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Analyzing China's provincial pollution and its influencing factors: A spatial analysis

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Abstract: In-depth analyses of the spatial heterogeneity in pollution, and the causes of differences are of great importance for contributing to provide reference for reduction policies. However, a spatial analysis of the existence and mechanism of China's pollution is still ignored. Using the province-level data of thirty provinces in China over 2005-2017, this paper constructs a spatial Durbin model (SDM) to empirically address the existence and spatial transmission mechanism of pollution. The main results are as follows: first, China's pollution shows significant characteristics of spatial dependence and clustering from global and local perspectives, indicating that the existence of spatial autocorrelation in pollution across regions. Second, both per capita GDP and urbanization have positive impacts on pollution, but the impacts of environmental regulation and FDI are insignificant. Third, urbanization not only directly influences pollution, but also indirectly influences pollution. Our analysis provides valuable information for developing policies to effectively alleviate pollution.

Keywords: Pollution; Spatial econometric model; Influencing factors; Spatial effects

1. Introduction

Since the reform and opening-up policy in the past 40 years, China's economy has achieved an annual growth of 9.4% from 1979 to 2018 (Chen et al., 2019). In 2009, China exceeded the U.S. and became the largest consumer in the world. Meanwhile, from a value of 396.6 million tons oil equivalent (Mtoe) in 1978, China's energy consumption rose to a maximum of 3237.5 Mtoe in 2018 (BP, 2019). As the coal-based energy, environmental degradation has become increasingly serious along with large energy consumption (Yang et al., 2017; Withagen, 1994; Zhou et al., 2016). In 2013, the haze weather posed a massive threat to the nationwide area of the country (Nie et al., 2020). Moreover, more than 64% of Chinese cities exceed the standards for air quality in 2018 (Li et al., 2020).

To deal with the heavy pollution, China formulated a series of environmental policies to mitigate pollutant emissions. In 2016, China issued its 13th Five-Year Plan, which clearly emphasized its goal of reducing carbon intensity by 18%, energy intensity by 15%. Facing the increasingly severe environmental degradation problems, an effective approach to achieving win-win goals for both economic growth and emissions reduction is to reduce pollutant emissions. China has actively made great efforts to control and mitigate pollution. However, China's pollution is continually growing at an

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alarming rate. The following questions, therefore, arises: 1) Do pollution have spatial externalities? 2) What is the distribution characteristics of pollution? 3) Does pollution have a spatial spillover effect in China? Answers to these three questions are of utmost significance in designing reduction policies and further to solve environmental pollution problems.

As for the relationship between pollution and its influencing factors, the extant research in the field of pollution can be broadly classified into two perspectives: first, the analysis of the influencing factors affecting pollution. A considerable amount of research has examined the validity of the EKC hypothesis and investigate whether environmental quality gradually improved economic growth. Based on this view, many research studies have been carried out on pollution (e.g., Guo and Lu,2019; Li et al., 2016; Stern et al., 1996; Stern, 2004). There is considerable amount of literature on pollution and its determinants. For example, Zhang et al. (2020) have analyzed the environmental regulation and carbon emissions nexus; Li and Lin (2014) measured China's energy intensity and found that industrial structure plays an important role in energy intensity; and Zhao et al. (2020) used a mediating effect model, revealing that environmental regulation plays a significant role in carbon emissions via investment. As mentioned previously, many influencing factors affect environmental pollution, including urbanization (Xu et al., 2019), transportation (Zhao et al., 2018), environmental regulation (Yang et al., 2020; Zhao et al., 2020). Second, construction of various models of empirical studies on pollution. Various methodologies have been used to empirically investigate the driving factors of pollution. From a methodological point of view, the extant researches have addressed two widely used methodologies, namely index decomposition analysis (Zhang et al., 2019) and structural decomposition analysis (Cao et al., 2019). However, these studies failed to take into consideration the spatial dependence, which makes the results biased. The spatial panel model is one of the novel characteristics of this paper, suggesting everything is more closely related to each other in spatial distribution (Tobler, 1970). Spatial econometric models consider both the effects of influencing factors and spillover effects with neighboring regions. In recent years, spatial econometric models have been widely applied to tackle environmental problems. For instance, Zhong et al. (2018) examined the factors influencing embodied carbon emissions using spatial econometric models to; You and Lv (2018) investigated the economic globalization and CO_2 emissions nexus, and tested the spatial spillover effects; and Zhu et al. (2020) analyzed the energy technology innovation and air pollution nexus utilizing spatial panel models.

In summary, previous scholars have extensively focused on pollution and its influencing factors. However, there are still some research gaps. Extant researches ignore the existence and mechanism of pollution from a spatial perspective. Undoubtedly, an accurately comprehensive understanding of the spatial transmission mechanism of pollution through a spatial econometric approach is a scientific basis for promulgating environmental policies to effectively control pollution. Regional heterogeneity and spatial correlation are essential characteristics affecting the impacts of driving factors of pollution. Due to the presence of spatial interconnection, the local pollution may exert spillover effects on the pollution of adjacent regions through

diffusion or radiation (Pan et al., 2015). Therefore, the environmental pollution of various regions are both interrelated and distinct. Whereas the spatial dependence and spatial correlation of economic units may exist among adjacent regions, ignoring significant spatial spillover effects would lead to bias in estimation results. On one hand, the exchange of resources or technology between regions may lead to the spatial spillover and diffusion effects of environmental pollution of one area, which affects neighboring areas. On the other hand, the gravitational effects of spatial units can lead to spatial correlations in pollution.

To fill these gaps, using a province-level data of thirty provinces spanning from the year 2005 to 2017, this paper explores the influencing factors on China's pollution, specifically to test the existence and spatial transmission mechanism from direct and spillover effects perspectives. More importantly, we provide a corresponding tailored strategy that can effectively examine the spatial spillover effects. This mostly differs from extant literature that hardly focuses on the spatial spillover effects of pollution. Therefore, considering the similarity of economic units among regions (Tobler, 1970), spatial effects cannot be ignored in policy effects. By performing these analyses, we expect to offer empirical evidence for the existence of spatial agglomeration in pollution, and to provide some policy implications for alleviating and curbing the growth of pollutant emissions.

The contributions of this paper are drawn as follows: First, this paper analyzes the impact of the main influencing factors on China's pollution from direct and spillover effects perspectives, to specifically clarify the potential spatial transmission mechanism. Our analysis not only contributes to the extant literature by investigating the influencing factors and mechanisms from the spatial spillover effects perspective, but also provides a new perspective for policy markers to promulgate pollution policies. Second, this paper quantitatively investigates the spatial characteristics and evolutionary patterns of pollution among different regions from global and local perspectives. This approach may identify the disparities more effectively. Third, considering the potential spatial dependence, we extend the extant literature by integrating the externalities of spatial units into the field of environmental economics, which provide some reference for future studies. Fourth, this paper also tests whether there is an Environmental Kuznets Curve (EKC) causal nexus between environmental degradation and economic development, which may fill such research gaps.

The structure of the paper is as follows. Section 2 describes the methodologies. Section 3 demonstrates the primary results of the paper. Section 4 discusses the implication of the results. Section 5 gives the conclusions.

