Convergence Study of Water Pollution Emission Intensity in China: Evidence From Spatial Effects

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Convergence study of water pollution emission intensity in China: evidence from spatial effects

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Abstract

One of the challenges that China currently faces is how to reduce the emissions of the water pollution. However, the study of water pollution convergence has certain policy significance for controlling the emissions of water pollution. This article firstly uses **chemical oxygen demand** (*COD*) and **ammonia nitrogen** (*NH₃-N*) as indicators of water pollution. Due to the obvious spillover effect of water in space, this article adds spatial effect to the convergence model. Based on panel data of 30 provinces and cities from 2006 to 2017, this article uses a dynamic spatial Dubin model to analyze the convergence of water pollution emission intensity to address the endogenous problem in the model. The empirical results of this paper show that there is absolute β -convergence and conditional β -convergence in the intensity of water pollution emissions. The spatial autocorrelation test shows that there is a positive spatial autocorrelation of water pollution emissions, which means that the pollution emissions in neighboring areas will affect the emissions in the local area. The industrial structure has a certain promoting effect on the emission of water pollution, which means that adjusting the industrial structure and alleviating the structure of the secondary industry is the trend of future development. Economic growth can curb the emissions of water pollution. The influences of urbanization and foreign investment on the emissions of the two pollutants are inconsistent, and policies can be formulated according to local conditions in the future.

Key word: Water pollution; Regional convergence theory; Dynamic spatial panel model; β -convergence; Space measurement; Spatial effects

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets analysed during the current study are available in the [Statistical Yearbook Of China and China Environmental Statistical Yearbook] repository, [<http://www.stats.gov.cn>]

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Conceptualization, N.L.; methodology, N.L. and Y.H.; software, Y.H.; validation, Y.H.; formal analysis, Y.H.; data curation, Y.H.; writing—original draft preparation, Y.H.; writing—review and editing, R.G., R.Y. and Z.S.; supervision, H.M. All authors have read and agreed to the published version of the manuscript.

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Hailin Mu

1. Introduction

In recent years, China has gradually emerged as the world's second leading country in terms of GDP. However, the environmental situation is still not optimistic, especially the current situation of water pollution. At present, groundwater in China's seven major water systems, major lakes, coastal waters, and some areas have been polluted to varying degrees. The polluted rivers and lakes are as high as 82%. The main pollutants include *COD* and *NH₃-N*. Water pollution will exacerbate the shortage of water resources and have a huge impact on people's lives. With the accelerated growing economy of China, pollutant emissions are increasing day by day(Pang et al. 2021). China must not only maintain economic development, but also improve environmental quality. For this reason, China is facing enormous challenges. The 18th National Congress of the Communist Party of China clearly proposed to advocate the consciousness of "community with a shared future for mankind". In the face of the complex situation of the world economy and global issues, especially environmental issues, it is impossible for any country to stand alone. Being the world's largest developing country, China shoulders a huge responsibility for improving environmental quality.

Different scholars use different indicators to classify water pollution,(Tsuzuki 2009) defines biological oxygen demand, total phosphorus, and total nitrogen as water pollution,(Cai et al. 2020) thinks that wastewater, *NH₃-N*, and *COD* are indicators of water pollution. In China's "Eleventh Five-Year Plan", *COD* was proposed as an important pollutant for emission reduction in environmental management. In the 12th Five-Year Plan, *NH₃-N* was listed as an important emission reduction pollutant in environmental governance. Based on the main pollutant types of rivers in China, this study uses *NH₃-N* and *COD* as indicators for studying water pollution. Previous studies mostly use per capita pollutant emissions as the core variable of the study(Lee et al. 2010). This article believes that the discharge of pollutants is inseparable from the country's economy. For the purpose of capturing the dynamic relationship between the economy and pollutants, pollutant emission intensity is taken as the core variable of the paper.

How to effectively control the discharge of water pollutants is an important challenge. And one of the major economic principles that determining the reduction of water pollution is the regional convergence (Fan & Xu 2020). The theory of regional convergence can not only show the dynamic evolution of pollutants, but also provide a theoretical basis for reducing the discharge of water pollution. The different speed of convergence of water pollution intensity means that the trend of pollution discharge is different. For regions with higher initial pollutant emission levels, the faster the rate of reduction will be. In addition, the convergence of water pollution intensity can be used as a theoretical basis for a reasonable allocation of carbon intensity reduction targets. Therefore, it is important to analyze the convergence of China's provincial water pollution intensity. However, no scholar in the existing research has explored the convergence of water pollution emissions(Cai et al. 2020, Lee et al. 2010, Zhou et al. 2021). Therefore, based on existing research, this article tries to analyze the convergence of China's water pollution emission intensity. Considering the mobility of water, we add spatial effects to test its spatial dependence and make the model results more rigorous.

Based on the above background, the purpose of this paper is to explore whether there is a convergence in the discharge of water pollution in China? To this end, this research has made the following three contributions: First, this article explores the dynamic trend of China's water pollutant emissions based on the theory of regional convergence. This paper provides theoretical guidance on the direction of national water pollution management by analyzing the convergence of water pollutant discharge intensity in 31 provinces, municipalities, and autonomous regions from 2006-2016. Secondly, NH_3-N and COD are defined as the water pollution indicators in this paper, and the discharge intensity is taken as the core variable of the study. The emission intensity of water pollutants can be used as an indicator to measure the relationship between the national economy and pollution levels, which enriches the existing research system. Thirdly, the traditional convergence model cannot explain the spatial dependence of water pollution, so this article adds spatial effects to the convergence model and aims to explore the mutual influence of water pollution emissions in various regions of China.

The remaining chapters of this paper are arranged as listed below: Chapter 2 briefly describes the relevant literature on the convergence of pollutants at home and abroad. Chapter 3 introduces the theoretical methods that is used in this study and explains the variables and data used in the study. Chapter 4 gives the results of the model and analyzes the results. Chapter 5 gives the policy recommendations of this research.

