	-	-1.021***	-

Note: “***”, “**”, and “*” in the table represent values that have passed the 1%, 5% and 10% significance tests, respectively; “-” represents the variables eliminated by the model due to the probability (p) and VIF (variance inflation factor) of its parameter estimation value exceeding the preset level.

In order to test whether the residuals of the model conform to the normal distribution, the P-value of the Jarque-Bera statistic series calculated by ArcGIS 10.2 was selected to test the OLS analysis. The results showed that the P values in 2004, 2010 and 2015 were 0.581, 0.367 and 0.148, both confirmed that the residuals conform to the normal distribution. Therefore, the OLS model is selected with credibility. Through the data exploration and analysis, we found that there were multiple collinearities for different years, and there were influences from multiple factors such as industrial development levels, relevant national policies and location-based factors. The finalized variables among the three years were substantially different. As such, based on separately conducted analyses, the similarities and differences in various years were compared to provide a targeted solution for alleviating wastewater pollution.

As shown by the OLS estimation results in Table 5, except for X_4 and X_6 in 2004, the variables all passed the significance level test. The intensity of the influence of the various variables on dependent variables was as follows: $X_1>X_2>X_3>X_5$ in descending order. Except for X_5, the variables had a promotive effect. In 2010, the model exhibited overall significance (with R^2 amounting to 0.787), and all the independent variables had an inhibitory effect on the dependent variables. The findings were in line with the theoretical expectations. The degree of influence on inhibiting wastewater pollution could be presented as such (in descending order): Industrial structure> Nationalization level of industry> Environmental protection measures> Industrial welfare standards. In 2015, variables X_1, X_2 and X_6 were eliminated because of their high VIF values. The other variables were consistent with the effects of the 2010 estimation results. Overall, the OLS model shows that the increased economic scale did result in increased wastewater discharge to a certain degree. In contrast, adjusting the industrial structure could effectively control the state of pollution.

3.4.2. Evaluation of the OLS model and GWR model

The OLS model is a global regression model assuming that the relationships between dependent variables and independent variables are stationary among areas. This, in turn, could cause biases in the model specifications. In contrast, the GWR model is a local regression model that takes spatial characteristics into consideration. As such, to ensure the accuracy of the data analysis, the results of the OLS and GWR models were compared to determine the driving factors of wastewater pollution.

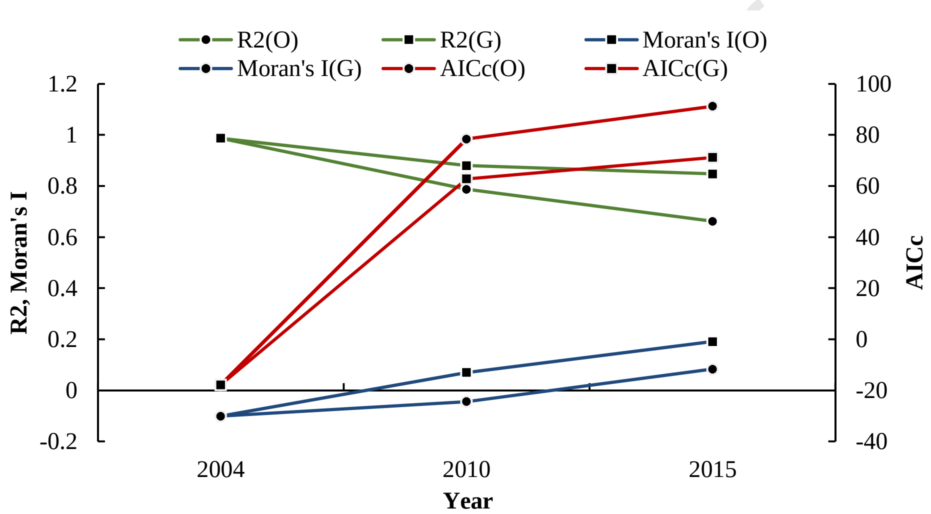

Fig. 4. Comparison of the performances of the OLS and GWR models.