2. Methods and Variable

2.1. Spatial autocorrelation test

Following Anselin (1988) and Elhorst (2010), the potential spatial autocorrelation is vital for spatial econometric analysis. The results that are based on the traditional panel model may be biased because the model does not capture the spatial autocorrelation. Based on this reason, appropriate spatial panel models should be used. Before performing spatial econometrical analysis, it is essential to explore the spatial autocorrelation of core variables. We use both the global and local spatial

autocorrelation tests for core variables. The calculation formulas are denoted as Eqs. (1)-(2):

$$I_{Global} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

$$I_{Local} = \frac{n(x_i - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \cdot \sum_{j=1}^{n} W_{ij}\,(x_j - \bar{x}) \tag{2}$$

where $\bar{x}$ represents the mean of x. W_{ij} represents a spatial weight matrix.

2.2. Regression models

The specification of the EKC is presented in Eq. (3):

$$\ln c_{it} = \beta_1 \ln y_{it} + \beta_2 (\ln y_{it})^2 + \delta z_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{3}$$

where c_{it} represents the pollution; $\ln y_{it}$, $(\ln y_{it})^2$ represent GDP per capita and squared GDP per capita. z_{it} indicates other variables. β_1, β_2, δ are the coefficients of explanatory variables. α_i represents cross-section effect. γ_t is the time effect, respectively. ε_{it} is a random error term.

First law of geography indicates everything is more closely interrelated to each other in spatial distribution (Tobler, 1970). The results of the traditional panel models would lead to bias if omitting the spatial autocorrelation (Anselin, 1988; Apergis, 2016; Maddison, 2006). To effectively consider potential spatial dependence, spatial panel models are necessary. The spatial panel model expands the ordinary least squares model (as shown in Eq. (4)). LeSage and Pace (2009) indicate the SDM integrates the spatial lag terms of explained variables and explanatory variables. The panel data SDM model is specified as Eq. (4):

$$\ln c_{it} = \rho \sum_{j=1}^{n} W_{ij}\, c_{jt} + \beta_1 \ln y_{it} + \beta_2 (\ln y_{it})^2 + \delta z_{it} + \sum_{j=1}^{n} W_{ij}\, X_{it}\theta + \alpha_i + \gamma_t + \varepsilon_{it} \tag{4}$$

where ρ is spatial autoregression coefficient. θ is the spatial lag term, denoting the effect from the independent variables on the explained variables.

Based on these above analytical models, this paper analyzes the impact of influencing factors on pollution from the perspective of spatial effects. Therefore, the detailed effect model of driving factors on pollution is constructed, and the basic form of the SDM model is established by integrating spatial factors, which is specified as Eq. (5):

$$ln\, c_{it} = \alpha + \rho \sum_{j=1}^{30} W_{ij}\, ln\, c_{jt} + \beta_1 lnfdi_{it} + \beta_2 lny_{it} + \beta_3 (lny)^2{}_{it} + \beta_4 tech_{it} + \beta_5 lnregu_{it}$$

$$+ \beta_6 urb_{it} + \theta_1 \sum_{j=1}^{30} W_{ij} lnfdi_{jt} + \theta_2 \sum_{j=1}^{30} W_{ij} lny_{jt} + \theta_3 \sum_{j=1}^{30} W_{ij} (lny)^2{}_{jt}$$

$$+ \theta_4 \sum_{j=1}^{30} W_{ij} tech_{jt} + \theta_5 \sum_{j=1}^{30} W_{ij} lnregu_{jt} + \theta_6 \sum_{j=1}^{30} W_{ij} urb_{jt} + \gamma_t + \mu_i$$

$$+ \varepsilon_{it} \tag{5}$$

where $tech_{it}$, $lnfdi_{it}$, $lnregu_{it}$, and urb_{it} denote technology, foreign direct investment, environmental regulation, and urbanization of thirty provinces.

Considering that different regions may have adjacent boundaries, and a possible spatial relationship among different regions, three kinds of spatial weight matrices are constructed (e.g., adjacent, geographical distance, and geography-economy weight matrices).

The adjacent matrix is based on the geographic location between the units, which is calculated as Eq. (6):

$$W_1 = \begin{cases} 1 & i \neq j \\ 0 & i = j \end{cases} \tag{6}$$

The geography-economy matrix is based on both geographical distance and spatial economic linkages, which is calculated as Eq. (7):

$$W_2 = \begin{cases} \frac{1}{d_{ij}} * \frac{1}{\left|\overline{GDP}_i - \overline{GDP}_j\right|} & i \neq j \\ 0 & i = j \end{cases} \tag{7}$$

Where $\overline{GDP_i}$ refers to the average actual GDP of the region i.

The geographical distance matrix is based on the latitude and longitude coordinates of the regions, which is calculated as Eq. (8):

$$W_3 = \begin{cases} \frac{1}{{d_{ij}}^2} & i \neq j \\ 0 & i = j \end{cases} \tag{8}$$

2.3. Decomposition effects

To consider the potential spatial spillover effects, the increase of explanatory variables will not only bring about the increase of local pollution, but also exert its spillover effects of adjacent regions through spillover effects, and then causes loop feedback effects. LeSage and Pace (2009) put forward a method to calculate the decomposition effects. The matrix form of the SDM is denoted as Eq. (9):

$$E(Y) = (I - \rho W)^{-1}\mu + (I - \rho W)^{-1}(X\beta + WX\delta) \tag{9}$$

Formally, Eq. (9) can be rewritten as:

$$\left[\frac{\partial Y}{\partial X_{1r}} \cdots \frac{\partial Y}{\partial X_{nr}}\right] = \begin{bmatrix} \frac{\partial Y_1}{\partial X_{1r}} & \cdots & \frac{\partial Y_1}{\partial X_{nr}} \\ \vdots & \vdots & \vdots \\ \frac{\partial Y_n}{\partial X_{1r}} & \cdots & \frac{\partial Y_n}{\partial X_{nr}} \end{bmatrix}$$

$$= (I - \rho W)^{-1} \begin{bmatrix} \beta_r & W_{12}\theta_r & \cdots & W_{1n}\theta_r \\ W_{21}\theta_r & \beta_r & \cdots & W_{2n}\theta_r \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1}\theta_r & W_{n2}\theta_r & \cdots & \beta_r \end{bmatrix} \tag{10}$$

As displayed in Eq. (10), the direct, total, and indirect effects can be rewritten as:

$$M(r)_{direct} = (I - \rho W)^{-1}(\beta_r I)$$

$$M(r)_{indirect} = (I - \rho W)^{-1}(\theta_r W)$$

$$M(r)_{total} = (I - \rho W)^{-1}(\beta_r I + \theta_r W) \tag{11}$$

where $M(r)_{direct}, M(r)_{indirect}, M(r)_{total}$ represent the matrix of direct, indirect, and total effects of explanatory variables.

2.4. Variable

Since the Chinese government has promulgated a lot of reduction strategies in 2005, we use the provincial-level data of thirty provinces spans from 2005 to 2017 for analysis. The raw data employed in this paper are derived from the China Statistical Yearbook. The descriptions of all variables are depicted in Table 1. Existing studies generally adopt a more comprehensive indicator to calculate the pollution (Liu and Lin, 2019). However, most of them are not sufficiently defined. In this paper, per capita industrial sulfur dioxide emissions (SO_2 emissions) is selected as pollution indicators based on the following reasons: SO_2 emissions in China are relatively high and causing severe harm to people than CO_2 does, and due to the data availability (Xia et al., 2017; Wang and Luo, 2020; Xin and Zhang, 2020).