2. Literature review

In recent years, water pollution has gradually become a major concern in most countries and has become such a factor that it affects social and economic development. Therefore, scholars begin to explore the factors affecting water pollution discharge and analyze the degree of influence of these factors. At first, scholars propose that there is a dynamic link between economic growth and water pollution and put forward the Environmental Kuznets curve (EKC). Researches believe that the degree of pollution will tend to increase as the economy grows. But when it has reached a definite level, the pollution level will begin to decline with economic growth. (Zhang et al. 2017a) uses two types of models to investigate the EKC curve relationship between COD and NH_3-N and economic growth. Based on the two variable coefficient panel data models, the study considers the contemporaneous correlation of wastewater, COD and NH_3-N . It better reflects the dynamic link of water pollution and economic growth (Cai et al. 2020). A quantitative response model is used to study the relationship between regional economic growth and water pollution in the Songhua River Basin (SRB)(Yu &Lu 2018). The study uses a semi-parametric panel data model to consider the limited effects of individuals and finds that COD and NH_3-N have a long-term two-way causal relationship with China's economic growth(Zhang et al. 2017b).

With the deepening of research, scholars have discovered that water pollution is affected by more than just a single factor of economic growth, it may also be affected by industrial structure and urbanization and other factors. Subsequently, a measurement model such as STIRPAT is proposed to evaluate the effect of various factors on the levels of pollution. Based on the spatial error model, the study finds that economic standards, population, agricultural

economy, and urbanization are the main factors affecting water pollution emissions in the Yangtze River Economic Zone in China (Zhou et al. 2021). The study finds that factors such as the level of economic development and technological expenditures will reduce the intensity of industrial wastewater pollution discharge(Liu et al. 2015).Based on provincial panel data in China, the study uses an extended STIRPAT model to find that population density and industrial output ratio have a positive effect on industrial wastewater and to test the EKC hypothesis. The study uses the STIRPAT model and finds that industrial wastewater in China increases with the rate of urbanization and also finds that there is an inverted U-shaped relationship between urbanization and industrial wastewater pollution, which supports the hypothesis of the EKC curve(Xu et al. 2020). The study uses the system's generalized moment (GMM) estimator and ARDL model to run the dynamic panel model, and the research demonstrates there is a positive impact of energy consumption on wastewater, while trade and urbanization have a negative impact on the environment(Li et al. 2016). This paper explores the direct and spatial spillover effects of industrialization and urbanization factors on pollutant emissions in 53 cities in the Yellow and Huaihai Sea region of China based on the SDM Model(Li et al. 2018).

The concept of convergence was first proposed in the economic field. It is thought that economically underdeveloped regions would develop faster than developed regions until the same equilibrium state is reached among the regions (Solow 1956). Now the scope of applications of convergence is becoming wider and wider, and it has been gradually involved in the energy field. Scholars often choose carbon emissions as their research object when conducting extended research on the field of convergence. The emission indicators used in different literatures are also different (Zhang &Hao 2020).For example, some documents have selected the total amount of CO₂ emissions as an indicator for the study. The heterogeneous effects of endogenous and foreign innovations on the convergence of CO₂ emissions in 30 Chinese provinces are explored(Luo et al. 2020). There are also some documents that use per capita CO₂ emissions to reveal the relationship between pollutant emissions and population. The study uses the spatial panel model to study the convergence of CO₂ per capita in urban areas (Huang &Meng 2013). The study uses a continuous dynamic distribution method to analyze the convergence of per capita CO₂ in 286 cities(Wu et al. 2016). (Awaworyi Churchill et al. 2020) uses LM and RALS-LM unit root tests to study the convergence of CO₂ per capita, and the results obtains evidence of random convergence. (Wang &Zhang 2014) analyzes the convergence of per capita CO₂ in 6 departments in 28 provinces in China and investigates the factors that affect the convergence. (Matsuki &Pan 2021) uses the ADF test to prove that the per capita CO₂ emissions of the seven developing economies in Asia are similar, and(Rios &Gianmoena 2018)etc. By studying the convergence of carbon emissions intensity, the relationship between carbon emissions and economic growth can be effectively understood, which can help to use economic factors to control CO₂ emissions(Zhang &Hao 2020). (Huang et al. 2019a) uses the dynamic spatial panel method to study the existence of China's carbon emission intensity convergence and the factors affecting the convergence. The research uses a spatial panel model to study the convergence of carbon intensity in the Yangtze River Delta cities at the prefecture level. It has evidence to conclude

that there is β -convergence and that factors such as industrial structure has an impact on the convergence of carbon intensity(Li et al. 2017). Based on provincial panel data, (Hao et al. 2015) examines the convergence of carbon intensity and demonstrates the existence of β -convergence by using the GMM estimation method. (Zhao et al. 2015) uses three types of panel model to estimate the convergence of carbon emission intensity among provinces and the conclusion is that the carbon intensity of China's provinces is converging.

Among the studies conducted on the convergence of pollutant emissions, for the most part the literature has focused only on the convergence of carbon emissions, which is obviously not sufficient. In the last few years, scholars have gradually focused on studying the convergence of other pollutants, such as the study of the convergence of air pollutant emissions. (Payne et al. 2014) uses RALS-LM unit root test and structural fracture to obtain the result that show stochastic conditional convergence in per capita SO₂ emissions across US states. (Nourry 2009) presents a comparative analysis of 81 developed and developing countries and examines the convergence of per capita SO₂ emissions. By a combination of club convergence and logit regression analysis, the study analyzes the impact of China's industrial transfer on the convergence of sulfur dioxide and smoke from 285 prefecture-level cities(Liu et al. 2018). In order to solve the endogeneity and consider the dynamic factors, the study uses the DFE model and the GMM model to analyze the convergence of per capita sulfur dioxide in 113 cities in China (Hao et al. 2015).

In the current literature on water pollution discharge, there are only few documents on the influencing factors of water pollution discharge, and there is no research on the convergence of water pollution discharge. Therefore, in order to make up for the vacancy in the research field, based on previous scholars' research, this paper empirically investigates the β -convergence of NH_3-N and COD emission intensity in water pollution by using a dynamic spatial panel model.

