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Original Research

Spatio-Temporal Evolution Characteristics and Influencing Factors of Industrial Pollution: Evidence from Chinese Cities

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Abstract

Based on panel data of 285 Chinese cities from 2005 to 2020, this paper uses a set of regional economic analysis tools to explore the spatial and temporal characteristics of urban industrial pollution and its drivers. The results of the research show that the Urban Industrial Pollution Index (UIPI) has shown a significant downward trend overall. However, high levels of industrial pollution are found in the areas where the four major industrial bases are located. The overall development gap of the UIPI shows a fluctuating upward trend. In terms of the contribution of development differences, supervisory density is the highest, followed by intra-regional differences, and inter-regional differences are the lowest. The UIPI has a strong spatial dependence, with a concentration in Henan Province. It is spatially distributed in a "northeast-southwest" direction, with a tendency of diffusion and transfer to surrounding cities. Urban industrial pollution is significantly suppressed by human capital, capital stock, technological innovation and economic agglomeration. Human capital and economic agglomeration can suppress industrial pollution in surrounding cities through spatial spillovers. In addition, a number of influencing factors have a heterogeneous impact on urban industrial pollution across regions.

Keywords: industrial pollution, spatial and temporal evolution characteristics, influencing factors, Chinese cities

Introduction

China's reform and opening-up has made brilliant achievements that are widely recognised, and China has become the world's second largest economy and the largest industrialised country. However, the rapid growth of the industrial economy based on the extensive growth model not only causes environmental problems such as resource wastage and serious ecological damage, but also harms people's physical and mental health, and is not conducive to the sustainable development

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of the economy and society [1]. According to the statistics of the Blue Book of China Corporate Citizenship Report, industrial pollution sources are the main source of environmental pollution, and the total amount of pollutant emissions can account for about 70% of the total emissions, and cities are the main sources of industrial pollution. As a priority for environmental protection in China, urban industrial pollution control is a focus of overall and long-term interest. According to the statistics of the Second National Pollution Source Survey, urban industrial pollution control has achieved remarkable results. Chemical oxygen demand, ammonia nitrogen, sulphur dioxide and nitrogen oxides decreased by 83.89%, 77.56%, 75.05% and 45.65% respectively compared to the first national source survey. China's industrial economy accounts for a large share of total economic output, and many industrial pollutants are still emitted at high levels. In some cities, the potential environmental risks are greater because the level of industrial pollution control is still low. Therefore, urban industrial pollution control still requires a variety of measures and continuous efforts, which is of great practical importance for achieving high-quality economic development.

At present, literature research on industrial pollution has received considerable attention from environmental science, geography, ecology, economics and other academic circles. The existing literature mainly focuses on the spatial and temporal distribution characteristics, regional differences and influencing factors of industrial pollutant emissions [2-4]. In order to better identify the current characteristics of regional industrial pollution, it is necessary to quantify the level of industrial pollution. Generally, single indicators such as industrial wastewater, industrial exhaust gas and industrial solid waste are used as proxy industrial pollution levels [5], and some scholars use entropy value method, principal component analysis method, DEA data envelopment analysis method and other methods to evaluate the comprehensive industrial pollution level [6-8]. The temporal and spatial distribution of industrial pollution is an important characteristic of industrial pollution and an important and complex task in environmental monitoring. Researchers commonly use Dagum Gini coefficient, Theil index, kernel density estimation method, coefficient of variation method, Markov transfer matrix, standard deviation ellipse, spatial exploratory analysis tool and other methods to reveal the spatio-temporal distribution and evolution characteristics and regional differences of environmental pollution [9-15]. Discussion of the factors influencing industrial pollution can provide empirical guidance for industrial pollution control, and has also become the focus of related research fields. Methodologically, researchers use geographically weighted regression models, grey association models, geographic detectors, and spatial econometric models [16-19]. Economic and social factors such as economic development, foreign investment, share of secondary industry, financial development, technological innovation, institutional pressure, corporate environmental responsibility and disclosure of environmental information are important factors that have an impact on industrial pollution [20-25].

The existing literature provides a lot of research ideas for this article, but there are still the following research gaps. First, researchers mainly focus on the current situation of industrial pollution in regions, provinces and specific industries. They neglect the extent of industrial pollution from the perspective of cities. This article uses the entropy method rather than subjective weighting to measure the industrial pollution index of Chinese cities. At the regional level, the surveyed cities were divided into four major regions to better understand the industrial pollution situation in heterogeneous regions. Second, few scholars have paid attention to the spatio-temporal evolution characteristics of industrial pollution in heterogeneous regions, as most studies consider regions as a whole. This paper uses the Dagum Gini coefficient to reflect the degree of regional inequality in urban industrial pollution, and uses standard deviation ellipses and spatial correlations to reveal the spatial characteristics of urban industrial pollution. In addition, existing research suggests that the drivers of industrial pollution are independent of each other. There is a lack of research on the spatial spillover effects of industrial pollution and its drivers. This paper presents a spatial Durbin model decomposition to explore key factors in industrial pollution reduction and to strengthen the investigation of spatial spillovers of drivers. This study provides experience and reference for identifying the current situation of urban industrial pollution and formulating effective policies to control urban industrial pollution.

Materials and Methods

Data Source

Due to the severe lack of data in Turpan, Zhongwei, Shigatse and other cities, these cities were excluded from this study. The data sources are China Statistical Yearbook, local city statistical yearbooks, CNRDS data platform, etc. There are some missing data and this study completes the data using moving average and interpolation methods.

Variable Selection

Explained Variable: Urban Industrial Pollution Index (UIPI). Industrial pollution can be divided into the "three industrial wastes" (waste water pollution, waste gas pollution, waste residue pollution) and various types of noise pollution, of which the three industrial wastes are the main pollutants actually generated by industrial production. Based on the availability of data and following the methods of Zou and Pan (2022) [26], this paper selects indicators such as industrial waste water, industrial sulphur dioxide and industrial smoke dust as proxy indicators of industrial pollution, and obtains a comprehensive UIPI.