Similar to previous studies (Xin and Zhang, 2020), this paper select the following variables as independent variables: Economic development (PGDP), which is defined by the per capita GDP of each province. To control the EKC hypothesis, GDP per capita and squared GDP per capita are employed (Xie et al., 2019). Foreign direct investment (FDI), which is defined by the actual foreign investment of each province. Many studies confirmed that FDI is a key factor affecting environmental pollution (Zhang et al., 2020). Technology (TEC), which is measured by the number of patents. Theoretically, the higher the technology, the better the environment will be (Liu and Lin, 2019; Sun et al., 2019). Urbanization (UR), measured by the share of the urban population (Zhu et al., 2019). Environmental regulation (RE), which is represented by the share of the total industrial pollution-elimination in the GDP (Yin et al., 2015).

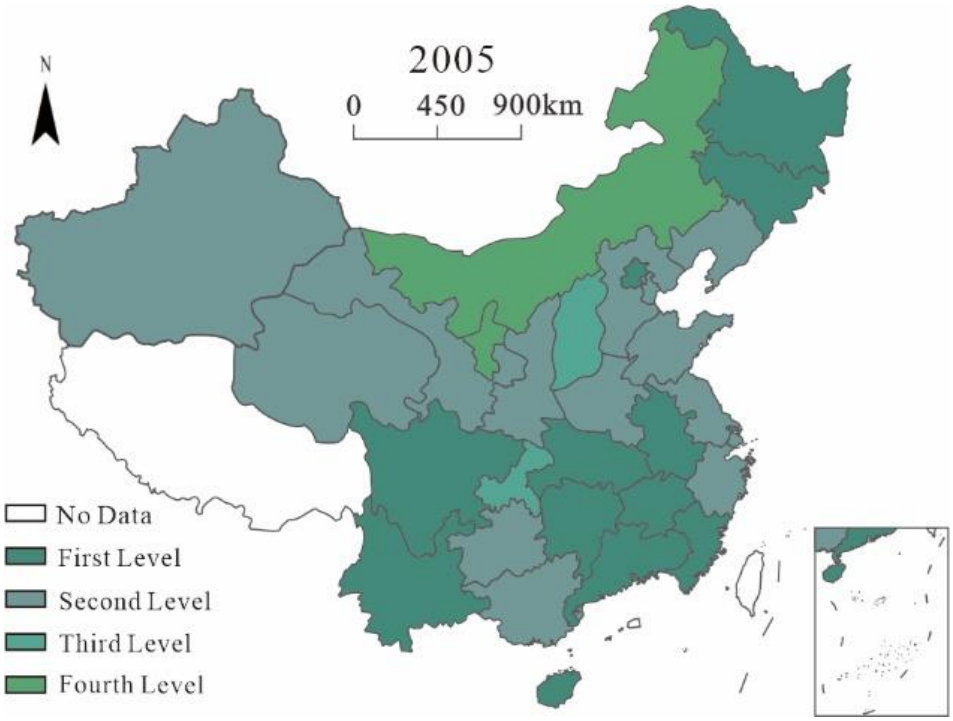
Table 1 The descriptive statistics of variables.

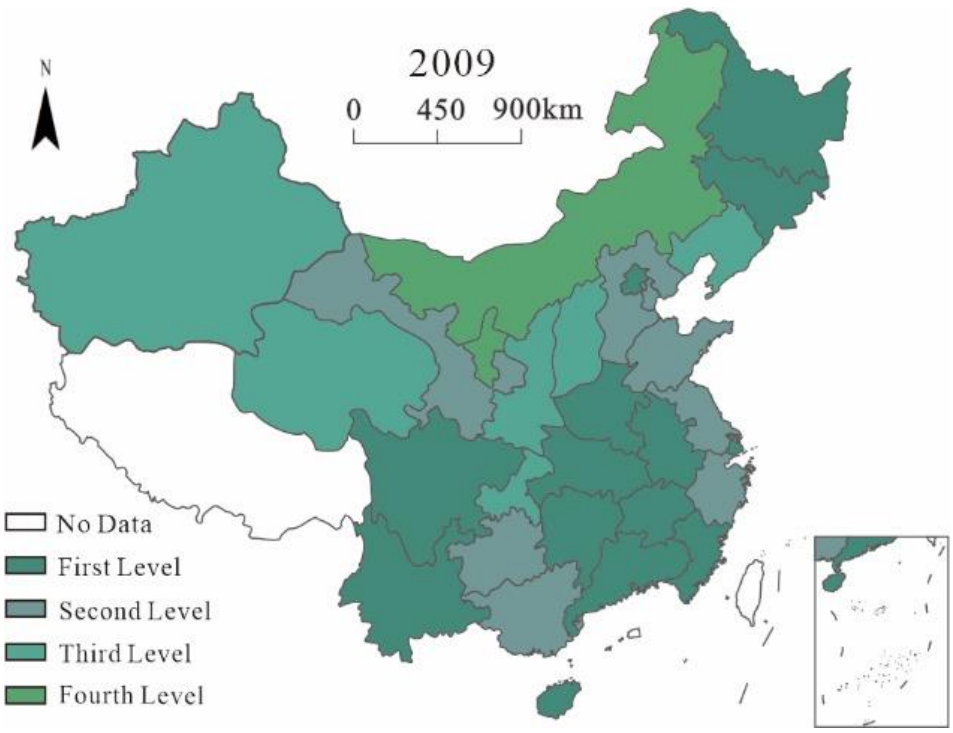
Variable	Definition	Mean	S.D
SO_2 emissions	industrial sulfur dioxide emissions per capita	0.016	0.011
economic level	GDP per capita	10.023	0.589
	squared GDP per capita	100.812	11.805
foreign direct investment	the share of FDI in the GDP	12.294	1.638
technology	number of patents	6.048	8.633
urbanization	urbanization rate	52.963	13.957
environmental regulation	the share of industrial pollution-elimination in the GDP	0.16	0.153