A comparison of the evaluation indexes of the fitting result of the OLS and GWR models indicated that the GWR fitting results for wastewater discharge and the correlation among variables were superior to those of the OLS model (Fig. 4). The OLS model fitting degree for 2004 was largely the same as that of the GWR model, showing that both models can effectively explain the influence of various variables on dependent variables. This could be due to the limitations of the variables selected and the influence of the model error. However, in terms of the fitting degree, the GWR model's fitting degree (0.989) was higher than that of the OLS model (0.987). For the other years, the GWR's fitting degrees were all higher than those of the OLS model, with significantly lower AIC values. Furthermore, Moran's I of the OLS model regression residual ranged between 0.070-0.191, showing that the residual had significant spatial autocorrelation. In contrast, Moran's I of the GWR model regression residual ranged between -0.044-0.083, showing that its residual had a higher possibility of following an independent random spatial distribution and further proving the feasibility of the GWR model's fitting results.

3.4.3. Analysis of the GWR Model Results

Before running the GWR model, the sample was tested for multiple collinearity and significance according to the availability principle of the sample data. The results showed that the maximum correction R^2 of the resulting conclusion was higher than 0.8, there was no multiple collinearity problem and the model fit is more than 80%.

In the GWR model, as various spatial units had specific coefficients, the estimated parameters differed with the different focuses of the independent variables. As such, the paper further explored the spatial variation characteristics of various factors on wastewater discharge based on the statistical analysis of the various coefficient values, with the estimated values of each unit coefficient being spatially expressed using ArcGIS10.2 to determine the degrees of influence that different variables had on wastewater pollution. In summary, from 2004 to 2015, the inter-regional effects of variables on wastewater discharge were not changed, but there were significant changes in the inter-annual effects, that is, in different years, there was a significant change in the extent and spatial distribution of the indicators on wastewater discharges in different provinces.

Table 6. Descriptive statistic of the regression coefficients in the GWR model, 2004.

Variable	Average	Maximum	Minimum	Upper quartile	Median	Lower quartile
X_1	1.08857	1.08861	1.08856	1.08858	1.08857	1.08857
X_2	0.54999	0.55011	0.54985	0.55004	0.55000	0.54994
X_3	0.44003	0.44012	0.43992	0.44006	0.44003	0.44000
X_5	-0.59105	-0.59074	-0.59146	-0.59091	-0.59103	-0.59119

Note: As the statistical changes upon statistical counting for the variable coefficient values were small in that year, to demonstrate the partial differences, five decimal places were retained. The range of the model's local regression standard residual values was [-2.163, 2.332], with 100% of the residual values falling within the range of [-2.58, 2.58].

Table 7. Descriptive statistic of the regression coefficients in the GWR model, 2010 and 2015.

Index	2010		2015	
	X_5	X_6	X_3	X_5
Average	-1.402	-0.917	-3.408	-3.513
Maximum	-0.624	0.060	4.444	-1.784
Minimum	-2.898	-1.404	-6.794	-7.070
Upper quartile	-0.878	-0.482	-0.968	-2.636
Median	-1.228	-1.093	-4.581	-3.492
Lower quartile	-1.931	-1.346	-5.819	-3.884

Note: In 2010, the range of the model's local regression standard residual values was [-4.054, 1.476], with 94.12% of the residual values falling within the range of [-2.58, 2.58].