3. Methods and data

3.1 Methodology

3.1.1 β -convergence

β -convergence is divided into absolute β -convergence and conditional β -convergence. Absolute β -convergence refers to the area with initially high levels of pollutant intensity will decrease faster than areas with initially low levels, but eventually the intensity of pollutants in different areas will converge to the same stable level and the differences in pollutant intensity will no longer exist. Conditional β -convergence means that the rate of decline in the intensity of regional pollutants will be affected by multiple aspects such as their initial levels, industrial structure, and economic level. When the conditions under consideration are different, the steady state of convergence tends to be different(Sala-I-Martin 1996). The β -convergence formula used in this paper is as follows:

$$\ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) = \beta_0 + \beta_1 \ln(P_{i,t-1}) + \beta_2 C_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

Where $\ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$ represents the rate at which the emission intensity of pollutants decreases, $\ln(P_{i,t-1})$ indicates the initial level of water pollution intensity, β_1 is used to test for β -convergence. When β_1 is less than 0, there is β -convergence, otherwise it does not exist.

Since both sides of the equation have the first-order lag $\ln(P_{i,t-1})$ of the dependent variable, considering that there may be endogenous problems, this paper adds $\ln(P_{i,t-1})$ on both sides of the equation to convert the static panel model into a dynamic panel model. The formula is as follows:

$$\ln(P_{i,t}) = \beta_0 + \beta_1' \ln(P_{i,t-1}) + \beta_2 C_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

Where $\beta_1' = \beta_1 + 1$, when β_1' is less than 1, there is β -convergence, otherwise it does not exist. $C_{i,t-1}$ represents a column vector composed of control variables. β_2 for the test of absolute β -convergence of the water pollutant discharge intensity, or the convergence of the test is called conditional β -convergence. $\varepsilon_{i,t}$ is the error term of the equation. β_0 is a constant term.

3.1.2 Spatial autocorrelation test

The traditional panel model ignores the impact of spatial effects, which means there is no consideration of the impact of water pollution discharges from neighboring areas on pollution discharges to the region. Owing to the obvious spatial relevance of water pollution emissions in my country, this paper adds spatial effects to the ordinary panel model and evolves into a spatial panel model. Before using the model of spatial econometrics, this paper first performs a spatial autocorrelation test. The result of the spatial autocorrelation test can be that there is a positive or negative spatial autocorrelation, and the spatial model can be used to test. The second is that there is no spatial autocorrelation, and then the ordinary model is used to test it.

For the study of global spatial autocorrelation of variables, the existing literature uses the Moran's I index, and this paper also chooses the Moran's I index as the method to study the global spatial autocorrelation. The test value of Moran's I index is $[-1, 1]$. If Moran's I index is greater than 0, there is a positive autocorrelation, otherwise, there is a negative autocorrelation, and the closer the absolute value of Moran's I index is to 1, the greater the correlation. If Moran's I index is 0, then there is a lack of spatial correlation.

$$Moran's I = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{i,j} (X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{i,j}} \quad (3)$$

Where X_i stands for the pollutant intensity in province i . $\bar{X}$ is the average of X_i , $W_{i,j}$ represents the spatial weight matrix, n stands for the number of provinces, S^2 is the variance of X_i . In particular, the 0-1 spatial weight matrix $W_{i,j}$ is calculated as follows:

$$W_{i,j} = \begin{cases} 1 & \text{The distance between } i \text{ and } j \text{ is less than } d \\ 0 & \text{The distance between } i \text{ and } j \text{ is greater than } d \end{cases} \quad (4)$$

Most of the commonly used tests in the literature for testing the local spatial autocorrelation of variables are Moran scatter plots and LISA cluster plots. And we choose Moran scatter plot as the method to test the local spatial autocorrelation. If the distribution is in the first and third quadrants of the Moran scatter plot, then a positive spatial correlation exists. The distribution in the first quadrant is also called "high-high" aggregation, and the distribution in the third quadrant is called "low-low" aggregation. On the contrary, the second and fourth quadrants of the distribution have negative spatial autocorrelation, which are called "high-low" aggregation and "low-high" aggregation.

3.1.3 Spatial panel model

Considering the spatial effect of water pollution discharge, this study constructs the SDM model and the DSDM model as theoretical models for the study of the convergence of pollutant emission intensity.

The establishment of the SDM Model is as follows:

$$\ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) = \beta_0 + \beta_1 \ln(P_{i,t-1}) + \beta_2 C_{i,t-1} + \rho \sum_{j=1}^n W_{i,j} \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right) + \beta_3 \sum_{j=1}^n W_{i,j} C_{j,t-1} + \lambda \sum_{j=1}^n W_{i,j} \ln(P_{i,t-1}) + \varepsilon_{i,t} \quad (5)$$

The establishment of the DSDM Model is as follows:

$$\ln(P_{i,t}) = \beta_0 + \beta_1' \ln(P_{i,t-1}) + \beta_2 C_{i,t-1} + \rho \sum_{j=1}^n W_{i,j} \ln(P_{i,t}) + \beta_3 \sum_{j=1}^n W_{i,j} C_{j,t-1} + \lambda' \sum_{j=1}^n W_{i,j} \ln(P_{i,t-1}) + \varepsilon_{i,t} \quad (6)$$

Where $\sum_{j=1}^n W_{i,j} \ln(P_{i,t})$ represents the spatial lag of the dependent variable, ρ is the spatial autocorrelation coefficient. $\sum_{j=1}^n W_{i,j} C_{j,t-1}$ represents the spatial lag of the control variable, $\sum_{j=1}^n W_{i,j} \ln(P_{i,t-1})$ represents the spatial lag term of the independent variable. Where $\beta_1' = \beta_1 + 1$ and $\lambda' = \lambda - \rho$, β_1' is consistent with the meaning of the variables in equation (2), λ' is the temporal and spatial lag term of the intensity of water pollution discharge, which represents the dynamic relationship between the water pollution in the neighboring area in the early period and the local area in the current period.

When the spatial lag of the control variable ($\beta_3=0$) is not considered, it is a Dynamic Spatial Autoregressive Model (SDAR), and when the spatial lag of the control variable is considered, it is a DSDM Model.

3.2 Variables and data

3.2.1 Water pollution

This study selects NH_3-N and COD as indicators to measure the level of water pollution, and selects panel data from 30 provinces, cities, and autonomous regions (excluding Hong Kong, Macao, Taiwan, and Tibet Autonomous Region) from 2006 to 2017. The data comes from China Statistical Yearbook, China Environmental Statistical Yearbook. From 2006 to 2010, the emissions of NH_3-N and COD have been on a downward trend, but in 2011, the emissions suddenly increased. By consulting the yearbook, it is found that the COD and total NH_3-N counted before 2010 include industrial pollution sources and domestic pollution sources. The statistical total after 2010 consists of

four parts: industrial pollution sources, domestic pollution sources, agricultural pollution sources, and centralized pollution control facilities. In order to maintain the consistency of the data indicators, the water pollution variables studied in this paper only include two parts: industrial pollution sources and domestic pollution sources.