Explanatory variables: Based on the existing research literature, this paper selects representative drivers to further explore the key factors for reducing industrial pollution [27-30]. These include industrial structure (*Ind*): measured by the share of secondary industry in GDP. Human capital (*Edu*): measured by the number of tertiary students per 10,000 enrolled students. Fiscal decentralisation: measured by the ratio of local government revenue to local government expenditure. Financial development (*Fin*): measured by the balance of deposits and loans of financial institutions at the end of the year as a percentage of GDP. Foreign investment (*FDI*): measured as foreign direct investment as a percentage of GDP. Capital stock (*Cap*): Based on the perpetual inventory method of Shan Junjie, measured as the ratio of capital stock to employment and logarithmised. Technological innovation (*Tech*): Measured by the number of patent applications. Economic agglomeration (*Agglo*): Measured by the ratio of the sum of the output value of the secondary and tertiary sectors to the urban built-up area. Economic growth (*GDP*): Measured by GDP per capita and log GDP.

Method

Entropy Method

The entropy method is an objective weighting method. The basic principle is the allocation method of determining the weight of each index in the system through the information entropy theory, which can accurately and objectively judge the contribution of each index in the system to the overall evaluation. In this paper, the entropy weighting method is used to objectively evaluate the current situation of urban industrial pollution in China, and the UIPI is obtained through normalisation, information entropy calculation and weight calculation. For specific calculation steps, see Xiao et al. (2022) [31].

Dagum Gini Coefficient

The traditional Gini coefficient is a measure of the degree of inequality in the distribution of income. Compared with the traditional Gini coefficient, the Dagum Gini coefficient can decompose the Gini coefficient into three parts: the contribution of the difference within groups, the contribution of the net value of the differences between groups, and the contribution of the supervariable density between groups. In this paper, the Dagum Gini coefficient is used to measure the UIPI through Matlab software programming, and it is decomposed into intra-regional differences, inter-regional differences and supervariable density. The equations are taken from Zhou et al. (2022) [32].

Standard Deviation Ellipse

The standard deviation ellipse is a spatial statistical technique that measures the distribution pattern of geographic features, reflecting the spatial distribution characteristics of geographic features and the temporal and spatial change process from different perspectives, such as the centre of gravity, distribution direction and shape. In this paper, tools in ArcGIS software are used to visualise the standard deviation ellipse to summarise the spatial characteristics of the UIPI. For the specific calculation procedure, see Zhang et al. (2022) [33].

Spatial Durbin Model

Spatial econometric models are a set of methods used to study different properties induced by space. The spatial lag model, the spatial error term model and the spatial Durbin model are the classical spatial econometric models. The spatial Durbin model is a combination of the spatial lag model and the spatial error term model. The spatial Durbin model has a wider range of applications because it takes into account the spatial correlation of both the dependent and independent variables. This paper uses the spatial Durbin decomposition model to study the spatial spillover effects of urban industrial pollution, because the results of the spatial Durbin model do not objectively reflect the results of the spatial effects. For the specific formula, see Wu and Liu (2021) [34].

Results and Discussion

Time Distribution Characteristics of the UIPI

In this article, the urban industrial ‘three wastes’ are weighted and the UIPI is calculated using the entropy method. Fig. 1 shows the evolution of urban industrial pollution from 2005 to 2020. According to Fig. 1, the UIPI generally shows a clear downward trend. In particular, since 2016, the UIPI has shown a steep decline. This shows that China's efforts to prevent and control urban industrial pollution have begun to pay off, and that environmental governance has continued to improve steadily. Between 2005 and 2020, the UIPI decreased from 0.0480 in 2005 to 0.0085 in 2020, a decrease of 82.2444%, or an average annual decrease of 9.9830%. The decrease of the UIPI can be divided into three phases: 2005-2010, 2011-2015 and 2016-2020. The decrease in the UIPI is more pronounced in the third of these phases. During this period, the average annual value of the UIPI was 0.0143, which represents an average annual decrease of 24.5293%. As the 19th National Congress clearly proposed to speed up the institutional reform of ecological civilisation and fight

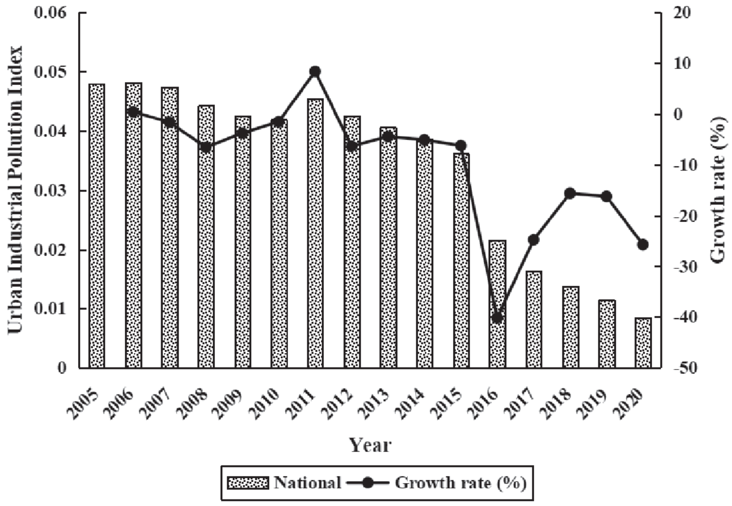

Fig. 1. Time-series characteristics of industrial pollution in Chinese cities.

the battle of pollution prevention and control, this may be an important reason for the reduction of urban industrial pollution in the third phase.

In this paper, Chinese cities are divided into four major regions: eastern, central, western and northeastern, in order to further investigate regional differences in urban industrial pollution. The time trend of industrial pollution in the four major regions of China from 2005 to 2020 is shown in Fig. 2. According to Fig. 2, there is a clear overall downward trend in the index of industrial pollution in the four cities of the region, which is similar to the overall picture. For the annual average of the UIPI, western cities (0.0471) > north-eastern cities (0.0308) > eastern cities (0.0286) > central cities (0.0280). The largest decrease was in central cities (-83.9714%) with an annual average decrease of 10.1940%, followed by western cities (-82.5647%) with an annual average decrease of 9.8327%. The central and western regions are implementing the "Rise of Central China" and "Western Development" strategies in the face of the new ecological and environmental management situation. Strengthening ecological environmental protection and construction is the basis and starting point for the implementation of the strategy, which provides a direction for the work of urban industrial pollution control.