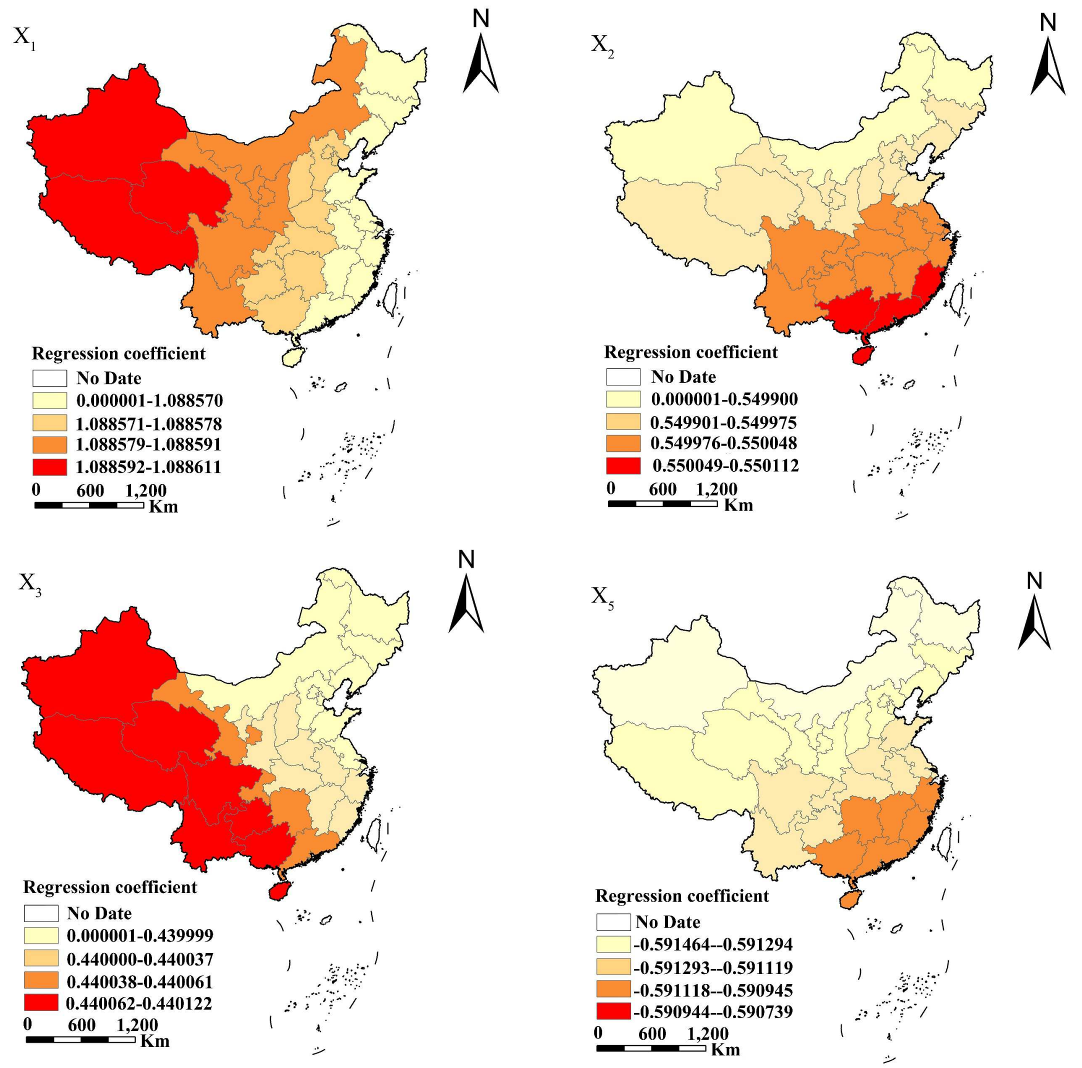

Fig. 5. Spatial distribution of regression coefficients of the GWR model, 2004.

(X_1: Population size, X_2: urbanization level, X_3: industrial structure, X_5: the nationalization level of industry)