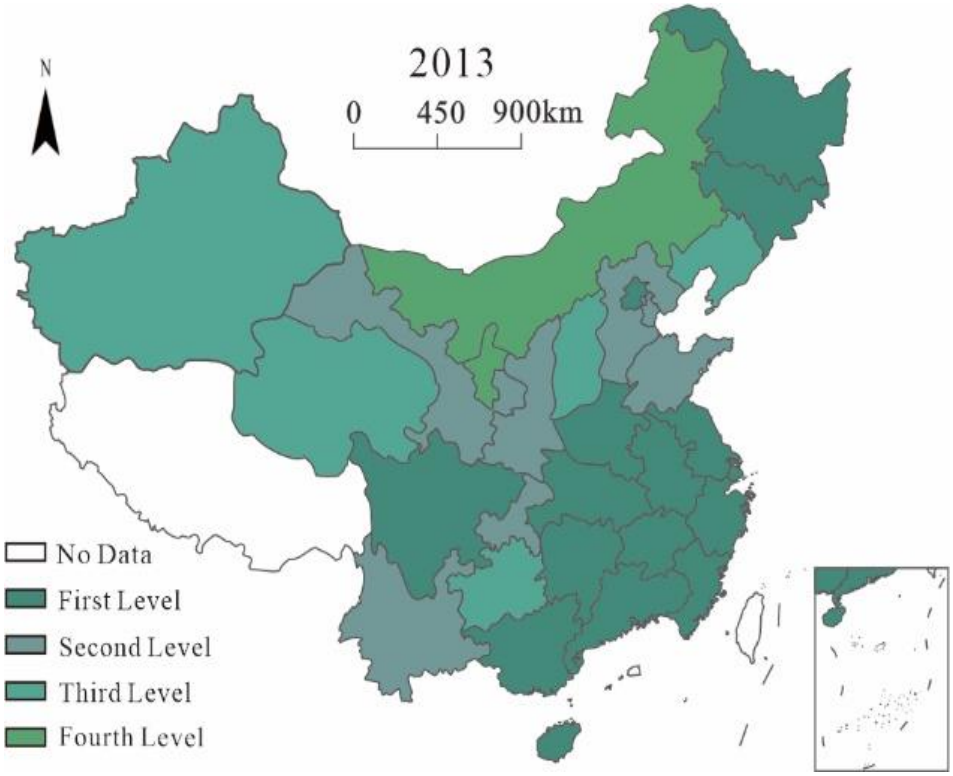
3. Results

3.1. Spatial autocorrelation analysis

The economic structure in various regions leads to significant differences in regional development modes. So, how are these differences reflected in the spatial distribution patterns and trends of provincial SO_2 emissions? Is SO_2 emissions dependent and clustered in space? According to the first law of geography, the spatial units on a geographical location are interrelated, which means that no region is isolated. Based on the above hypothesis, the quartile maps are mainly used to explore the tendency of provincial SO_2 emissions. Fig.1 shows the quartile maps of provincial SO_2 emissions in some years. As seen in Fig.1, SO_2 emissions displays both spatial disparity and clustering. In addition, Fig.1 shows that the provinces with the highest SO_2 emissions include Ningxia, Inner Mongolia, Guizhou, Xinjiang, Shanxi, and Qinghai while Hunan, Henan, Guangdong, Hainan, Shanghai, and Beijing had the lowest SO_2 emissions in 2017. In summary, there is a spatial agglomeration trend of the SO_2 emissions in regions.




2009
N
0 450 900km
No Data
First Level
Second Level
Third Level
Fourth Level


2013
N
0 450 900km
No Data
First Level
Second Level
Third Level
Fourth Level

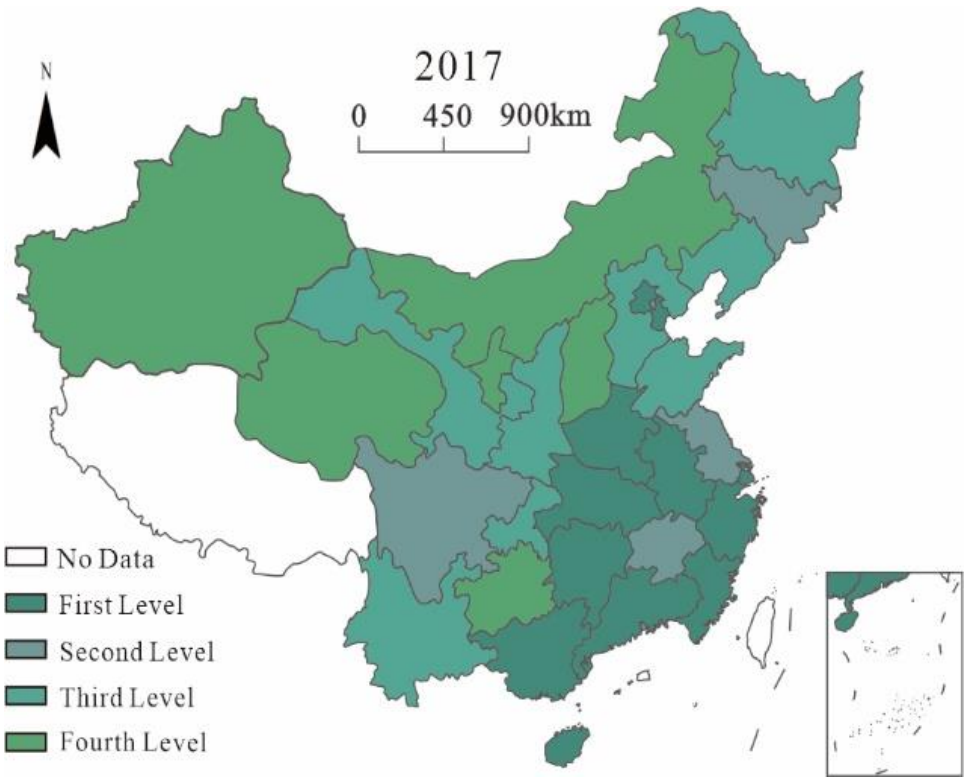


Fig.1. Quartile maps of SO_2 emissions

To further investigate the existence of spatial autocorrelation, the Moran's I indices are listed in Fig.2. Fig.2 indicates, Moran's indices from 2005 to 2017 are greater than 0, suggesting that the spatial distribution of SO_2 emissions among different regions presents positive spatial autocorrelation. That is, China's SO_2 emissions exhibits obvious spatial agglomeration characteristics. This indicates that provinces with higher SO_2 emissions are surrounded by those of higher SO_2 emissions, while those of lower SO_2 emissions are surrounded by provinces with lower SO_2 emissions. Meanwhile, the Moran's I index exhibits a slightly changed increasing trend, suggesting that the positive spatial autocorrelation gradually rises.

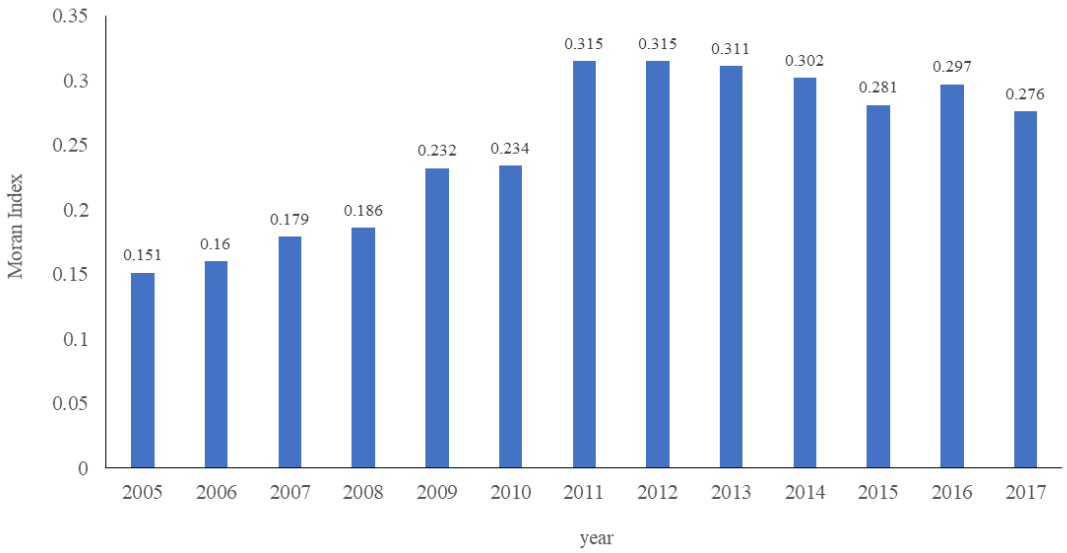
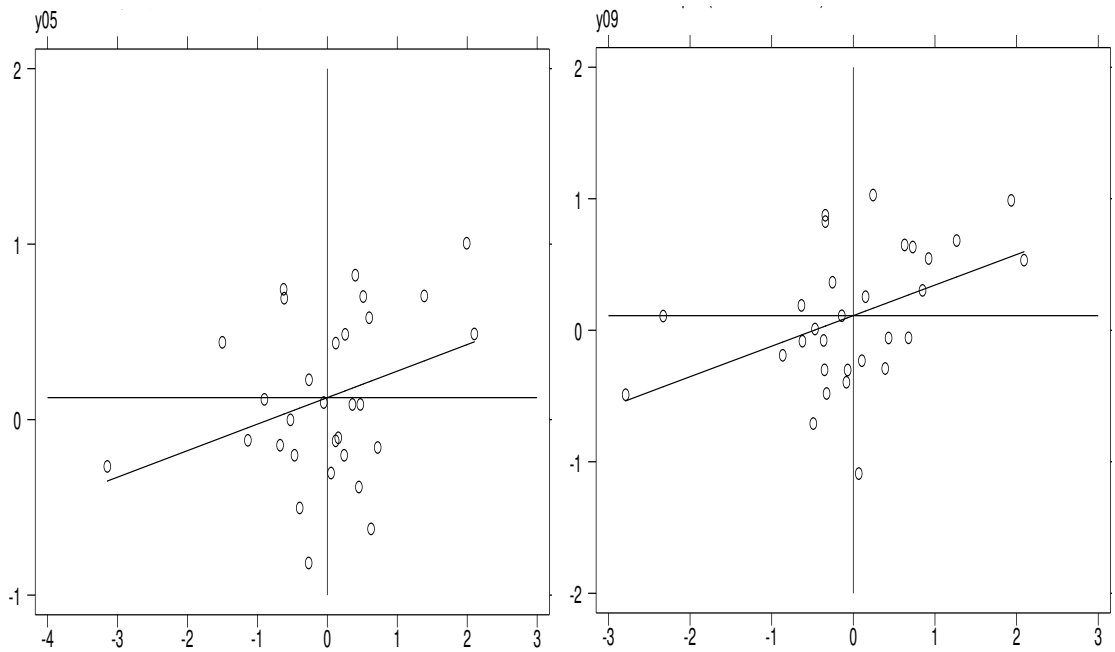