Spatial Distribution Characteristics of UIPI

In this paper, the UIPI is divided into the first to fifth echelon, corresponding to high industrial pollution area, high industrial pollution area, medium industrial pollution area, low industrial pollution area and low industrial pollution area, respectively, using the natural fracture method in ARCGIS10.5 software to more intuitively reflect the spatial agglomeration and distribution characteristics of the whole UIPI,

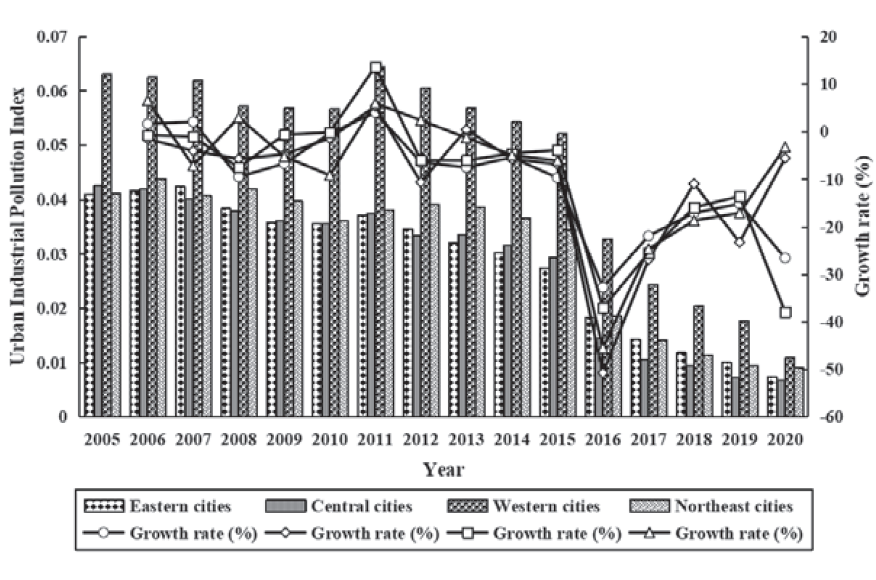

Fig. 2. Time-series characteristics of industrial pollution in China’s four regions.

and the plot time is 2005-2020 (due to space limitation, only 2005, 2010, 2015 and 2020 are shown).

The spatial distribution characteristics of China's UIPI are shown in Fig. 3. As shown in Fig. 3, the UIPI shows local clustering characteristics with large differences in spatial distribution. The northern region, the Liaocentral-Southern urban agglomeration, the Yangtze River Delta urban agglomeration and the Pearl River Delta urban agglomeration show obvious characteristics of spatial agglomeration. Most of them are located in areas with high industrial pollution and areas with higher industrial pollution. The above areas correspond to the distribution areas of the four major industrial bases in China. The Shanghai-Nanjing-Hangzhou industrial base is the largest comprehensive industrial base in China; the Liaoning-China-South industrial base is the heavy industrial base in northern China; the Beijing-Tianjin-Hebei urban cluster is the largest comprehensive industrial base in northern China; and the Pearl River Delta urban cluster is a comprehensive industrial base with a focus on light industry. From a spatial distribution perspective, the northern cities of Jinchang, Wuhai, Eldos, Shizuishan, Jiayuguan, Yangquan and Yuncheng have relatively high industrial pollution indices. On the one hand, because the north is a heavy industrial agglomeration, the steel industry in Hebei, the coal industry in Shanxi, the traditional heavy industry in central and southern Liaoning, and the Beijing-Tianjin-Hebei industrial hub, urban industrial pollution is more severe. On the other hand, the north has cold winters and a coal-dominated energy structure. Large amounts of coal are used for production and heating, exacerbating urban industrial pollution.

Spatio-Temporal Evolution Characteristics of Urban Industrial Pollution Indices

Analysis of Dagum Gini Coefficient

The overall degree of change in China's UIPI from 2005 to 2020 is shown in Fig. 4. Over the sample period, the overall Gini coefficient increases from 0.5009 in 2005 to 0.5571 in 2020, an increase of 11.2098%, or an average annual increase of 0.7437%. Over the sample period, the overall Gini coefficient increases from 0.5009 in 2005 to 0.5571 in 2020. This corresponds to an increase of 11.2098% and an average annual increase of 0.7437%. The results show that the evolution of inequalities in the industrial pollution index in Chinese cities has an overall fluctuating upward trend. In particular, the overall Gini coefficient rises even faster between 2015 and 2020, increasing by 11.0546%, with an average annual increase of 2.1664%. The reason may be that the 19th Party Congress has pushed the construction of ecological civilisation to a new level,