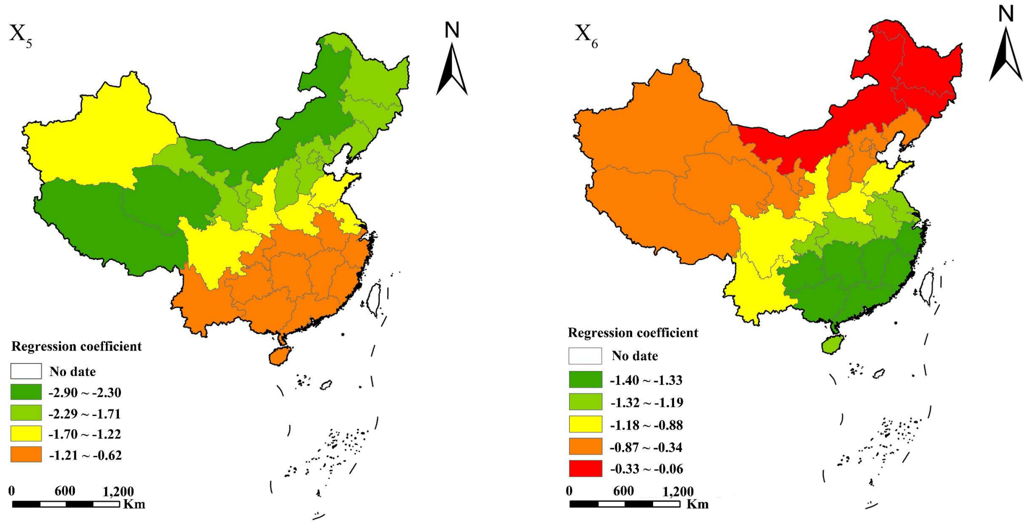

Fig.6. Spatial distribution of regression coefficients of the GWR model, 2010.

(X_5: the nationalization level of industry, X_6: environmental protection measures)

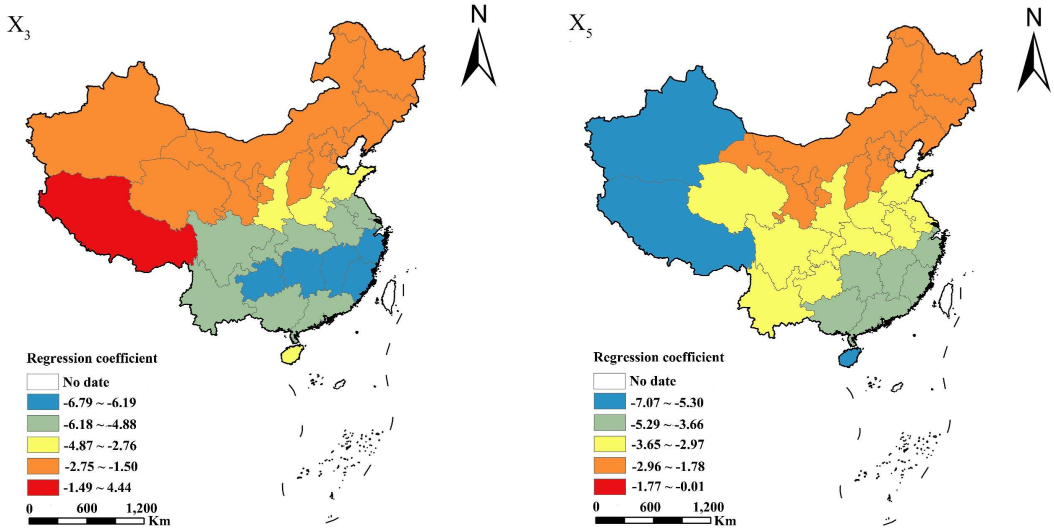

Fig.7. Spatial distribution of regression coefficients of the GWR model, 2015.

(X_3: industrial structure, X_5: the nationalization level of industry)

In 2004, there were spatial differences in the four attribute variables on wastewater discharge (Table 6). Except for X_5, the regression coefficients of the independent variables were rather stable, with a "promotive" effect, demonstrating the influence of the economic improvement and industrial developmental limitations during that period. The population size, urbanization level and industrialization structure were all factors that caused an increase in wastewater discharge, and relying solely on a relatively low nationalization level of the industry could not limit the state of pollution. In the regression coefficient distribution diagram (Refer to Fig. 5), the gradual increase of X_1 and X_3 from eastern regions to western regions shows that the stress of China's population on wastewater discharge had gradually increased from the east to the west. Shanghai had the lowest value and Xinjiang had the highest value for X_1, whereas Heilongjiang had the lowest value and Tibet had the highest value for X_3. In X_2 and X_5, the gradual increase from the northern regions to the southern regions shows that areas with higher urbanization and nationalization levels of industry faced higher wastewater pollution stress. In both 2010 and 2015, there was spatial variability in two variables on wastewater discharge, and except for the rather huge spatial fluctuations in the regression coefficients of X_6 and X_3 in individual areas, the spatial variation patterns of X_6 and X_3 were all relatively significant (Refer to Table 7, Fig. 6). The negative correlations of the nationalization level of the industry, the strength of environmental protection measures and industrial structure on wastewater discharge reflect the effectiveness of energy conservation and discharge reduction and the accelerated industrial structure optimization and improvement in alleviating wastewater pollution. In contrast to the overall changes and variations of X_5 being relatively small for 2010, with a trend of high levels in the south and low levels in the north, the X_6 of 2010 and X_3 and X_5 of 2015 showed a trend of high levels in the north and low levels in the south (Fig. 7).