Fig. 2 Histogram of Moran's I.

To reveal the spatial autocorrelation in each province, the Moran scatter plots of SO_2 emissions in 2005, 2009, 2013, and 2017 are reported in Fig. 3. The SO_2 emissions can be broadly divided into four levels. Specifically, in 2017, the “H-H”-type includes Xinjiang, Chongqing, Shanxi, Yunnan, Ningxia, Inner Mongolia, Shaanxi, Jilin, Qinghai, Heilongjiang, Gansu, Liaoning. The “H-L”-type includes Henan, Guangxi, and Sichuan. The “L-L”-type includes Zhejiang, Hainan, Shanghai, Fujian, Beijing, Hunan, Guangdong, Anhui, Tianjin, Jiangxi, Hubei, Jiangsu. The “L-H”-type includes Hebei, Shandong, and Guizhou. Fig.3 shows that most provinces are located in “H-H”-type and “L-L”-type. In particular, 24 cities (“H-H” and “L-L”) had the same spatial autocorrelation, accounting for 80% of the total proportion. Six cities (HL and LH) had different negative spatial autocorrelations, accounting for 20% of the total proportion. More specifically, in 2005, the “H-H”-type include Liaoning, Gansu, Ningxia, Inner Mongolia, Hebei, Xinjiang, Shaanxi, and Shanxi. Those with high SO_2 emissions levels are spatially unchanged, indicating that there exists a stable agglomeration characteristic of SO_2 emissions. Consequently, these results show the significance of using spatial autocorrelation for the analysis of pollution. In summary, most branches of pollution are characterized by similar spatial correlation, and few branches show dissimilar spatial correlation.



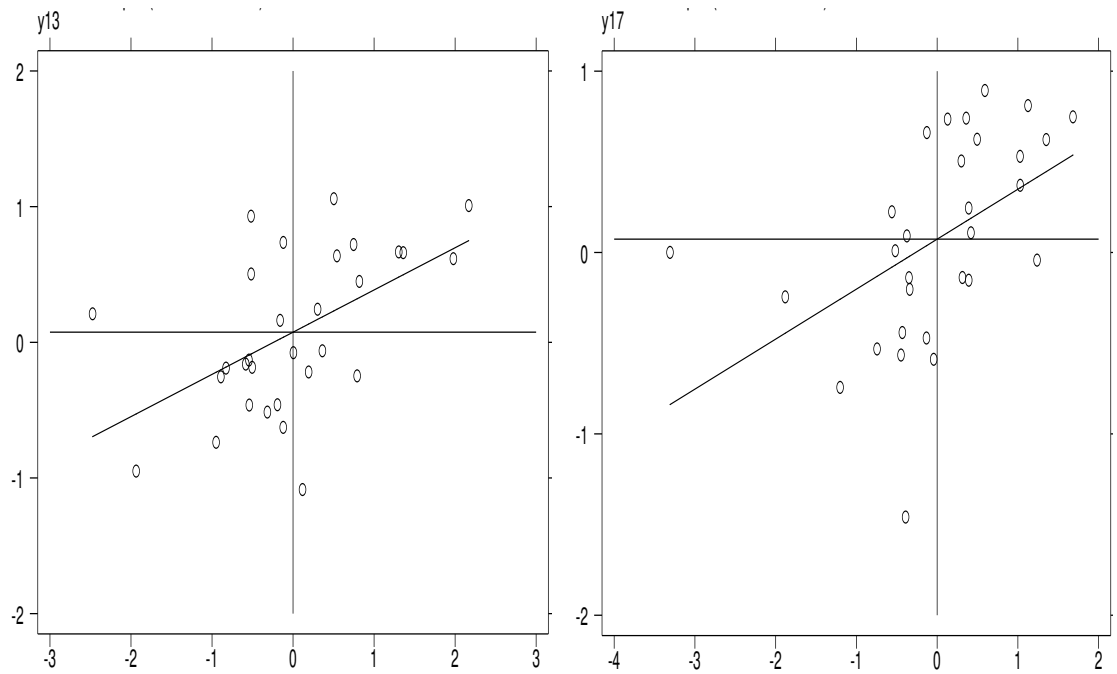


Fig. 3. Scatter plots of SO_2 emissions.

3.2. Analysis of regression results

The estimation results for the SDM model with matrices W1 and W2 are shown in Table 2. It is noteworthy that R^2 are relatively high, which suggests better fitting models. Thus, an analysis of the SDM model will then illustrate its driving factors. Specifically, the spatial lag coefficients have passed the 1% significant tests with matrices W1 and W2, which consequently confirms the presence of spatial autocorrelation of pollution during the research period. More importantly, the coefficients are significantly positive with matrices W1 and W2, suggesting that a growth in pollution of adjacent regions increases the local pollution. This result implies spatial spillover effects are significant on pollution in thirty provinces of China. Thus, it is vital for performing spatial econometric models, considering spatial effects, to analyze the driving factors affecting pollution and, to examine the spatial spillover effects.

As seen in Table 2, TEC exerts a negative impact on pollution with matrices W1 and W2, indicating that a higher technological level will result in less pollution. One possible reason, as suggested by the finding of Liu and Lin (2019), who argue that the improvement of technology can alleviate pollution. However, the coefficient of W*TEC is significantly positive with matrices W1 and W2, suggesting that the development of technology in other regions increases pollution in the local region. The coefficient of UR are both significantly positive with matrices W1 and W2, indicating that a higher proportion of urban population will result in more pollution. However, the coefficient of W*UR is significantly negative with matrices W1 and W2, suggesting that the increase of local urbanization reduces pollution. Meanwhile, the impact of FDI is not significant with matrices W1 and W2, indicating that the increase of foreign direct investment exerts no remarkable impact on the local pollution. However, the coefficient of W*lnFDI negatively influenced pollution with matrices W1 and W2, indicating that an increase in FDI of adjacent provinces decreases the local pollution. Moreover, the

influence of RE is significantly positive with matrix W2 whereas with matrix W1 is not significant. The coefficients of PGDP and squared PGDP are significantly positive and negative with matrices W1 and W2, respectively. It indicates an inverted U nexus between pollution and economic growth. Besides, W*lnPGDP positively influenced environmental pollution with matrices W1 and W2, suggesting that higher economic growth of adjacent provinces could increase the local pollution.

To overcome the limitations due to "point" parameter estimates in multivariate spatial regression, we examined the decomposition effects of the SDM, which bases its knowledge upon the methods presented by LeSage and Pace (2009). However, one change in the independent variables will not only bring about the growth of local pollution, but also affect the increase of pollution in its neighbors through spillover effects. Moreover, the gravitational effects of spatial units can lead to spatial correlations among variables. However, the aggregated composite effect cannot effectively capture the potential relationships between variables. Therefore, we apply this decomposition effects to the analysis of each influencing factor on pollution. In general, the decomposition effects can be divided into three categories: direct, total, and indirect effects. Specifically, the direct effect indicates the influence of factors on the local region's pollution, whereas the indirect effect suggests the influences of factors on other regions' pollution. The decomposition effects are calculated in Table 3.

Table 2 Regression results with SDM

	Variable	Coefficient	Variable	Coefficient
W1	lnFDI	-0.0199 (-0.9247)	W*lnFDI	-0.0938** (-2.4427)
	lnPGDP	2.4932*** (2.6043)	W*lnPGDP	4.3017*** (3.2104)
	$lnPGDP^2$	-0.1181** (-2.5665)	W*$lnPGDP^2$	-0.1916*** (-2.8991)
	TEC	-0.0194*** (-6.0601)	W*TEC	0.0150*** (3.2115)
	lnRE	0.0193 (0.9106)	W*lnRE	0.0677** (2.0289)
	UR	0.0449*** (5.7535)	W*UR	-0.1011*** (-7.9457)
	ρ	0.5420*** (11.6355)	R^2	0.9431
W2	lnFDI	-0.0295 (-1.3461)	W*lnFDI	0.025501 (0.4473)
	lnPGDP	1.8986* (1.8731)	W*lnPGDP	4.4415*** (2.7622)
	$lnPGDP^2$	-0.0914* (-1.8598)	W*$lnPGDP^2$	-0.2077*** (-2.6583)
	TEC	-0.0227*** (-7.3003)	W*TEC	0.0168*** (3.2658)
	lnRE	0.0441** (2.1677)	W*lnRE	-0.0116 (-0.3454)
	UR	0.0476*** (6.3840)	W*UR	-0.0948*** (-6.9087)
	ρ	0.5940*** (11.9951)	R^2	0.9449

Notes: *, **, and *** respectively represent significance at 10%, 5%, and 1%.

As listed in Table 3, the first column displays the direct effects. The direct effect of TEC is significantly negative with matrices W1 and W2. This indicates that the technology is further improved, the industrial structure has been gradually upgraded and optimized, and thus reducing the pollution. By using innovative clean technologies,

the cost of producing and using clean energy is greatly reduced. Therefore, a wider use of clean energy may be possible, which significantly decreases pollution. The direct effects of PGDP and UR are significantly positive with matrices W1 and W2, indicating that the development of and economic and urbanization increase pollution. However, the direct effect of FDI is not significant with matrices W1 and W2. The direct effect of RE is significant with matrices W2 whereas not significant with matrices W1.

In column 2 of Table 3 shows the indirect effects. The indirect effect of PGDP is positive and significant with matrices W1 and W2, implying that an increase in economic growth in neighboring provinces drives up the pollution. The indirect effect of RE is also positive and significant with matrix W1, whereas not significant with matrices W2. The indirect effect of UR influences pollution significantly negative with matrices W1 and W2, indicating that urbanization negatively affected pollution in neighboring regions through the spatial spillover effects. The indirect effect of FDI influences pollution is negative and significant with matrices W1. Moreover, the indirect effect of TEC is positive but insignificant with matrices W1 and W2.

In column 3 of Table 3 shows the total effects. The total effect of PGDP positively influenced pollution with matrices W1 and W2. The total effect of RE is also positive and significant with matrices W1. However, the total effect of UR negatively influenced pollution with matrices W1 and W2. FDI is also negative and significant with matrices W1.

Table 3 Decomposition effects of SDM

	Variable	Direct	Indirect	Total
W1	lnFDI	-0.0384 (-1.5317)	-0.2138** (-2.5375)	-0.2522** (-2.5220)
	lnPGDP	3.4396*** (3.5205)	11.4189*** (4.6590)	14.8585*** (5.2725)
	$\ln PGDP^2$	-0.1608*** (-3.3997)	-0.5166*** (-4.2901)	-0.6774*** (-4.8860)
	TEC	-0.0187*** (-5.6785)	0.0087 (0.9329)	-0.0101 (-0.9254)
	lnRE	0.0318 (1.4231)	0.1565** (2.5361)	0.1883** (2.6980)
	UR	0.0319*** (4.0952)	-0.1541*** (-6.1747)	-0.1221*** (-4.5408)
W2	lnFDI	-0.0288 (-1.1881)	0.0148 (0.1124)	-0.0141 (-0.0993)
	lnPGDP	2.6723** (2.5791)	13.1223*** (3.6242)	15.7946*** (4.0184)
	$\ln PGDP^2$	-0.1279** (-2.5307)	-0.6168*** (-3.4866)	-0.7447*** (-3.8571)
	TEC	-0.0222*** (-6.6553)	0.0078 (0.6436)	-0.0144 (-1.0371)
	lnRE	0.0460** (2.1326)	0.0287 (0.3845)	0.0746 (0.8963)
	UR	0.0388*** (5.3121)	-0.1568*** (-4.7933)	-0.1180*** (-3.4174)

Notes: *, **, and *** respectively represent significance at 10%, 5%, and 1%.

3.3. Robustness test

To further test the validity of the above results, this paper utilizes the geographical distance matrix and, the result is shown in Table 4. As shown in Table 4, the coefficients are coherent with their coefficients in Table 2, suggesting that the empirical results are robust.

Table 4 Robustness test

Variable	Coefficient	Variable	Coefficient
lnFDI	-0.0489** (-2.2383)	W*lnFDI	0.3288** (2.1608)
lnPGDP	2.9080*** (2.7777)	W*lnPGDP	19.5952*** (4.3328)
$\ln PGDP^2$	-0.1529*** (-2.9460)	W*$\ln PGDP^2$	-1.1156*** (-4.6343)
TEC	-0.0247*** (-7.7656)	W*TEC	0.1052*** (4.2494)
lnRE	0.0255 (1.2283)	W*lnRE	0.2019*** (3.5633)
UR	0.0477*** (6.1470)	W*UR	0.0859** (2.0375)
ρ	0.6250*** (9.6695)	R^2	0.9446

Notes: *, **, and *** respectively represent significance at 10%, 5%, and 1%.

4. Discussion

Based on the decomposition effects of the SDM, foreign direct investment, economic growth, technology, environmental regulation, and urbanization all exert significant spatial effects.

Our results suggest that the direct effect of FDI is negative though insignificant, indicating that the effect of FDI on pollution is not clear yet. This is coherent with prior results from Cheng et al. (2017). On one hand, FDI can improve pollution through technology spillover effects. On the other hand, FDI can exacerbate pollution by transferring high-polluting industries. The interaction between two mixed effects makes the significance of FDI, which is not significant. Therefore, China should not only optimize the FDI structure in terms of quantity but also promote the FDI quality. In addition, technology has a negative effect on pollution, which is consistent with the finding by Sun et al. (2019). This indicates that the development of technology can remarkably decrease pollution, that is, the improvement of technological progress is helpful to reduce pollution. Technology brings negative impacts on pollution through the optimization of industrial structure, which greatly reduced a greater reduction of pollutant emissions, through the development of low-emission technologies, to reduce its production cost, and to enhance environmental quality.

Our results indicate that economic growth will not only promote the increase of local pollution through direct effects, but also bring about the growth of pollution in neighboring regions through spatial spillover effects and enhance the influence on local environmental pollution through feedback effects. Since the spillover effect being about much bigger than the direct effect, ultimately lead to the increase of neighboring pollution. The coefficients of PGDP and squared PGDP are significantly positive and negative, respectively. It indicates an “inverted U” nexus between economic growth and pollution, that is, environmental pollution rise first and then drop with economic growth. This result is consistent with the results of Grossman and Krueger (1995), Apergis (2016), and Bae (2018). An increase in economic growth may inevitably increase pollution. This may be because economic growth consumes more fossil energy consumption, thus increasing pollution in the local region (Mikayilov et al., 2018; Zhang et al., 2013).

Our results also indicate that the direct effect of urbanization is positive, which is consistent with the results of Zhu et al. (2019). The increase in urbanization in the region may give a significant boost to pollution, possibly because higher urbanization consumes more fossil energy consumption, thus further contributes to pollutant emissions in the local region. However, urbanization indirectly influences pollution, suggesting that the increase of urbanization will depress the growth of pollution in its neighboring. This may be because, with the growth of urbanization, the government has sped up the environmental regulation, allowing high-polluting enterprises to close down, and encouraging enterprises to develop environment-friendly products, resulting in a greater reduction of pollutant emissions (Wang and Zhou, 2021).

5. Conclusions

Due to the existence of spatial autocorrelation in pollution across regions, the spatial dependence of units is incorporated into research. Using a province-level data of thirty provinces spanning from the year 2005 to 2017, this paper explores the influencing factors on China's pollution from the direct and indirect effects perspectives, in order to make the results more reliable and robust. The empirical analyses confirm the existence of regional disparity and the strong spatial autocorrelation in China's pollution. Moreover, both per capita GDP and urbanization have positive impacts on pollution, but the impacts of environmental regulation and FDI are insignificant. Decomposition effects indicate that urbanization has not only direct, but also indirect influence on pollution. Based on these results, several corresponding policy implications are proposed.

1. Policy implementation need to be differentiated based on local conditions and economic development levels. As the disparities of pollution among different regions vary tremendously, the government should promulgate corresponding tailored strategies to control pollutant emissions. For instance, the eastern region should take advantage of the rapidly increasing economic growth and advanced technology to continuously accelerate industrial restructuring and upgrading. Therefore, the local government should attach great importance to continuous optimization of service-oriented industries. Also, the local government should establish a benign competition mechanism to improve the management experience and efficiency of enterprises. The central region should utilize its resource endowment advantages, adjust and optimize the industrial structure, and take advantage of the quality of industrial restructuring to control pollution. In contrast, the economy in the western regions is relatively backward. Thus, it is necessary for the region to digest and absorb the advanced low-carbon technologies and energy-saving experience with the eastern region. For example, take advantage of the technical progress to control pollution through cooperation with the eastern region.

2. Promotion and strengthening of interregional cooperation under the principle of a cross-regional joint mechanism. The local governments should establish a cross-regional joint mechanism and stronger regional cooperation to combat pollution. Since there is valid evidence for the existence of spatial spillover effects in pollution, the governments should take into consideration the status of neighboring regions when

promulgating environmental policies. The governments should not copy the experiences of neighboring regions to develop pollution-intensive enterprises with the pursuit of economic growth. Specifically, the governments should actively develop energy-conservation and emission-reduction technology. Furthermore, the governments should attach great importance to strengthen the links among regions, to establish an efficient cooperation mechanism that can effectively control pollution.

3. Promulgation of stringent environmental regulation policies to improve FDI quality. Since China has uneven resource endowments and remarkable regional differences, the central government should develop differentiated investment policies to allocate the resources optimally based on local conditions and economic levels. For example, for the regions with relatively low levels of FDI quality, the government should effectively expand the scale of foreign investment based on the consideration of promoting FDI quality, learn management experience and implement technology innovation strategies; for the regions with generally high levels of FDI, the government should actively improve the quality of FDI, optimize FDI structure, expand the introduction of foreign investment in high-quality and low-pollution service industries, and subsequently promote low-carbon transformation.

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Compliance with ethical standards

Ethics approval and consent to participate Not applicable.
Consent to publish Not applicable.
Competing interests The authors declare that they have no competing interests.

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Figures

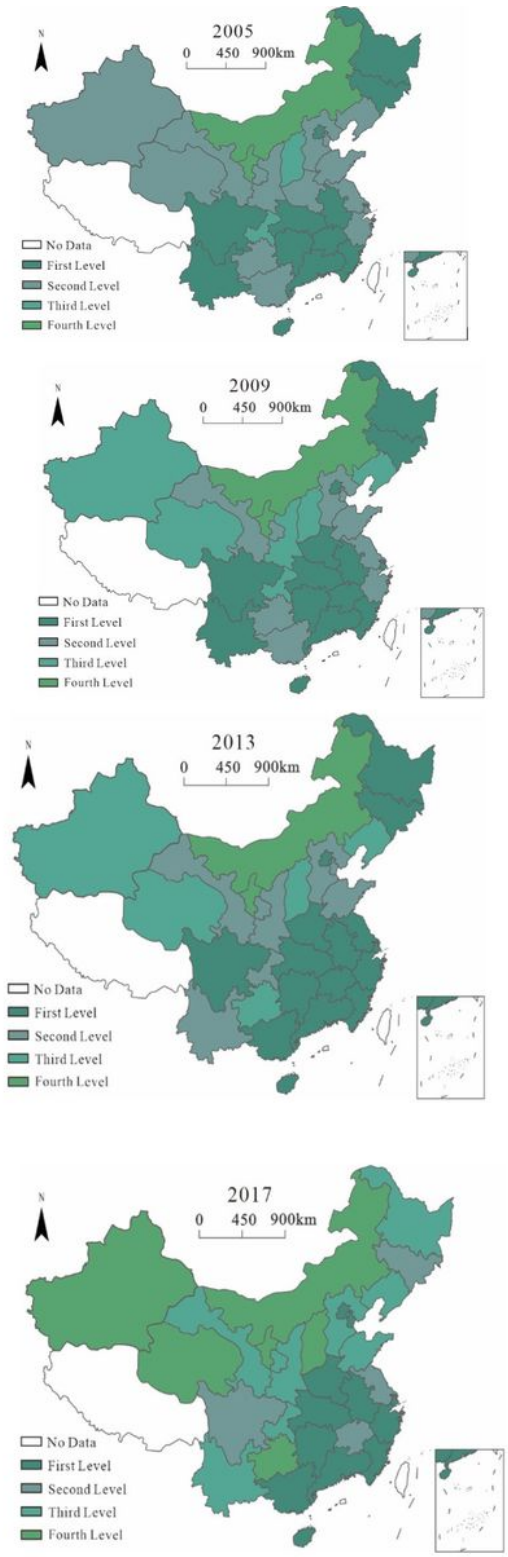

Figure 1

Quartile maps of SO2 emissions. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square

concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

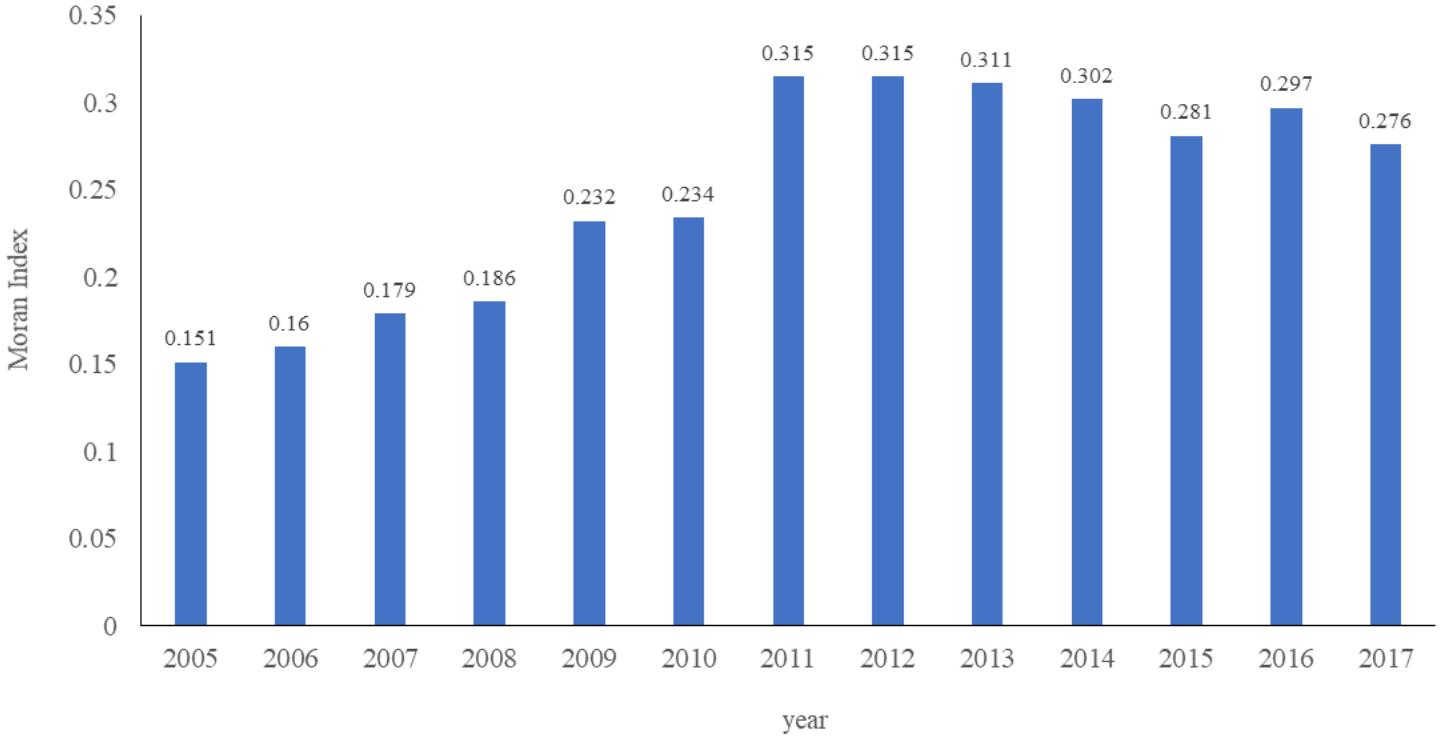

Figure 2

Histogram of Moran's I.

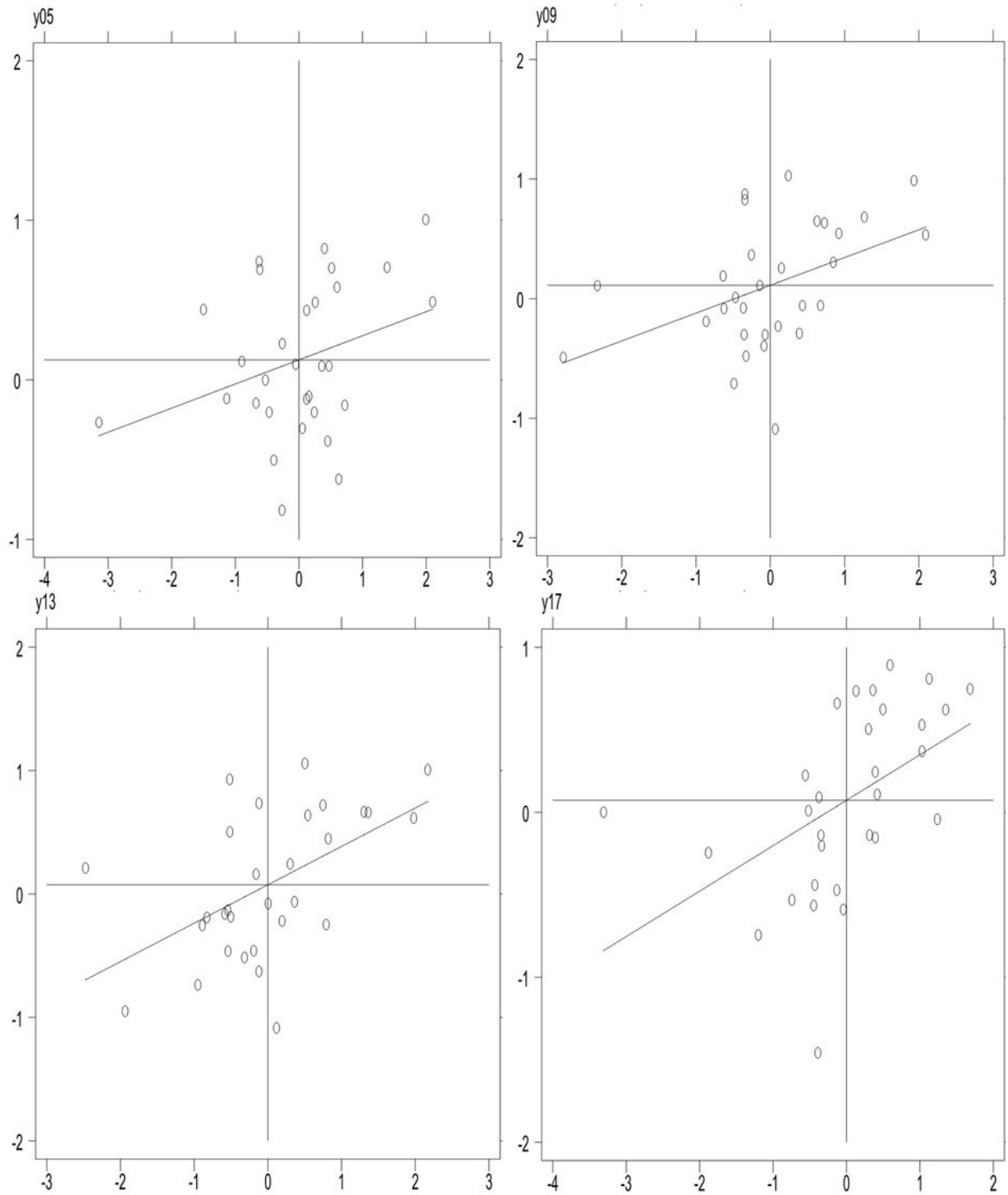

Figure 3

Scatter plots of SO2 emissions.