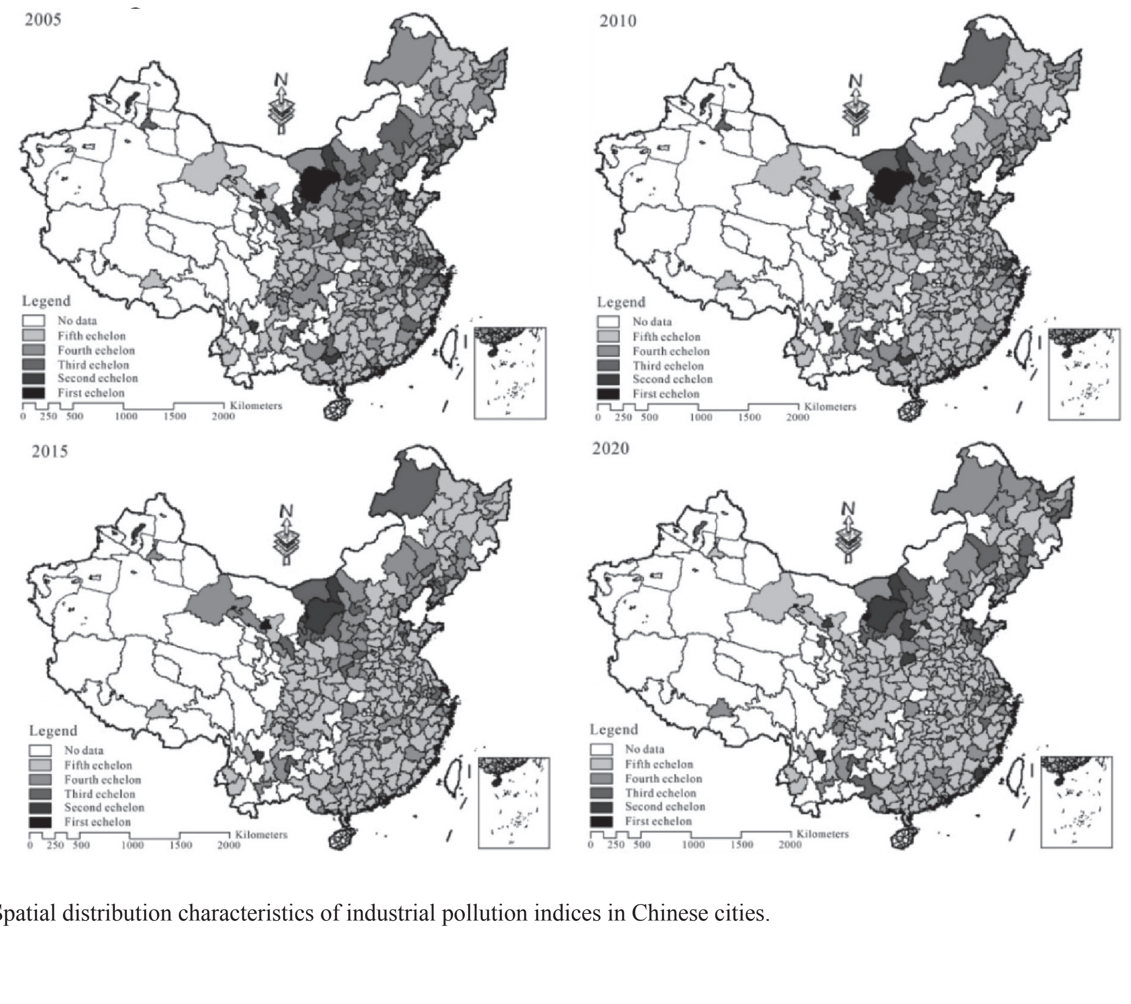

Fig. 3. Spatial distribution characteristics of industrial pollution indices in Chinese cities.

Fig. 4. Time-series characteristics of overall Gini industrial pollution index in Chinese cities.

and the structural adjustment and pollution treatment of key regions and industries have continued to increase. As a result, the UIPI has been reduced to varying degrees and the overall differentiation has improved.

The degree of regional variation in urban industrial pollution in China, the sources of variation and the degree of contribution are shown in Fig. 5. In terms of the magnitude of the annual average of the contribution, the contribution of the super-variable density is the largest (46.4479%). This means that the problem of overlap between different regions has an important impact on the UIPI in China. This is followed by the contribution rate of intra-regional differences (27.4615%), and the contribution rate of inter-regional differences is the lowest (26.0905%). However, the contribution of inter-regional differences has gradually increased in recent years, exceeding the contribution of intra-regional differences since 2015 and mostly exceeding 30% since 2016. In terms of trends, the contribution of intra-regional variation has slightly decreased, by only 0.1897%. The contribution of inter-regional variation has increased significantly, by 66.3253%. The contribution of hypervariable density has decreased by 24.1831%.

The temporal trend characteristics of the intra-regional and inter-regional variation of industrial pollution in Chinese cities are shown in Fig. 6. Due to the differences in socio-economic development between different regions, in order to explore the differences in industrial pollution development in heterogeneous regions, this article divides the cities into four major regions: East, Central, West and Northeast. In terms of intra-regional variation, there has been an increase in

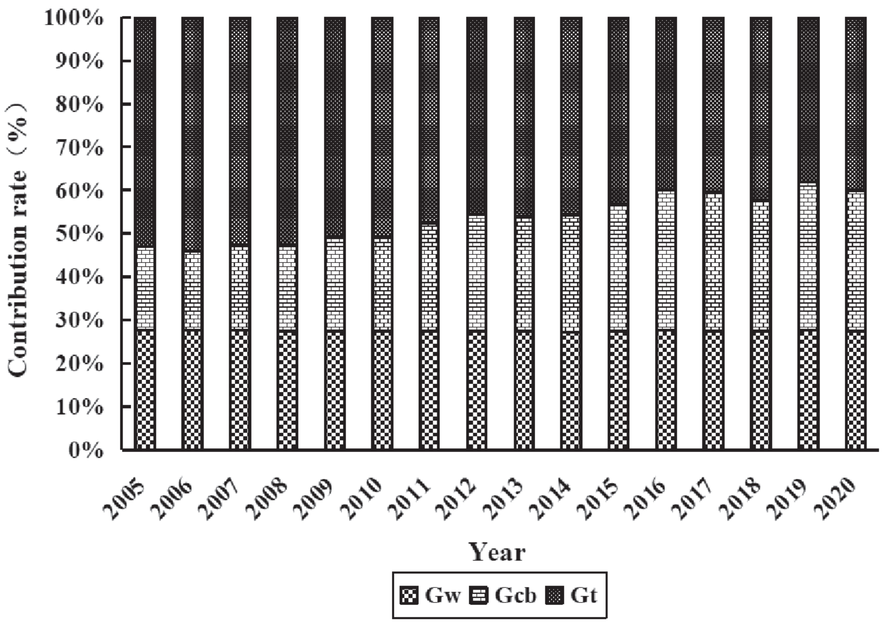

Fig. 5. Time-series characteristics of regional contribution to industrial pollution in Chinese cities.

intra-regional variation in the eastern and central regions, with a larger increase in intra-regional variation in the east. From the annual mean of intra-regional differences, the western region (0.6206), central region >central region (0.4691)>eastern region (0.3921)>north-eastern region (0.3201). In terms of interregional differences, the descending order is as follows Central-West (0.5862)> East-West (0.5557)>West-North-East (0.5365)>Central-East (0.4387)>Central-North-East (0.4126)>East-North-East (0.3632). In terms of the development trend of interregional differences, the regional differences of the West-Northeast, East-Northeast, East-Central and Central-Northeast are in an expansion trend. Among them, the West-Northeast increased by 10.4822% and tended to expand more. Possible reasons for the large differences between the western and northeastern regions are that the northeastern region is an old industrial base, where most of the country's traditional industries such as steel, machinery, automobiles and chemicals are concentrated, and therefore there is more pressure to reduce industrial pollution. The western region has a diverse ecological environment and is an important ecological barrier in China. With the gradual promotion of the western development policy, the latter advantage of environmental protection has gradually emerged, and industrial pollution in western cities has been well controlled.

Analysis of Standard Deviation Ellipse

To further explore the spatial distribution state and variation characteristics of urban industrial pollution, the standard deviation ellipse analysis tool is used. The parameters of the ellipse of standard deviation of China's UIPI are shown in Table 2. Overall, the average geometric centroid of the ellipse is approximately (112°37′25″E, 34°41′23″N). It is located in Henan Province. However, the distribution of urban industrial pollution in Henan Province is not normal as it is not a catchment area for urban industrial pollution. The standard deviation ellipse is mainly north-east-south-west oriented, but in 2015 it was north-west-south-east oriented. The most likely reason for this is that the intensity of urban pollution control in some areas is different from previous years due to policy changes. This has led to a change in the direction of the spatial distribution of urban industrial pollution. The area of the oval gradually increases from 3,067,460,000 km^2 in 2005 to 3,457,540,000 km^2 in 2020, an increase of 12.7167%. This indicates a general trend of diffusion and transfer of urban industrial pollution. The shape of the distribution shows that both the long and short axes of the ellipse have become longer. The length of the long axis has increased by 10.7685% and the length of the short axis has increased by 1.7590%, with the long axis telescoping more than the short axis. The shape index shows a flattening trend of "increase - decrease - increase - decrease" with an overall decrease.

Fig. 7 shows the ellipse of the standard deviation of China's UIPI and its centroid migration trajectory. The centroid of China's UIPI shows a development trend of migration from northwest to southeast, as shown in Fig. 7. The spatial distribution of China's UIPI gradually shows a more variable pattern of change, with the average annual migration rate changing roughly from slow to accelerated.

Global Moran Index Test

Stata 15.0 software was used to calculate the global Moran index for China's industrial pollution index from 2005 to 2020, and the results are shown in Table 1. The results in Table 1 show that the global Moran index of the industrial pollution index in Chinese cities varied between 0.056 and 0.214 over the sample period, and all of them passed the 1% significance level. This indicates that the overall industrial pollution index in Chinese cities has a strong spatial dependence and is not randomly distributed in space.

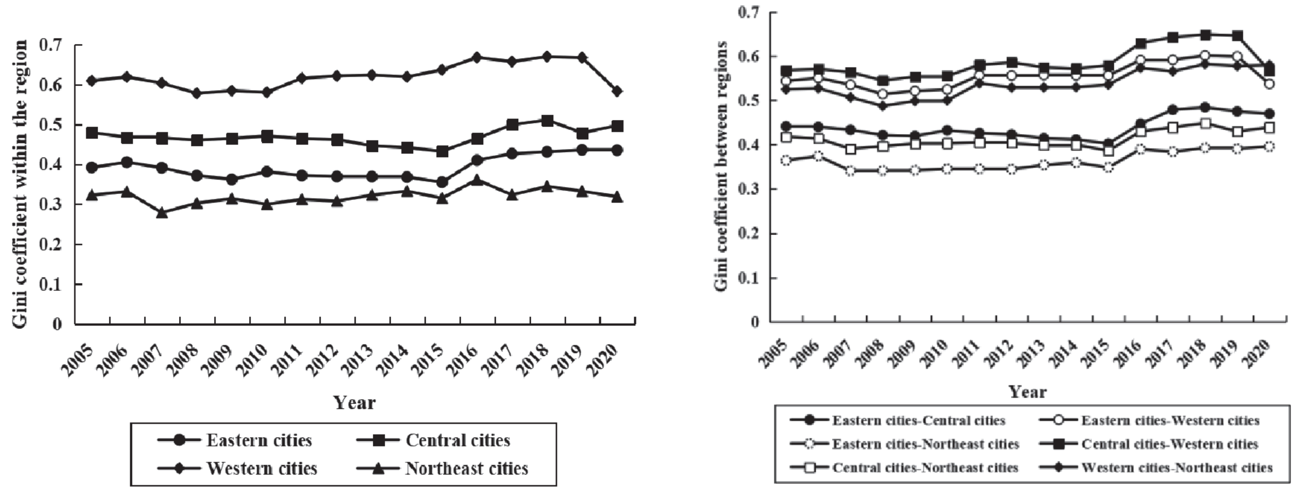

Fig. 6. Temporal characteristics of intra-regional and inter-regional industrial pollution in Chinese cities.

Table 2. Standard deviation ellipse parameters for industrial pollution in Chinese cities.

Year	Center of gravity	Long half shaft / km	Short half shaft /km	Azimuth /(°)	Area / millio km^2	Shape Index
2005	(112°48′03″E, 34°49′49″N)	1045.387	934.060	7°25′18″	306.746	0.894
2010	(112°34′54″E, 34°46′55″N)	1098.186	963.804	5°47′53″	332.500	0.878
2015	(111°52′41″E, 35°33′52″N)	1056.190	1019.78	160°39′09″	338.357	0.966
2020	(113°14′01″E, 35°12′26″N)	1157.959	950.490	25°16′04″	345.754	0.821

Note: Data measured using ArcGIS 10.5 software; data for Hong Kong, Macau and Taiwan are not included.

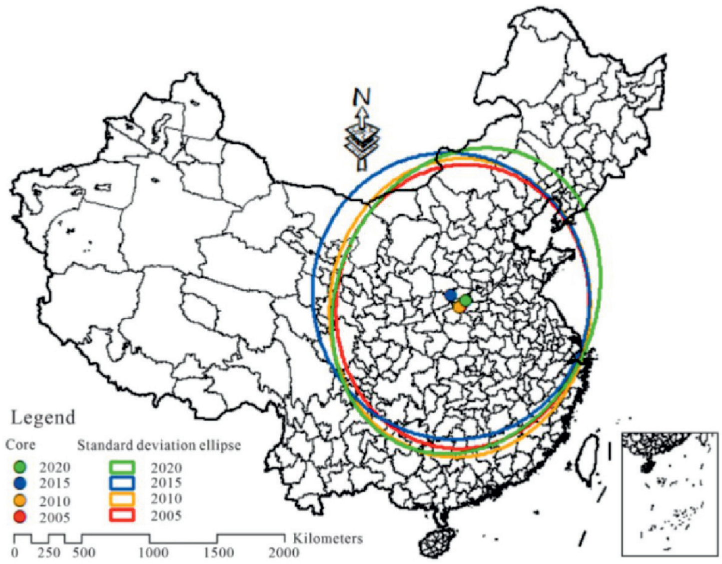

Fig. 7. Standard deviation ellipses of industrial pollution indices and their centroid migration trajectories for Chinese cities.

Local Moran Index Test

The global Moran index test tests the spatial correlation of the UIPI but does not know the spatial agglomeration status, whereas the local Moran index can detect outliers or areas where the agglomeration is located. The local Moran index test is presented as a Moran index scatterplot and the results are shown in Fig. 7. The Moran index scatterplot is divided into four quadrants, with the first and third quadrants representing high value (H-H) and low value (L-L) agglomerations, and the second and fourth quadrants representing low-high (L-H) and high-low (H-L) agglomerations. The dispersion of the Moran index

Table 1. Global Moran index of industrial pollution index in Chinese cities.

Year	Moran'I	Z value	Year	Moran'I	Z value
2005	0.125***	4.711	2013	0.170***	6.443
2006	0.184***	6.846	2014	0.183***	6.905
2007	0.188***	6.927	2015	0.151***	5.97
2008	0.214***	7.843	2016	0.056***	3.237
2009	0.185***	6.793	2017	0.126***	4.906
2010	0.181***	6.656	2018	0.130***	5.053
2011	0.159***	5.953	2019	0.067***	2.832
2012	0.181***	6.815	2020	0.097***	3.704

Note: ***/**/* indicates significance at 1%/5%/10% level.

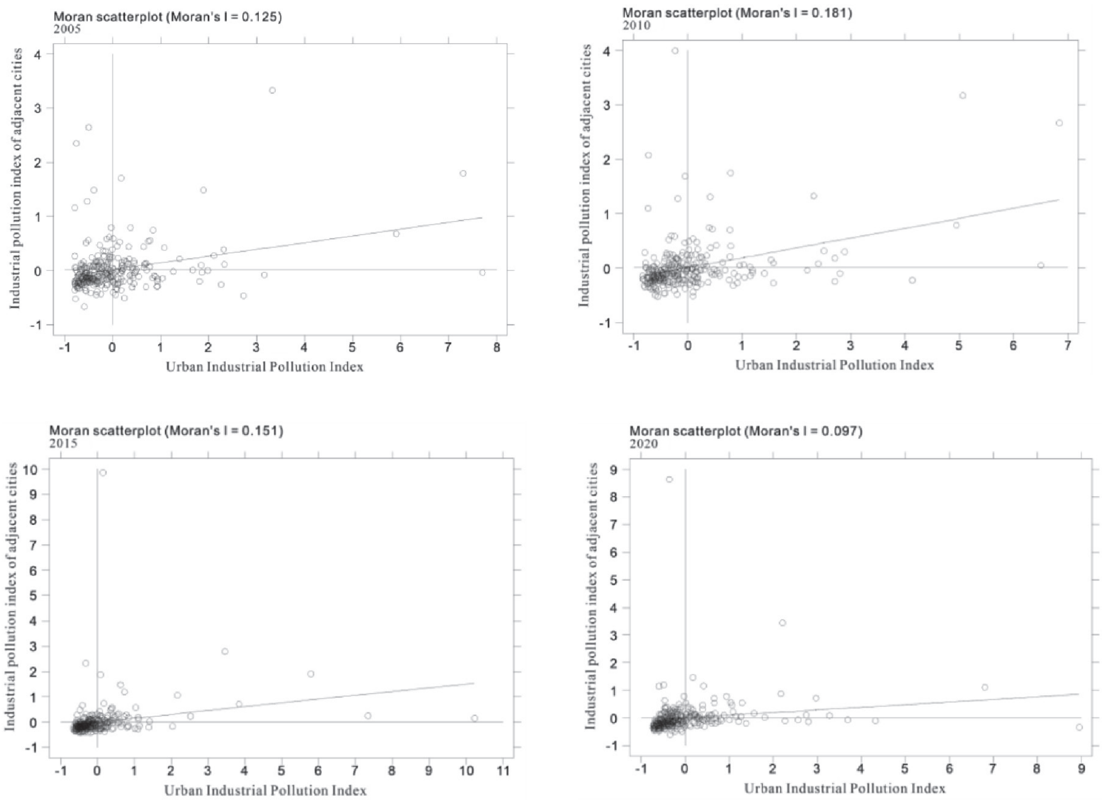

Fig. 8. Scatter plot of local Moran index of industrial pollution in Chinese cities.

of urban industrial pollution is mainly concentrated in the first and third quadrants, as can be seen in Fig. 7. This indicates that there is a positive spatial correlation in the distribution of the UIPI and that the spatial distribution pattern is dominated by the clustering of areas with lower industrial pollution.

Analysis of Influencing Factors

After correlation testing, the optimal model is selected as the analytical model in this paper. The models all pass the Hausman test at the 1% significance level and the fixed effects model is superior. According to the LR test, the spatio-temporal dual fixed effects model and the spatial Durbin model selected in this paper are the optimal models. The decomposition model of the spatial Durbin model is selected as the core object of analysis in this paper because the spatial Durbin model cannot accurately estimate the spatial spillover effects of indicators. The regression results of the spatial Durbin decomposition model on the UIPI for the national cities and the four regional cities are shown in Tables 2 and 3. Among them, models (1) (3) (5) (7) (9) are direct effect models and models (2) (4) (6) (8) (10) are indirect effect models.

The empirical results of the national model of direct urban effects are shown in model (1). The empirical results show that three factors, including human capital, capital stock, technological innovation and agglomeration, significantly inhibit urban industrial pollution. Human capital is an important production factor. Cities with high human capital have a greater ability to attract technology, which is conducive to the diffusion and diffusion of new technologies and the reduction of urban industrial pollution emissions. The capital stock has been revitalised, and the vigorous promotion of environmental infrastructure projects will be more conducive to the rapid development of the environmental protection industry. To reduce pollution from urban industries, scientific and technological innovation can provide more efficient, economical and sustainable environmental solutions. Economic agglomeration promotes the efficient concentration of production factors. It generates economies of scale, improves the efficiency of resource use and reduces industrial pollution emissions.

The empirical results of the indirect effects model for national cities are presented in model (2). The empirical results show that there is a spatial spill-over effect on the inhibitory effect of human capital and economic agglomeration on industrial pollution in neighbouring cities. Human capital, as a carrier of knowledge and technological progress, effectively promotes clean technology R&D and innovation transfer and transformation. It also has a spatial spillover effect in controlling industrial pollution in neighbouring cities. Economic agglomeration accelerates the regional flow, convergence and diffusion of production factors between cities and has a spillover effect on neighbouring cities. This also improves the factor and industrial structure of neighbouring cities and helps to reduce industrial pollution in neighbouring cities.

The regression results for the four main regional cities are shown in models (3) to (10). The empirical results show that each factor has a heterogeneous effect on urban industrial pollution in different regions. From the perspective of eastern cities, industrial structure, fiscal decentralisation, foreign investment and technological innovation are conducive to reducing urban industrial pollution. Capital stock has a suppressive effect on industrial pollution in neighbouring cities. From the perspective of central cities, human capital, capital stock and economic agglomeration have a significant inhibitory effect on industrial pollution in local cities. Factors such as industrial structure, human capital and technological innovation are conducive to reducing industrial pollution in neighbouring cities. From the western cities, factors such as industrial structure, foreign investment, capital stock and technological innovation have a significant inhibitory effect on industrial pollution in local cities. On the other hand, factors such as financial development and economic agglomeration help to reduce industrial pollution in neighbouring cities. Factors such as fiscal decentralisation, financial development, capital stock and technological innovation are conducive to reducing industrial pollution in neighbouring cities, while factors such as human capital and economic agglomeration have a significant inhibitory effect on industrial pollution in local cities. Possible reasons for the differences in drivers between regions are: on the one hand, industrial pollution has regional imbalance characteristics, and different industrial pollutants also have regional differences. As a result, the effectiveness of regional industrial pollution control varies. On the other hand, due to differences in economic development conditions

Table 2. Decomposition model of the spatial Durbin model for the national and eastern cities.

VARIABLES	National cities		Eastern cities	
	(1)	(2)	(3)	(4)
	LR_Direct	LR_Indirect	LR_Direct	LR_Indirect
Ind	-0.00002	0.00041	-0.00017*	0.00042*
	(0.00009)	(0.00026)	(0.00010)	(0.00025)
Edu	-0.00617***	-0.00705*	0.00707***	0.00929***
	(0.00107)	(0.00391)	(0.00126)	(0.00355)
Fiscal	0.00351	0.02927*	-0.01160**	0.02544*
	(0.00495)	(0.01664)	(0.00563)	(0.01465)
Fin	0.00143***	-0.00182	0.00046	-0.00064
	(0.00028)	(0.00119)	(0.00039)	(0.00095)
FDI	-0.00021	0.00070	-0.00042*	0.00039
	(0.00018)	(0.00078)	(0.00024)	(0.00075)
Cap	-0.00288*	0.01056**	0.00572***	-0.00699**
	(0.00154)	(0.00473)	(0.00143)	(0.00353)
Tech	-0.00017***	0.00030***	-0.00015***	-0.00006
	(0.00005)	(0.00010)	(0.00002)	(0.00006)
Agglo	-0.00218**	-0.02512***	0.00063	-0.00063
	(0.00105)	(0.00429)	(0.00092)	(0.00244)
GDP	0.02100***	0.01046*	0.01825***	0.00057
	(0.00205)	(0.00585)	(0.00239)	(0.00535)
SDM-SAR	165.03***		168.63***	
SDM-SEM	228.13***		230.74***	
BOTH--IND	58.98***		48.71***	
BOTH--TIME	5015.44***		1525.57***	
Hausman Test	109.73***		62.69***	
Observations	4,560		1,392	
R-squared	0.0414		0.0692	
Number of id	285		87	

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.

Table 3. Decomposition models for the central, western and north-eastern urban areas Durbin decomposition models.

VARIABLES	Central cities		Western cities		Northeastern cities	
	(5)	(6)	(7)	(8)	(9)	(10)
	LR_Direct	LR_Indirect	LR_Direct	LR_Indirect	LR_Direct	LR_Indirect
Ind	0.00047***	-0.00046*	-0.00053**	-0.00028	-0.00019	-0.00044
	(0.00011)	(0.00028)	(0.00022)	(0.00060)	(0.00014)	(0.00036)
Edu	-0.01207***	-0.01079***	-0.00457	-0.00129	-0.00507***	0.00130
	(0.00121)	(0.00365)	(0.00288)	(0.00915)	(0.00162)	(0.00473)
Fiscal	0.00060	-0.02289	0.02017	0.21733***	0.01329	-0.03156*
	(0.00477)	(0.01494)	(0.01397)	(0.04371)	(0.00947)	(0.01909)
Fin	0.00165***	-0.00052	0.00389***	-0.00663*	0.00034	-0.00282**
	(0.00026)	(0.00087)	(0.00110)	(0.00370)	(0.00029)	(0.00134)
FDI	0.00033	0.00164***	-0.00248**	0.00128	-0.00001	0.00191***
	(0.00023)	(0.00060)	(0.00106)	(0.00344)	(0.00016)	(0.00061)
Cap	-0.00555***	0.00755**	-0.00964*	0.03538***	0.00465	-0.01714***
	(0.00163)	(0.00359)	(0.00500)	(0.01364)	(0.00295)	(0.00632)
Tech	-0.00001	-0.00111***	-0.00112***	-0.00054	0.00028	-0.00449***
	(0.00013)	(0.00030)	(0.00041)	(0.00082)	(0.00036)	(0.00104)
Agglo	-0.00648***	0.00092	-0.00192	-0.04609***	-0.00404**	0.00393
	(0.00159)	(0.00447)	(0.00252)	(0.00967)	(0.00200)	(0.00723)
GDP	0.03963***	0.01067	0.01995***	0.04088***	0.01251**	0.00824
	(0.00345)	(0.00905)	(0.00412)	(0.01236)	(0.00488)	(0.01153)
SDM-SAR	108.08***		94.89***		92.64***	
SDM-SEM	112.34***		108.81***		108.93***	
BOTH--IND	89.53***		32.31***		24.70***	
BOTH--TIME	1240.45***		1267.76***		377.96***	
Hausman Test	45.29***		58.95***		20.34***	
Observations	1,280		1,344		544	
R-squared	0.1608		0.0325		0.5138	
Number of id	80		84		34	

Note: In parentheses denote the standard error of the respective coefficients, ***/**/* indicates the significance at the 1%/5%/10% levels, respectively.

and resource endowments, there are differences in the focus of industrial pollution control in different regions.

Conclusions

This paper explores the spatial and temporal evolution characteristics of urban industrial pollution in China based on the panel data of 285 cities above prefecture level in China from 2005 to 2020, using the entropy method to measure the comprehensive index of urban industrial pollution, and the natural break method, Dagum Gini coefficient, standard deviation ellipse and exploratory spatial analysis tools. A spatial Durbin decomposition model was applied to study the influencing factors of industrial pollution in Chinese cities. The results of the study are as follows:

(1) In terms of the characteristics of the trend over time, the UIPI generally shows a clear downward trend, especially since 2016, the UIPI shows a discontinuous decrease. Western cities, northeastern cities, eastern cities and central cities are ranked according to the annual average value of the UIPI. Spatial distribution characteristics, the UIPI shows

local clustering characteristics, the spatial distribution of large differences. The northern region, the central-southern urban agglomeration, the Yangtze River Delta urban agglomeration and the Pearl River Delta urban agglomeration show obvious spatial agglomeration characteristics. Most of them are located in areas with high industrial pollution and areas with higher industrial pollution. In the northern cities, the industrial pollution index is relatively high.

(2) In terms of evolutionary characteristics, the differences in the evolution of China's UIPI show an overall fluctuating upward trend. In terms of the magnitude of the annual mean contribution, the hypervariable density contribution is the largest, followed by the intra-regional variation contribution, and the inter-regional variation contribution is the smallest. There has been an increase in intra-regional variation in the eastern and central regions, with a greater increase in intra-regional variation in the east. The largest differences were found between the western and north-eastern regions. The UIPI has a non-normal distribution, with a cluster in Henan Province. The migration speed plus gradually accelerated the development trend of the migration direction of the centre of gravity from northwest to southeast. The UIPI is distributed in the "northeast-southwest" direction, and there is a development trend of diffusion and transfer to surrounding cities.

(2) In terms of evolutionary characteristics, the differences in the development of China's UIPI show an overall fluctuating upward trend. In terms of the magnitude of the annual mean contribution, the hypervariable density contribution is the largest, followed by the intra-regional variation contribution, and the inter-regional variation contribution is the smallest. There has been an increase in intra-regional variation in the eastern and central regions, with a greater increase in intra-regional variation in the east. The largest differences were found between the western and north-eastern regions. The UIPI has a non-normal distribution, with a cluster in Henan Province. The migration speed plus gradually accelerated the development trend of the migration direction of the centre of gravity from northwest to southeast. The UIPI is distributed in the "northeast-southwest" direction, and there is a development trend of diffusion and transfer to surrounding cities.

(3) In terms of spatial correlation, China's UIPI has a strong spatial dependence. The spatial distribution pattern is dominated by the clustering of areas with lower industrial pollution. In this paper, a decomposition model of the spatial Durbin model is selected to further explore the influencing factors of industrial pollution in Chinese cities. Among the influencing factors, three factors such as human capital, capital stock, technological innovation and economic agglomeration have important inhibiting effects on urban industrial pollution. The inhibiting effect of human capital and economic agglomeration on industrial pollution in surrounding cities has a spatial spillover effect. From a sub-regional perspective, each factor has a heterogeneous impact on urban industrial pollution in different regions.

The shortcomings of this article can be divided into two main parts. First, the study did not examine the likelihood of urban industrial pollution spreading between regions. The level of industrial pollution in cities is a dynamic development. It can be transformed into varying degrees of industrial pollution in space. The spatial transfer probability of urban industrial pollution can be measured using Markov chains in future research. The second is to measure the performance of industrial pollution control. The performance of urban industrial pollution control is also an important research topic, although it is necessary to study the level of urban industrial pollution. The effectiveness of industrial pollution control has become a hot topic. Future research is needed to understand which regions are more effective in controlling industrial pollution and what factors promote urban industrial pollution control.

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Conflict of Interest

The authors declare no conflict of interest.

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