In summary, from 2004 to 2015, the spatial variation trends of the regression coefficient of the two relatively significant factors on wastewater discharge in the GWR model estimation were as follows: High levels in the south and low levels in the north for the nationalization level of industry and a gradual developmental trend of high levels towards the northwest and low levels towards the southeast for the industrial structure.

4. Discussion

Using exploratory methods, this paper analyzed the spatial spillover effects of inter-provincial wastewater discharge and the differences in driving factors of wastewater discharge, which can effectively conserve resources and improve the environmental quality (Zhang et al., 2015).

Trend change analysis shows that there exists a rather large difference between discharge quantity and discharge intensity trends, which might be because industrial wastewater discharge remained in a state of natural discharge during the rapid economic growth of industrialization in China. For the distribution of the industrial wastewater discharge quantity and intensity, the result shows that in terms of the different patterns of China's industrial wastewater discharge, the increase of the number of regions in the high discharge zone is becoming insignificant, suggesting that energy conservation and discharge reduction measures have produced good results. As for spatial scale, eastern-central China was a hotspot area, with the agglomeration of high-discharge-quantity and second-high-discharge-quantity regions, such as Shandong, Jiangsu, Zhejiang and Fujian (Fig. 3a, 3b). Meanwhile, the industrial structure of the western regions and Inner Mongolia were mainly made up of light industrial zones, and these regions had the agglomeration of low- discharge-quantity regions, such as Tibet, Xinjiang, Qinghai and Ningxia. At the same time, the discharge intensity distribution is exactly the opposite, which also can be attributed to the difference between industrial structure and industrial output value. This result is consistent with the study with the research of Geng et al. (2014).

For the spatial statistical analysis, according to the results of LM-ERR and LM-LAG, the Spatial Error Model is more appropriate for analyzing the industrial wastewater discharge quantities of 2004 and 2010. This shows that the spatial functions of the industrial wastewater discharge among provinces in China were determined more so by the impact of the industrial wastewater discharge of geometrically proximate provinces. As such, the governance of the industrial wastewater discharge of different areas should not be guided just by local policies; there also should be cooperative efforts taken in partnerships with geometrically proximate areas. And the OLS test further indicates that population growth, improved urbanization level and increased industrial proportion exacerbated the industrial wastewater pollution to a certain degree, which also can be found in the previous studies (Yang et al., 2016). The Spatial Error Model results for the quantity of industrial wastewater discharge indicates that the industrial pollution control in

2010 could not meet the requirements of rapid industrial output growth. As such, based on the actual situations of the various provinces, there should be appropriate control of population size (Ma et al., 2020), optimization of the industrial structure (Wu and Zeng, 2013), improvement of the ratio of state-owned industrial assets to non-state-owned industrial assets, and intensification of industrial pollution governance measures while focusing on the interaction of industrial wastewater discharge among the various provinces.

For the driving factors of national industrial wastewater discharge, population size, urbanization level, and industrial structure are all factors that cause increased wastewater discharge. The relatively low level of industrialized state cannot limit pollution. Thus, industrial adjustment is beneficial for wastewater reduction (Wu and Zeng, 2013). The stress of China’s population on wastewater discharge had gradually increased from the east to the west. This phenomenon might be due to the following: Firstly, the population in the western region was smaller, the per capita wastewater discharge of the western region was far higher than that of the eastern region, resulting in a rather high regression coefficient on an objective level (Yang et al., 2016; Zhang et al., 2019). Secondly, due to the influence of the Western Development Strategy, the industrial sector gradually developed. However, due to the decontamination standards, which were far lower than those of the central and eastern regions, there was increased wastewater discharge. In fact, as a relatively underdeveloped area in Western China, it has a better environment and a higher ecological function. The developing industry is not the only option for these cities. Many places are protected areas for important ecological services, such as biodiversity and water conservation (Zhang et al. 2015; Luo et al. 2018). The wastewater released into the environment produced by the industry can severely damage the environment. Therefore, these areas should actively respond to the policy of establishing national parks and optimizing the reserve system (He et al. 2018) according to the development of local conditions, so as to avoid the blind development of the industry.