This paper defines the emissions of NH_3-N and COD divided by GDP as the emission intensity of pollutants and uses the nominal GDP of each province and the GDP index based on annual constant prices to calculate the actual annual GDP.

In order to study the convergence of the discharge intensity of water pollutants, this paper adds some factors to analyze the external driving force that affects the convergence of water pollutant discharge. It is found that the rate of decline in the intensity of water pollutants will be affected by various factors such as their initial level, economic growth, industrial structure, technological progress, and urbanization by consulting the literature.

3.2.2 Control variable

(1) Economic growth

This study uses per capita GDP as an indicator to measure economic growth. The main impact of per capita GDP on pollutant emissions is that as the economic level increases, more energy will be consumed, and more pollutants will be emitted. On the other hand, the concept of energy conservation, emission reduction, and environmental protection has become more and more popular, and everyone will spontaneously carry out activities to control pollutant emissions. At the same time, many literature studies on the EKC curve also show that pollutant emissions are closely related to economic growth.

(2) Industrial structure

The discharge of NH_3-N and COD in wastewater mainly comes from the industrial sector, and the pollutant emission intensity of the industrial sector of the secondary industry is significantly higher than that of the primary and tertiary industries. Therefore, in this paper, the value added of the secondary sector divided by GDP is used as an indicator of industrial structure.

(3) Technological progress

In this paper, the ratio of foreign direct investment to GDP is used as an indicator to measure technological progress, and the impact of technological progress on pollutant emission intensity mainly comes from two aspects. One is that the rapid increase of foreign investment industries has caused a large amount of pollutants to be discharged, and the other is that foreign investment has introduced many advanced technologies, which to a certain extent is conducive to the development of clean production technology and the control of pollutant emissions.

(4) Population density

Population density means the population of permanent residents per square kilometer. The main reason for population density as a factor influencing the intensity of pollutant emissions is a high population density means a high level of industrialization, which will aggravate the emission of pollutants. Secondly, an increase in population

will cause more people to realize the importance of protecting the environment, which on the contrary is more beneficial for national governments and enterprises to control pollutant emissions (Hao et al. 2015).

(5) Urbanization

As one of the key factors influencing carbon emissions, urbanization has an impact on energy consumption and environmental performance, mainly by means of scale effects(Huang et al. 2019b). Many studies have found that urbanization plays an important role in CO₂ emissions. According to other research and analysis, this article attempts to use urbanization as a factor in the study of water pollutant emission intensity.(Xiao-Xian) The urbanization index is divided into three parts: population urbanization, economic urbanization and social urbanization. This study selects the most important two parts as the urbanization indicators of this article. The ratio of the urban population to the total population is defined as the urbanization rate, which serves as an indicator of population urbanization. The consumption level of urban residents divided by the total population is defined as the per capita consumption of urban residents, which serves as an indicator of economic urbanization.

(6) Investment level

This study believes that fixed assets investment dominates the entire social investment, and fixed assets usually refer to the infrastructure of real estate and buildings, which may generate domestic and industrial wastewater. Therefore, this study attempts to introduce the ratio of fixed asset investment to gross national product of the whole society as an indicator of investment level to analyze the impact of investment level on water pollution emissions.

Table1 Variables, meanings, and descriptive statistics.

Variables	Meanings	Unit	Mean	S.D.	Min.	Max.	Obs.
NH ₃ -N [ln(P _{i,t-1})]	NH ₃ -N emission intensity (ln)	Ton/100 million yuan (price in 2006)	-.095	.376	-2.371	1.148	360
COD [ln(P _{i,t-1})]	COD emission intensity (ln)	Ton/100 million yuan (price in 2006)	3.453	.854	.394	5.535	360
PGDP	GDP per capita	2006-price yuan/person	38159.28	23226.96	6103	137596	360
INDUSTRY	Secondary industry output divided by GDP	%	.538	.112	.238	.908	360
POP	Population density	Person/square kilometers	2792.775	1229.544	598	6307	360
PCE	per capita consumption of urban residents	RMB/10 ² person	.059	.057	.009	.294	360

UR	urbanization rate	%	.552	.138	.278	.932	360
FDI	The ratio of foreign investment to GDP	%	.030	.025	.0005	.140	360
INVESTMENT	The ratio of investment in fixed assets throughout the country to GDP	%	.359	.128	.143	.808	360

4. Results and discussion

4.1 The spatial effect of pollutant emission intensity

4.1.1 Spatial distribution of pollutant emission intensity

For a clear view of the spatial distribution of pollutant emissions, this paper selects the average emission intensity data of water pollutants to draw the following map: It can be seen from Figure 1 and Figure 2 that Beijing has the lowest pollutant emission intensity. The reason may be that Beijing, as the capital, implements the best emission reduction policies. Therefore, Beijing has low pollution emissions and high GDP, which leads to the lowest emission intensity. This is followed by some of the more economically developed regions, such as the areas around Jiangsu and Zhejiang, Fujian and Guangzhou and other regions. There are also some developed regions in central China, such as Anhui, Chongqing and other regions. These areas are characterized by " Higher pollutant emissions but high GDP value ", so the emission intensity is low. Some areas with high emission intensity are underdeveloped areas such as Xinjiang, Qinghai, and Gansu, and some are industrially developed areas such as Hunan, Jilin, and Harbin. These areas are characterized by " Higher pollutant emissions but low GDP value." Therefore, its emission intensity is relatively high. The region with the highest water pollutant discharge intensity is Ningxia Autonomous Region. The reasons are as follows: First, Ningxia is one of the more economically underdeveloped regions with a low GDP value. Second, Ningxia's pollutant emissions are relatively high.

For the purpose of further investigating the dynamics of pollutant intensity, the research uses the nuclear density estimation method to explore the internal changes of convergence. Figure 3 shows the nuclear density

distribution of $\text{NH}_3\text{-N}$ emission intensity in 2006, 2009, 2012, and 2015. Figure 4 shows the nuclear density distribution of COD . The kernel density distribution graph shows a concentrated trend and increasing peak in the kernel density curve over the 12-year period from 2006 to 2017, indicating a possible convergence in the intensity of pollutant emissions between 06 and 17 years. However, kernel density profiles only give results for possible convergence trends, and the presence or absence of convergence of contaminants has to be analyzed using more accurate models.

Figure 1 Spatial distribution of $\text{NH}_3\text{-N}$ emission intensity in 30 provinces in China

Figure 2 Spatial distribution of COD emission intensity in 30 provinces in China

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Figure 3 Nuclear density distribution of NH_3-N emission intensity

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Figure 4 Nuclear density distribution of COD emission intensity

4.1.2 Spatial autocorrelation of pollutant emission intensity

This paper use geoda software to calculate Moran's I for the emission intensity of NH_3-N and COD in 30 provinces in China from 2006 to 2017. The selected spatial weight matrix is 0-1 matrix. The results of Moran's I value are shown in the table below.

Table 2 Global spatial autocorrelation test results of NH_3-N emission intensity

year	Moran's I	P 值
2006	0.239	0.023
2007	0.285	0.009
2008	0.376	0.002
2009	0.448	0.001
2010	0.352	0.002
2011	0.386	0.003
2012	0.366	0.002
2013	0.353	0.002
2014	0.352	0.002
2015	0.348	0.002
2016	0.197	0.04
2017	0.159	0.062

Table 3 Global spatial autocorrelation test results of COD emission intensity

year	Moran's I	P 值
2006	0.136	0.061
2007	0.138	0.062
2008	0.15	0.056
2009	0.157	0.052
2010	0.165	0.042
2011	0.39	0.002
2012	0.383	0.002
2013	0.383	0.002
2014	0.387	0.002
2015	0.41	0.002
2016	0.179	0.059
2017	0.091	0.15

According to the data in the table, the Moran's I value of **COD** emission intensity from 2006 to 2016 is above 0.1 and passes the significance test. From 2006 to 2016, the Moran's I value of **NH₃-N** emission intensity is above 0.2 and shows an upward trend and it passes the significance test. This means that there is a positive autocorrelation of the pollutant emission intensity, that is, the pollutant intensity of neighboring provinces and cities will have an impact on the pollutant intensity of neighboring provinces and cities. Therefore, this article should consider its spatial effect when studying the intensity of pollutant emission.

When studying spatial effects, the global spatial autocorrelation test only considers the overall spatial effects of the whole country. As for whether there is a clustering effect in local spatial regions, this paper needs to use Moran scatter plots for specific analysis.

Figure 5 Scatter plots of **NH₃-N** emission intensity in 2009 (left) and 2015 (right)

Figure 6 Scatter plots of *COD* emission intensity in 2009 (left) and 2015 (right)

It can be seen from the scatter plot that most of the points are distributed in one or three quadrants, which shows that both pollutants have local spatial autocorrelation. The distribution in the first quadrant is called "high-high" and also called high value aggregation, where the central region has a high observed value, and the surrounding region has the same high value as the central region. In the same way, the distribution in the third quadrant is also called "low-low" and also called low-value aggregation, that is, the observation value of the peripheral area is as low as the central area. In short, the scatter plot shows that there is a positive spatial dependence of pollutant emission intensity.

4.2 Convergence of pollutant emission intensity based on spatial effect

4.2.1 Absolute β -convergence

This article first analyzes the absolute β -convergence of *NH₃-N* and *COD* emission intensity based on four models. Tables 4 and 5 respectively reflect the results of the fixed effects model (FE), spatial Dubin model (SDM), dynamic spatial autoregressive model (DSAR), and dynamic spatial Dubin model (DSDM). Among them, models 1 and 5 are ordinary panel models, and the rest are spatial panel models. Models 1-2 and 5-6 are static panel models, and models 3-4 and 7-8 are dynamic panel models.

Table 4 Absolute β -convergence of *NH₃-N* emission intensity

Dependent variable	$\ln(P_{i,t}/P_{i,t-1})$	$\ln(P_{i,t}/P_{i,t-1})$	$\ln(P_{i,t})$	$\ln(P_{i,t})$
	Model 1	Model 2	Model 3	Model 4
$\ln(P_{i,t-1})(\beta / \beta')$	0.0219(0.351)	-0.2422*** (0.001)	0.3754*** (0.001)	0.7337*** (0.001)
$W * \ln(P_{i,t-1})$		0.2516*** (0.001)		-0.5385*** (0.001)
ρ		0.8106*** (0.001)	0.6673*** (0.001)	0.8099*** (0.001)
Models	FE	SDM	DSAR	DSDM
Approach	Fe	Fe	Fe	Fe
Observations	360	360	360	360
adj.R ²	0.0011	0.0258	0.7694	0.7795
Log-likelihood		40.8120	6.3661	47.1515

***, **, * represent significant at 1%, 5% and 10%, separately

In Table 4, when considering model estimation without spatial effects, the first-order lag coefficient of *NH₃-N* emission intensity in Model 1 is not significant. When considering the spatial effect model estimation, the coefficients of the three models are significant and the spatial sub-regression coefficient is significantly positive. It can be concluded that when considering the spatial effect, the *NH₃-N* emission intensity has absolute β -convergence and positive spatial autocorrelation.

In Table 5, when performing different model estimations, the first-order lags of the *COD* emission intensity of the four models are all significant, indicating that there is an absolute β -convergence in the *COD* emission intensity from 2006 to 2016. When considering the spatial effect, the coefficients of the spatial autoregression are all significantly positive, which proves that the discharge of water pollution in this area will promote the discharge of water pollution in neighboring areas.

Table 5 Absolute β -convergence of *COD* emission intensity

Dependent variable	$\ln(P_{i,t}/P_{i,t-1})$	$\ln(P_{i,t}/P_{i,t-1})$	$\ln(P_{i,t})$	$\ln(P_{i,t})$
	Model 5	Model 6	Model 7	Model 8
$\ln(P_{i,t-1}) (\beta / \beta')$	0.0482**(0.014)	-0.0864**(0.012)	0.5521*** (0.001)	0.8831*** (0.001)
$W * \ln(P_{i,t-1})$		0.1027*** (0.004)		-0.6611*** (0.001)
ρ		0.7894*** (0.001)	0.4974*** (0.001)	0.7887*** (0.001)
Models	FE	SDM	DSAR	DSDM
Approach	Fe	Fe	Fe	Fe
Observations	360	360	360	360
adj.R ²	0.0184	0.0302	0.8894	0.8985
Log-likelihood		198.1188	131.2961	204.4544

***, **, * represent significant at 1%, 5% and 10%, separately

4.2.2 Conditional β -convergence

In the analysis of convergence of water pollution emission intensity, the control variables include economic growth, industrial structure, technological progress, urbanization, population density, and investment level. Consistent with the absolute β -convergence analysis model, the static panel model, dynamic panel model, and spatial panel model are used for verification. The spatial weight matrices used by the model are all 0-1 matrices. The model passes Hausman test, and the test result is to choose a fixed-effect model to run. This paper use Stata15.0 for analysis and calculation, and the results are shown in the table below.

The first-order lag coefficients of water pollution intensity in Table 6 and Table 7 are both significant, which proves that there is conditional β -convergence in various provinces and cities in China. The spatial autocorrelation coefficients in the spatial panel model are all significantly positive, indicating that there is a positive spatial autocorrelation of water pollution emission intensity. In other words, the emission intensity of pollutants in this area will affect the emission intensity of pollutants in neighboring areas, and this effect is positive. That is, the higher the emission intensity of pollutants in this area, the higher the emission intensity of pollutants in neighboring areas. It is necessary to study its spatial effects

By comparing the goodness of fit of several models, the DSDM model has the highest goodness of fit. This article believes that the results of the DSDM model are very convincing. Therefore, this article will analyze the results based on the DSDM model.

Table 6 Conditional β -convergence of NH_3-N emission intensity

Dependent variable	$\ln(P_{i,t}/P_{i,t-1})$	$\ln(P_{i,t}/P_{i,t-1})$	$\ln(P_{i,t})$	$\ln(P_{i,t})$
	Model 1	Model 2	Model 3	Model 4
$\ln(P_{i,t-1})$	-0.3913***	-0.3503***	0.3191***	0.6350***
(β / β')	(0.001)	(0.001)	(0.001)	(0.001)
PGDP	-0.00001***	-4.44e-06**	-1.52e-06(0.392)	-4.15e-06**
	(0.001)	(0.012)		(0.018)
INDUSTRY	2.7089***(0.001)	0.8287***(0.001)	0.9331***(0.001)	0.7747***(0.001)
FDI	0.4441(0.786)	0.6392(0.494)	1.2272(0.258)	0.4915(0.595)
POP	-0.00001(0.731)	-0.00002(0.194)	-0.0001**(0.12)	-0.00002(0.191)
INVESTMENT	2.3415***(0.001)	1.1610***(0.001)	0.7249***(0.006)	1.0324***(0.002)
λ / λ'		0.1442**(0.015)		-0.5404***(0.001)
W*PGDP		-6.81e-06**		-6.37e-06*
		(0.047)		(0.06)
W* INDUSTRY		1.2503***(0.001)		1.2590***(0.001)
W*FDI		-4.5216**(0.039)		-4.2181*(0.051)
W*POP		0.0001*(0.094)		0.0001(0.121)
W* INVESTMENT		-0.6805 (0.122)		-0.5616(0.196)
ρ		0.7012***(0.001)	0.6086***(0.001)	0.7389***(0.001)
Models	FE	SDM	DSAR	DSDM
Approach	Fe	Fe	Fe	fe
Observations	360	360	360	360
adj.R ²	0.3074	0.5252	0.8292	0.8886
Log-likelihood		71.4847	21.2360	74.9685

***, **, * represent significant at 1%, 5% and 10%, separately

In Model 4, the coefficient of economic growth is significantly negative, which means that economic growth has an impact on the emission intensity of NH_3-N and the higher the per capita GDP, the lower the intensity of NH_3-N . This paper argues that a growing economy has improved people's awareness of environmental protection, and the positive impact it brings is far greater than its negative impact. The coefficient of the industrial structure is positive, which means that the industrial structure has a positive effect on the emission intensity of NH_3-N . Through

the coefficient of the investment level, it is found that the investment level has played a role in promoting the emission intensity of NH_3-N . The possible reason is that the more investment in fixed assets in the whole society, the higher the wastewater pollution produced, which leads to the higher the intensity of NH_3-N emission. The effects of foreign investment and population density on NH_3-N are small and their association with NH_3-N needs to be further investigated in a later study.

Table 7 Conditional β -convergence of COD emission intensity

Dependent variable	$\ln(P_{i,t}/P_{i,t-1})$	$\ln(P_{i,t}/P_{i,t-1})$	$\ln(P_{i,t})$	$\ln(P_{i,t})$
	Model 5	Model 6	Model7	Model 8
$\ln(P_{i,t-1})$	-0.3868***	-0.2442***	0.4334***	0.7348***
(β/β')	(0.001)	(0.001)	(0.001)	(0.001)
PGDP	-4.63e-06***	-8.26e-07	2.60e-06*	-5.08e-07
	(0.005)	(0.480)	(0.051)	(0.661)
INDUSTRY	1.5800***(0.001)	0.5008***(0.001)	0.6008***(0.001)	0.4523***(0.001)
FDI	-0.1625(0.871)	-0.1008(0.858)	0.3839(0.613)	-0.2380(0.692)
PCE	-2.941*** (0.007)	-2.1882*** (0.002)	-4.3818*** (0.001)	-2.3404*** (0.001)
UR	-1.3223** (0.022)	0.0220(0.955)	-0.0285(0.949)	-0.0525(0.892)
INVESTMENT	1.7413*** (0.001)	0.9344*** (0.001)	0.8240*** (0.003)	0.7918*** (0.004)
λ/λ'		-0.0009(0.987)		-0.6512*** (0.001)
W*PGDP		-4.47e-06** (0.04)		-4.00e-06* (0.063)
W*INDUSTRY		0.8359*** (0.001)		0.8427*** (0.001)
W*FDI		-2.7417* (0.06)		-2.4755* (0.087)
W*PCE		1.0631(0.505)		1.1821(0.453)
W*UR		-1.4864** (0.03)		-1.3209* (0.052)
W*INVESTMENT		-0.4138(0.239)		-0.2555(0.462)
ρ		0.6755*** (0.001)	0.4725*** (0.001)	0.6796*** (0.001)
Models	FE	SDM	DSAR	DSDM
Approach	Fe	Fe	Fe	Fe
Observations	360	360	360	360
adj.R ²	0.3120	0.5007	0.9161	0.9460
Log-likelihood		237.9843	163.3020	241.5026

***, **, * represent significant at 1%, 5% and 10%, separately

The coefficient of *INDUSTRY* in Model 8 is significantly positive, and this is coherent with the effect on NH_3-N . The added value of the secondary industry contributes positively to promoting the emission intensity of

COD. The coefficient of Investment is positive, considering that the increase in investment in fixed assets may aggravate the process of industrialization, thereby promoting the emission of **COD**. The coefficient of **PCE** is significantly negative, proving that the development of economic urbanization has a dampening effect on the intensity of **COD** emissions. The impact of foreign investment and economic growth on **COD** is not significant, and the relationship between these variables and pollutants needs to be further studied.

This article discusses the spatial influence of control variables. In Model 4 and Model 8, the coefficient of **W*PGDP** is significantly negative, indicating that due to the rapid economic growth of neighboring regions, it will also promote the enhancement of residents' awareness of environmental protection in the region and reduce local water pollution emissions. The coefficient of **W*FDI** represents a significant negative impact. The advanced technology introduced by foreign investment will not only achieve high-efficiency emission reduction results in the region, but also alleviate water pollution in neighboring areas. The coefficient of **W*INDUSTRY** is also positive, which means that the appreciation of secondary industries in neighboring provinces and cities is often accompanied by an increase in the intensity of pollutant emissions and aggravation of local **NH₃-N** emissions. The coefficient of **W*UR** in Model 10 is negative, and the spatial spillover effect brought about by population urbanization inhibits the emission intensity of local **COD**. This phenomenon is caused by the increase in urban population, the more residents notice that protecting the environment is the first task. The coefficient of **W*PCE** is not significant, and the impact of economic urbanization on **COD** emissions needs to be discussed in follow-up studies.

In general, the results of the FE model, SDM model, DSAR model, and DSDM model are basically the same, which makes the results of this article more robust. It strongly supports the existence of conditional β -convergence of China's water pollution intensity and positive spatial autocorrelation. Factors such as economic growth and industrial structure have varying degrees of impact on the intensity of water pollution emissions.

5. Conclusions and policy recommendations

This article examines the convergence of **NH₃-N** and **COD** emission intensity in 30 provinces on the basis of previous scholars' research on pollutant emissions. Based on panel data from 2006 to 2017 for each province in China, this study verifies the positive spatial autocorrelation of water pollutant emissions and uses the common panel model and the spatial panel model to discuss the convergence of water pollutant emission intensity.

The following policy recommendations are given based on the above research:

First, through the comparison of the two models, it is found that the emission intensity of **NH₃-N** and **COD** has an absolute β -convergence and a conditional β -convergence during the study period. After considering the spatial effect, the convergence trend of the two pollutants has become faster. This means that the discharge of pollutants has a significant spatial dependence. The discharge of pollutants from two neighboring provinces and cities will affect each other and this effect is positive, which means that the increase in pollutant emissions from neighboring provinces and cities will lead to pollutants in the province. Increase in emissions. Therefore, it is best to

unite with neighboring regions when formulating anti-pollution and emission reduction policies. This is based on regional joint governance, so that the regions can cooperate with each other to complete the governance goals. Never implement a "one size fits all" policy.

Second, based on the β -convergence of NH_3-N and COD emission intensity, this study concludes that government policies for controlling pollutant emissions should consider the long-term trend of convergence in pollutant emissions, and the government should set various emission reduction targets with respect to the emission sub-situations of pollutants in different regions. Specifically, for provinces and cities with low pollutant emission intensity, such as Beijing, Tianjin, Shandong, and Jiangsu, Zhejiang and Shanghai, the emission reduction targets can be appropriately reduced. These provinces and cities should make full use of their strengths in energy conservation and emission reduction, actively develop clean energy technologies, and help regions with slightly backward economies and high pollutant emissions to play a leading role. For provinces and cities with high pollutant emission intensity, such as Ningxia, Gansu, Hainan and other places, higher emission reduction targets should be assigned to these provinces and cities. These regions with slower economic development should proceed from their own interests, accelerate the adjustment and optimization of the industrial structure to achieve economic transformation.

Third, social and economic factors that affect pollutant emissions should also be taken into consideration when the government formulates policies. Specifically, the first task is to adjust and optimize the industrial structure, improve the structural characteristics of the secondary industry, encourage the development of clean energy technologies, and vigorously develop a low-carbon economy. The second is to introduce more foreign investment. The research results show that foreign investment is of great significance in reducing pollutant emissions. Regions with a slightly underdeveloped economy need to introduce foreign investment. Through the study of foreign advanced technology, the best of them can be converted into a method which suitable for their own national conditions and put into use. Third, the intensity of pollutant emission reflects the relationship between pollutant emission and economic growth. The higher the value of per capita GDP, the better the economic development level of the city, and the smaller the emission of pollutants. It means that economic development within a certain range can actually reduce the emission of pollutants. The fourth is to encourage the development of a new type of urbanization, not only to do a good job in the urbanization of one's own region, but also to link with other regions to achieve an efficient, energy-saving, and rapid urbanization development model.

In this study, the emission intensity of NH_3-N and COD in 30 provinces in China is used as the research object, and there are still some limitations and deficiencies. One is that the data used for this paper comes from provincial data in China. In future studies, it is encouraged to use city-level data to analyze the convergence of China's water pollution intensity. The second is to define NH_3-N and COD as water pollution. In future studies, variables such as nitrogen and phosphorus will be added to enrich water pollution indicators.

References:

- Awaworyi Churchill S, Inekwe J, Ivanovski K (2020): Stochastic convergence in per capita CO2 emissions: Evidence from emerging economies, 1921 – 2014. *ENERG ECON* 86, 104659
- Cai H, Mei Y, Chen J, Wu Z, Lan L, Zhu D (2020): An analysis of the relation between water pollution and economic growth in China by considering the contemporaneous correlation of water pollutants. *J CLEAN PROD* 276, 122783
- Fan X, Xu Y (2020): Convergence on the haze pollution: City-level evidence from China. *ATMOS POLLUT RES* 11, 141-152
- Hao Y, Zhang Q, Zhong M, Li B (2015): Is there convergence in per capita SO2 emissions in China? An empirical study using city-level panel data. *J CLEAN PROD* 108, 944-954
- Hao Y, Liao H, Wei Y (2015): Is China ' s carbon reduction target allocation reasonable? An analysis based on carbon intensity convergence. *APPL ENERG* 142, 229-239
- Huang B, Meng L (2013): Convergence of per capita carbon dioxide emissions in urban China: A spatio-temporal perspective. *APPL GEOGR* 40, 21-29
- Huang J, Liu C, Chen S, Huang X, Hao Y (2019a): The convergence characteristics of China's carbon intensity: Evidence from a dynamic spatial panel approach. *SCI TOTAL ENVIRON* 668, 685-695
- Huang J, Liu C, Chen S, Huang X, Hao Y (2019b): The convergence characteristics of China's carbon intensity: Evidence from a dynamic spatial panel approach. *SCI TOTAL ENVIRON* 668, 685-695
- Lee C, Chiu Y, Sun C (2010): The environmental Kuznets curve hypothesis for water pollution: Do regions matter? *ENERG POLICY* 38, 12-23
- Li J, Huang X, Yang H, Chuai X, Wu C (2017): Convergence of carbon intensity in the Yangtze River Delta, China. *HABITAT INT* 60, 58-68
- Li M, Li C, Zhang M (2018): Exploring the spatial spillover effects of industrialization and urbanization factors on pollutants emissions in China's Huang-Huai-Hai region. *J CLEAN PROD* 195, 154-162
- Li T, Wang Y, Zhao D (2016): Environmental Kuznets Curve in China: New evidence from dynamic panel analysis. *ENERG POLICY* 91, 138-147
- Liu C, Hong T, Li H, Wang L (2018): From club convergence of per capita industrial pollutant emissions to industrial transfer effects: An empirical study across 285 cities in China. *ENERG POLICY* 121, 300-313
- Liu Y, Zhou Y, Wu W (2015): Assessing the impact of population, income and technology on energy consumption and industrial pollutant emissions in China. *APPL ENERG* 155, 904-917
- Luo Y, Lu Z, Long X (2020): Heterogeneous effects of endogenous and foreign innovation on CO2 emissions stochastic convergence across China. *ENERG ECON* 91, 104893
- Matsuki T, Pan L (2021): Per capita carbon emissions convergence in developing Asia: A century of evidence from covariate unit root test with endogenous structural breaks. *ENERG ECON* 99, 105326

518 Nourry M (2009): Re-Examining the Empirical Evidence for Stochastic Convergence of Two Air Pollutants with a
519 Pair-Wise Approach. ENVIRON RESOUR ECON 44, 555-570

520 Pang J, Li N, Mu H, Zhang M (2021): Empirical analysis of the interplay between shadow economy and pollution:
521 With panel data across the provinces of China. J CLEAN PROD 285, 124864

522 Payne, Miller, Lee, Cho (2014): Convergence of per capita sulphur dioxide emissions across US states. APPL ECON
523 46, 1202-1211

524 Rios V, Gianmoena L (2018): Convergence in CO2 emissions: A spatial economic analysis with cross-country
525 interactions. ENERG ECON 75, 222-238

526 Sala-I-Martin XX (1996): The Classical Approach to Convergence Analysis. ECON J, 1019-1036

527 Solow RM (1956): A Contribution to the Theory of Economic Growth. Q J ECON, 65-94

528 Tsuzuki Y (2009): Comparison of pollutant discharge per capita (PDC) and its relationships with economic
529 development: An indicator for ambient water quality improvement as well as the Millennium Development Goals
530 (MDGs) sanitation indicator. ECOL INDIC 9, 971-981

531 Wang J, Zhang K (2014): Convergence of carbon dioxide emissions in different sectors in China. ENERGY 65,
532 605-611

533 Wu J, Wu Y, Guo X, Cheong TS (2016): Convergence of carbon dioxide emissions in Chinese cities: A continuous
534 dynamic distribution approach. ENERG POLICY 91, 207-219

535 Xiao-Xian MA Analysis on the Key Influence Factors of Urbanization and Its Effects in China. China
536 Population,Resources and Environment

537 Xu F, Huang Q, Yue H, He C, Wang C, Zhang H (2020): Reexamining the relationship between urbanization and
538 pollutant emissions in China based on the STIRPAT model. J ENVIRON MANAGE 273, 111134

539 Yu S, Lu H (2018): Relationship between urbanisation and pollutant emissions in transboundary river basins under
540 the strategy of the Belt and Road Initiative. CHEMOSPHERE 203, 11-20

541 Zhang C, Wang Y, Song X, Kubota J, He Y, Tojo J, Zhu X (2017a): An integrated specification for the nexus of
542 water pollution and economic growth in China: Panel cointegration, long-run causality and environmental Kuznets
543 curve. SCI TOTAL ENVIRON 609, 319-328

544 Zhang C, Wang Y, Song X, Kubota J, He Y, Tojo J, Zhu X (2017b): An integrated specification for the nexus of
545 water pollution and economic growth in China: Panel cointegration, long-run causality and environmental Kuznets
546 curve. SCI TOTAL ENVIRON 609, 319-328

547 Zhang P, Hao Y (2020): Rethinking China's environmental target responsibility system: Province-level convergence
548 analysis of pollutant emission intensities in China. J CLEAN PROD 242, 118472

549 Zhao X, Wesley Burnett J, Lacombe DJ (2015): Province-level convergence of China ' s carbon dioxide emissions.
550 APPL ENERG 150, 286-295

551 Zhou K, Wu J, Liu H (2021): Spatiotemporal variations and determinants of water pollutant discharge in the Yangtze

552 River Economic Belt, China: A spatial econometric analysis. ENVIRON POLLUT 271, 116320
553