5. Conclusion and policy implication

5.1 Conclusion

China has experienced excellent industrialization and urbanization over the past several years. Due to China's complex national conditions and unbalanced development, significant differences exist in industrial wastewater discharge, discharge intensity and driving factors between provinces.

This study explored the pattern of industrial wastewater discharge, discharge intensity and driving forces between provinces, which contributed to the understanding of significant policy implications. From 2004 to 2015, there was a dramatic temporal difference between the quantity and intensity of national wastewater discharge. There were significant positive spatial correlations and spatial spillover effects among provinces, with discharge quantities gradually increasing towards the western regions and discharge intensity transferring from low-value zones towards high-value zones. From 2004 to 2010, there was a significant spatial spillover effect in the industrial wastewater quantity. Population size, urbanization level, and industrial structure had a promotive effect, whereas industrial welfare standards, nationalization level of industry and environmental protection measures had an inhibitory effect. In contrast, from 2010 to 2015, the spatial effect exhibited a low impact on discharge. Through the analysis of the driving factors, we found during the initial study period, narrowing the gap between the western and eastern regions and increasing decontamination efforts were extremely important in alleviating water pollution. However, due to the changes brought about as time went along, adjustments in the industrial structure, the strength of environmental protection measures and the nationalization level of industry gradually became the key measures governing wastewater pollution.

Environmental pollution has become a key issue affecting sustainable development. This paper focused on the spatial characteristics of wastewater discharge and driving factors. Based on this, the relevant optimization methods are derived. Limitations of this study include the lack of consideration of the self-purification capacity of water systems and agricultural/household wastewater discharge. As such, subsequent investigations need to be more in-depth in this respect.

5.2 Policy implication

The prevention and control of industrial wastewater pollution in China should focus on improving the level of diversification of industries, strengthening the links between provinces and regions, and formulating measures to reduce emissions by concentrated wastewater. Through the analysis of the characteristics of the spatial and temporal distribution of industrial wastewater discharge and emission intensity in 31 provinces in China, it is found that there is a significant spatial correlation and spillover effect between the provinces. Therefore, it is suggested that the future discharge of industrial wastewater should break regional protectionism, promote the free flow of capital, and construct a cross-regional ecological and technological compensation mechanism to promote coordinated inter-regional development. In addition, while improving the level of industrial diversification, it is also necessary to increase the degree of inter-industry linkages, promote technology exchanges and cooperation.

Strengthen environmental control and develop differentiated wastewater pollution measures based on different regions. Generally, there are obvious regional differences in the level of economic development and environmental control in the middle, east and west regions of China, which shows that there are great differences in the area and space transfer of industrial wastewater, resulting in the different pollution risks in different regions. Therefore, according to the pollution situation in different regions, the industrial transfer and pollution prevention and control measures should be formulated, according to the actual situation in different regions to carry out the differential treatment. For example, for the development of industries in the central and western regions, we should step up environmental protection efforts, clearly reward and punish measures, introduce advanced industrial technology, and for the development of saturated or oversaturated eastern regions, we should strengthen the control of the total amount of industrial wastewater discharge and raise wastewater discharge standards to achieve the goal of coordinated development.

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Highlights

- Spatial econometric (OLS) model and GWR model were employed to trace drivers of industrial wastewater discharge.
- The industrial wastewater discharge showed a downward trend in China from 2004 to 2015.
- There was a significant positive spatial autocorrelation of industrial wastewater discharge among China's provinces
- The nationalization level of industry, industrial structure and environmental protection measures were major driving forces.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: