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RESEARCH ARTICLE

Analyzing China's provincial environmental emissions and its influencing factors: a spatial analysis

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Abstract
In-depth analyses of the spatial heterogeneity in environmental emissions and the causes of differences are of great importance to provide a reference for reduction policies. However, a spatial analysis of the specific mechanisms of China's environmental emissions is rarely scarce. Using the province-level data of 30 provinces in China over 2005–2017, this paper constructs a spatial Durbin model (SDM) to empirically address the existence and spatial mechanisms of environmental emissions. The results show that: first, China's environmental emissions show significant characteristics of spatial dependence and clustering from global and local perspectives, indicating the existence of spatial autocorrelation in environmental emissions across regions. Second, both per capita GDP and urbanization have positive impacts on environmental emissions, but the impact of environmental regulation is not significant. Third, urbanization not only directly influences environmental emissions, but also indirectly influences environmental emissions. These analyses provide comprehensive policy implications for government and policymakers to promote environmental quality.

Keywords Environmental emissions · Spatial econometric model · Influencing factors · Spatial effects

Introduction

Since the reform and opening-up policy in the past 40 years, China's economy has achieved annual growth of 9.4% from 1979 to 2018 (Chen et al. 2019). In 2009, China exceeded the USA 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 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 exceeded 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% and energy intensity by 15%. Facing the increasingly severe environmental degradation problems, an effective approach to achieving win-win goals for both economic growth and emission reduction is to reduce pollutant emissions. China has actively made great efforts to control and mitigate the pollution. However, China's environmental emissions are continually growing at an alarming rate. The following questions, therefore, arise: (1) Do environmental emissions have spatial externalities? (2) What are the distribution characteristics of environmental emissions? (3) Do environmental emissions have a spatial spillover effect in China? (4) What is the impact of influencing factors on environmental emissions in local and neighboring regions? Answers to these four questions are of utmost significance in designing reduction policies and further solving environmental pollution problems.

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In summary, scholars have extensively focused on environmental emissions and their influencing factors. However, few studies focused on the existence and specific mechanisms of environmental emissions from a spatial perspective. The existing papers mainly evaluate environmental emissions using traditional panel methods, ignoring the spatial spillover effects when analyzing the driving factors of environmental emissions. Moreover, few studies take into account both the direct impacts and spatial spillover effects of driving factors on environmental emissions and address the spatial mechanisms across regions. To fill these gaps, using province-level data of 30 provinces spanning from the year 2005 to 2017, this paper explores the influencing factors on China's environmental emissions, 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 existing literature that hardly focuses on the spatial spillover effects of environmental emissions. 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 environmental emissions and to provide some policy implications for alleviating and curbing the growth of pollutant emissions.

This paper contributes to the existing literature in the following four aspects. First, we conduct an in-depth analysis of the influencing factors affecting environmental emissions from the perspective of direct effects and spatial spillover effects, to specifically clarify the potential spatial transmission mechanism. Our analysis not only contributes to the existing literature by investigating the influencing factors and mechanisms from a spatial spillover effects perspective, but also provides a new perspective for policymakers to promulgate pollution policies. Second, we quantitatively investigate the spatial characteristics and evolutionary patterns of environmental emissions among various regions from global and local perspectives. This approach may identify the disparities more effectively. Third, considering the potential spatial dependence, we extend the existing literature by integrating the externalities of spatial units into the field of environmental economics, which provides some reference for future studies. Fourth, this paper also tests whether there is an environmental Kuznets curve (EKC) a causal relationship between environmental degradation and economic growth, which may fill the research gap in this field.

The structure of the paper is as follows. "Literature review" section summarizes the existing literature. "Methods and data" section describes the methodologies. "Results" section demonstrates the primary results of the paper. "Discussion" section discusses the implication of the results. "Conclusions" section gives the conclusions.

Literature review

The existing research in the field of environmental emissions can be broadly classified into two perspectives: (1) studying the influencing factors affecting environmental emissions and (2) providing methodologies of empirical studies on environmental emissions.

Studies on influencing factors affecting environmental emissions

A considerable amount of research has analyzed the causal relationships between environmental degradation and economic development, based on the EKC hypothesis. The EKC hypothesis was systematically proposed by Grossman and Krueger (1995), proving an inverted U-shaped relationship between economic growth and environmental quality. Based on this view, many research studies have been carried out on environmental pollution (e.g., Guo and Lu 2019; Li et al. 2016; Stern et al. 1996; Stern, 2004). There is a great number of studies that focus on environmental pollution and its determinants. For example, Zhang et al. (2020) analyzed the influence of environmental regulation on carbon emissions using a threshold regression model; Li and Lin (2014) measured China's energy intensity using a nonlinear threshold cointegration model and found that the influence of industrial structure on energy intensity in different periods is relatively different; and Zhao et al. (2020) used carbon-intensive industries as an example employing a mediating effect model, revealing that environmental regulation exerts a significant emission reduction effect either through the growth of costs, or the improvement of environmental technology, perspectives. As mentioned previously, many factors affect environmental emissions, including technological progress (Yi et al. 2020), urbanization (Xu et al. 2019), transportation (Zhao et al. 2018), environmental regulation (Yang et al. 2020; Zhang et al., 2020; Zhao et al. 2020), and foreign direct investment (Zhang et al. 2020).

Studies on methodologies for assessing environmental emissions

Various methodologies have been used to explore the influencing factors of environmental emissions. From a methodological point of view, the existing research has addressed two widely used methodologies, namely, structural decomposition analysis (Cao et al. 2019) and index decomposition analysis (Zhang et al. 2019). However, these studies did not take into account the spatial effects, which may result in an insufficient understanding of the impact of influencing factors on environmental emissions. Spatial econometric models are one of the novel characteristics of this paper, suggesting that everything is more closely related to each other in spatial distribution (Tobler 1970). Spatial econometric models consider both the effects of influencing factors and indirect effects or spatial autocorrelations with neighboring regions. Recently, spatial econometric models have been widely applied to tackle environmental problems. For instance, Zhong et al. (2018) applied the spatial econometric models to analyze the factors influencing embodied emissions; You and Lv (2018) investigated the impact of economic globalization on CO_2 and tested the spatial spillover effects; and Zhu et al. (2020) utilized spatial econometric models to analyze the relationship between energy technology innovation and air pollution.

To the best of the authors' knowledge, existing research ignores the existence and mechanism of environmental emissions from a spatial perspective. Undoubtedly, an accurate comprehensive understanding of the spatial transmission mechanisms of environmental emissions through a spatial econometric approach is a scientific basis for promulgating environmental policies to effectively control environmental emissions. To expand the existing research, using the provincial-level panel data of 30 Chinese provinces from 2005 to 2017, we focus on the influencing factors of environmental emissions and its mechanism based on the spatial Durbin model, taking into account the spatial dependence, from the perspective of direct and spillover effects. More importantly, we provide a corresponding tailored strategy that can effectively test the spatial spillover effects using the spatial Durbin model. This mostly differs from extant literature that hardly focuses on the spatial spillover effects of environmental emissions. 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 environmental emissions and to provide some policy implications for alleviating and curbing the growth of pollutant emissions.

Methods and data

Spatial autocorrelation test

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

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

$$I_{Local} = \frac{n\left(x_i - \overline{x}\right)}{\sum_{i=1}^{n} \left(x_i - \overline{x}\right)^2} \bullet \sum_{j=1}^{n} W_{ij}\left(x_j - \overline{x}\right) \tag{2}$$

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

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 environmental emissions; $\ln y_{it}$ and $(\ln y_{it})^2$ represent GDP per capita and squared GDP per capita. z_{it} indicates other variables, including foreign direct investment (FDI), technology (TEC), urbanization (UR), population size (P), and environmental regulation (RE). β_1, β_2, and δ are the coefficients of explanatory variables. α_i represents cross-section effect. γ_t is the time effect. ε_{it} is a random error term.

The first law of geography indicates that 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):

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

where ρ is the 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 environmental emissions from the perspective of spatial effects. Therefore, the detailed effect model of driving factors on environmental emissions is constructed, and the basic form of the SDM model is established by integrating spatial factors, which is specified as Eq. (5):

$$\begin{aligned} lnC_{it} &= \alpha + \rho \textstyle\sum_{j=1}^{30} W_{ij}lnc_{jt} + \beta_1 lnfdi_{it} + \beta_2 lny_{it} + \beta_3 (lny)^2_{it} + \beta_4 tec_{it} + \beta_5 lnre_{it} \\ &+\beta_6 ur_{it} + \beta_7 lnp_{it} + \theta_1 \textstyle\sum_{j=1}^{30} W_{ij}lnfdi_{jt} + \theta_2 \sum_{j=1}^{30} W_{ij}lny_{jt} + \theta_3 \sum_{j=1}^{30} W_{ij}(lny)^2_{jt} \\ &+\theta_4 \textstyle\sum_{j=1}^{30} W_{ij}tec_{jt} + \theta_5 \sum_{j=1}^{30} W_{ij}lnre_{jt} + \theta_6 \sum_{j=1}^{30} W_{ij}ur_{jt} + \theta_7 \sum_{j=1}^{30} W_{ij}lnp_{jt} + \gamma_t \\ &+\mu_i + \varepsilon_{it} \end{aligned} \tag{5}$$

where tec_{it}, $lnfdi_{it}$, $lnre_{it}$, lnp_{it}, and ur_{it} denote technology, foreign direct investment, environmental regulation, population size, and urbanization of 30 provinces.

Considering that different regions may have adjacent boundaries, and a possible spatial relationship among different regions, two kinds of spatial weight matrices are constructed (e.g., adjacent and geographical distance 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 geographical distance matrix is based on the latitude and longitude coordinates of the regions, which is calculated as Eq. (7):

$$W_2 = \begin{cases} \frac{1}{d_{ij}^{\ 2}} & i \neq j \\ 0 & i = j \end{cases} \tag{7}$$

Decomposition effects

To consider the potential spatial spillover effects, an increase in the explanatory variable will not only bring about an increase in local environmental emissions, 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. (8):

$$Y = \rho WY + \beta X + \theta WX + \varepsilon \tag{8}$$

where β is the parametric vector of X. WY refers to the spatial lag of explained variables. ρ stands for the coefficient of spatial lag regression. Y is the dependent variable. X is the independent variable. ε represents the random error. WX represents the spatial lag of explanatory variables. θ denotes the parameter vector, suggesting the impacts of explanatory variables of neighboring regions on the dependent variables in a given region. W refer to a spatial weight matrix.

Formally, Eq. (8) can be rewritten as:

$$\left[\frac{\partial Y}{\partial X_{1r}} \cdots \frac{\partial Y}{\partial X_{nr}}\right] = \begin{bmatrix} \frac{\partial Y_1}{\partial X_{1r}} & \cdots & \frac{\partial Y_1}{\partial X_{nr}} \\ \vdots & \vdots & \vdots \\ \frac{\partial Y_n}{\partial X_{1r}} & \cdots & \frac{\partial Y_n}{\partial X_{nr}} \end{bmatrix} = (I - \rho W)^{-1} \begin{bmatrix} \beta_r & W_{12}\theta_r & \cdots & W_{1n}\theta_r \\ W_{21}\theta_r & \beta_r & \cdots & W_{2n}\theta_r \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1}\theta_r & W_{n2}\theta_r & \cdots & \beta_r \end{bmatrix} \tag{9}$$

As displayed in Eq. (9), the direct, total, and indirect effects can be rewritten as:

$$\begin{aligned} M(r)_{direct} &= (I - \rho W)^{-1}\left(\beta_r I\right) \\ M(r)_{indirect} &= (I - \rho W)^{-1}\left(\theta_r W\right) \\ M(r)_{total} &= (I - \rho W)^{-1}\left(\beta_r I + \theta_r W\right) \end{aligned} \tag{10}$$

where I refers to an $n \times n$ identify matrix; $(I - \rho W)^{-1}$ denotes the spatial multiplier matrix. $M(r)_{direct}$, $M(r)_{indirect}$, and $M(r)_{total}$ represent the matrix of direct, indirect, and total effects of explanatory variables.

Data

Since the Chinese government has promulgated a lot of reduction strategies in 2005, we use the provincial-level data of 30 provinces spanning 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 shown in Table 1. Existing studies generally adopt a more comprehensive indicator to calculate pollution (Liu and Lin, 2019). In this paper, per capita industrial sulfur dioxide emissions (SO_2 emissions) are selected as environmental emissions indicators based on the following reasons. Traditional pollutants, such as SO_2 emissions, cause severely affect human health and environment in China than CO_2 does (Xia et al. 2017; Wang and Luo 2020; Xin and Zhang 2020). Similar to previous studies (Xin and Zhang, 2020), this paper selects 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 granted. Theoretically, the higher the technology, the better the environment will be (Liu and Lin 2019; Sun et al. 2019). Urbanization (UR), measured by the proportion of the urban population (Zhu et al. 2019). Population size (P), measured by the total population of each province. Environmental regulation (RE), which is represented by the

Table 1 The descriptive statistics of variables

Variable	Unit	Definition	Mean	S.D
SO_2	Tons/person	Industrial sulfur dioxide emissions per capita	0.016	0.011
pgdp	Yuan	GDP per capita	10.023	0.589
$pgdp^2$	–	Squared GDP per capita	100.812	11.805
fdi	Yuan	The ratio of FDI in the GDP	12.294	1.638
tec	One piece/ten thousand people	Number of patents granted	6.048	8.633
ur	%	Urbanization rate	52.963	13.957
p	Thousand people	The total population	4452.069	2671.46
re	–	The share of industrial pollution-elimination in the GDP	0.16	0.153

share of the total industrial pollution-elimination in the GDP (Yin et al. 2015). In this study, all empirical analyses are calculated by MATLAB15 software. We further conduct a multicollinearity test for all variables in the model, and the test results show that the maximum VIF is 4.78, the average value is 2.85, and the VIF of all variables is less than 10, indicating that there is no multicollinearity in our model.

Results

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 2005, 2009, 2013, and 2017. As seen in Fig. 1, SO_2 emissions display 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.

To further investigate the existence of spatial autocorrelation, the Moran's *I* indices are listed in Fig. 2. As shown in Fig. 2, Moran's indices from 2005 to 2017 are greater than 0, suggesting that the spatial distribution of SO_2 emissions among different regions present positive spatial autocorrelation. That is, China's SO_2 emissions exhibit obvious spatial agglomeration characteristics. This indicates that provinces with higher SO_2 emissions are surrounded by provinces with

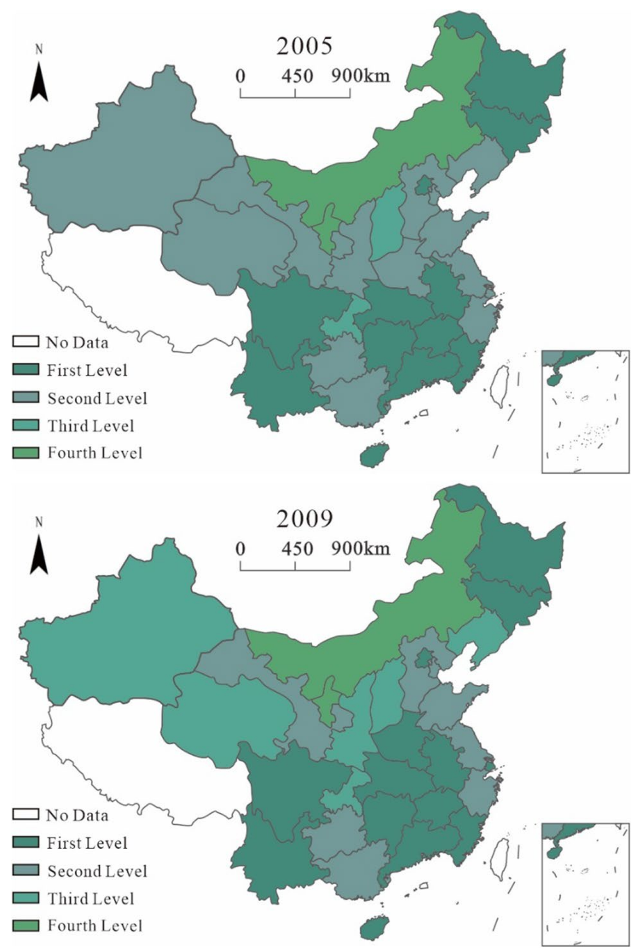


Fig. 1 Quartile maps of SO_2 emissions

higher SO_2 emissions, while those with lower SO_2 emissions are surrounded by provinces with lower SO_2 emissions. Meanwhile, the Moran's *I* index exhibits a slightly up to 2012, then it decreases, suggesting that the positive spatial autocorrelation gradually decreases.

To reveal the spatial autocorrelation in each province, the Moran scatter plots of SO_2 emissions in 2005, 2009, 2013,

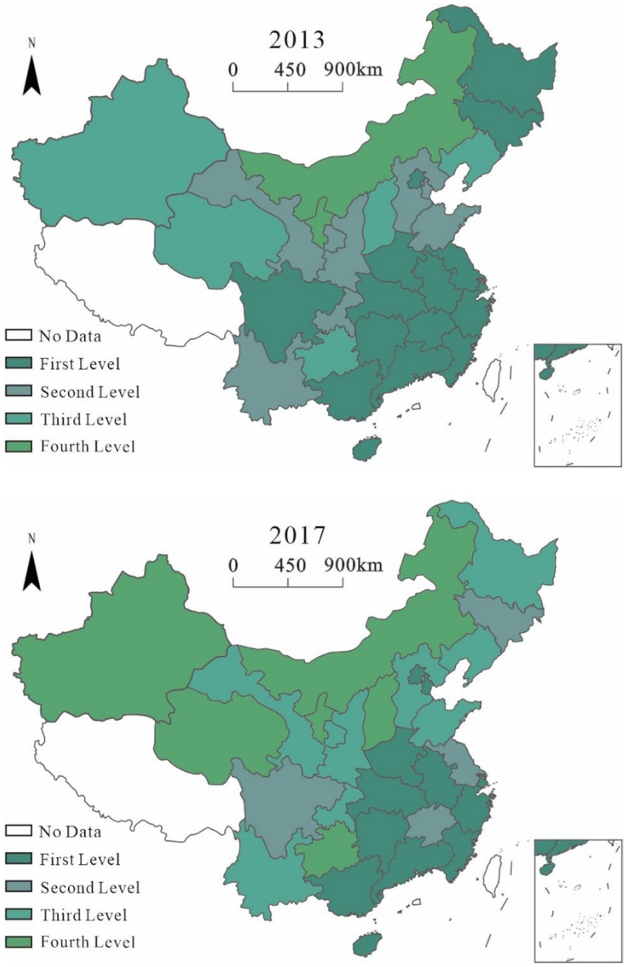


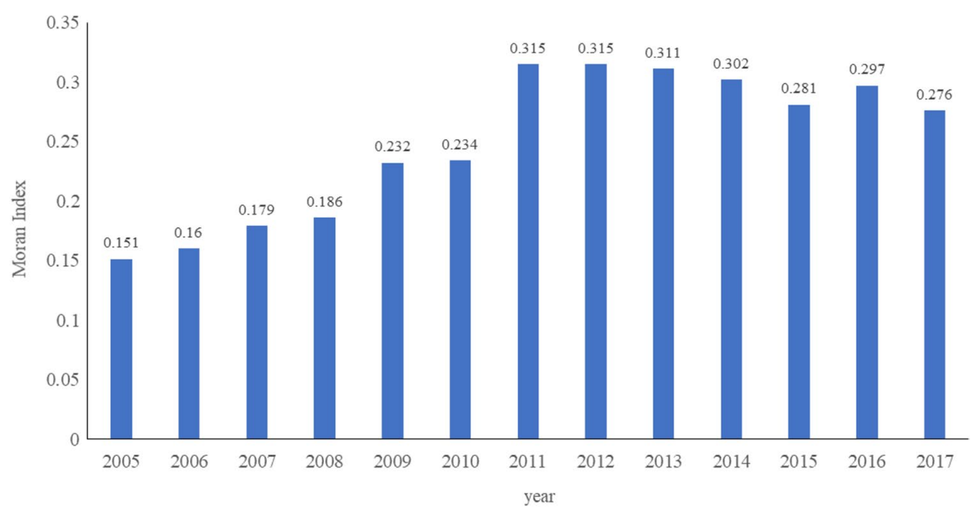
Fig. 1 (continued)

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, and 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, and Jiangsu. The "L-H"-type includes Hebei, Shandong, and Guizhou. Fig. 3 shows that most provinces are located in the "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.

Analysis of regression results

The estimation results for the SDM model with matrices W_1 and W_2 are shown in Table 2. It is noteworthy that R^2 are relatively high, with values of 0.9465 and 0.9448, 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 W_1 and W_2, which consequently confirms the presence of spatial autocorrelation of environmental emis-

Fig. 2 Histogram of Moran's *I*



sions during the research period. More importantly, the coefficients are significantly positive with matrices W_1 and

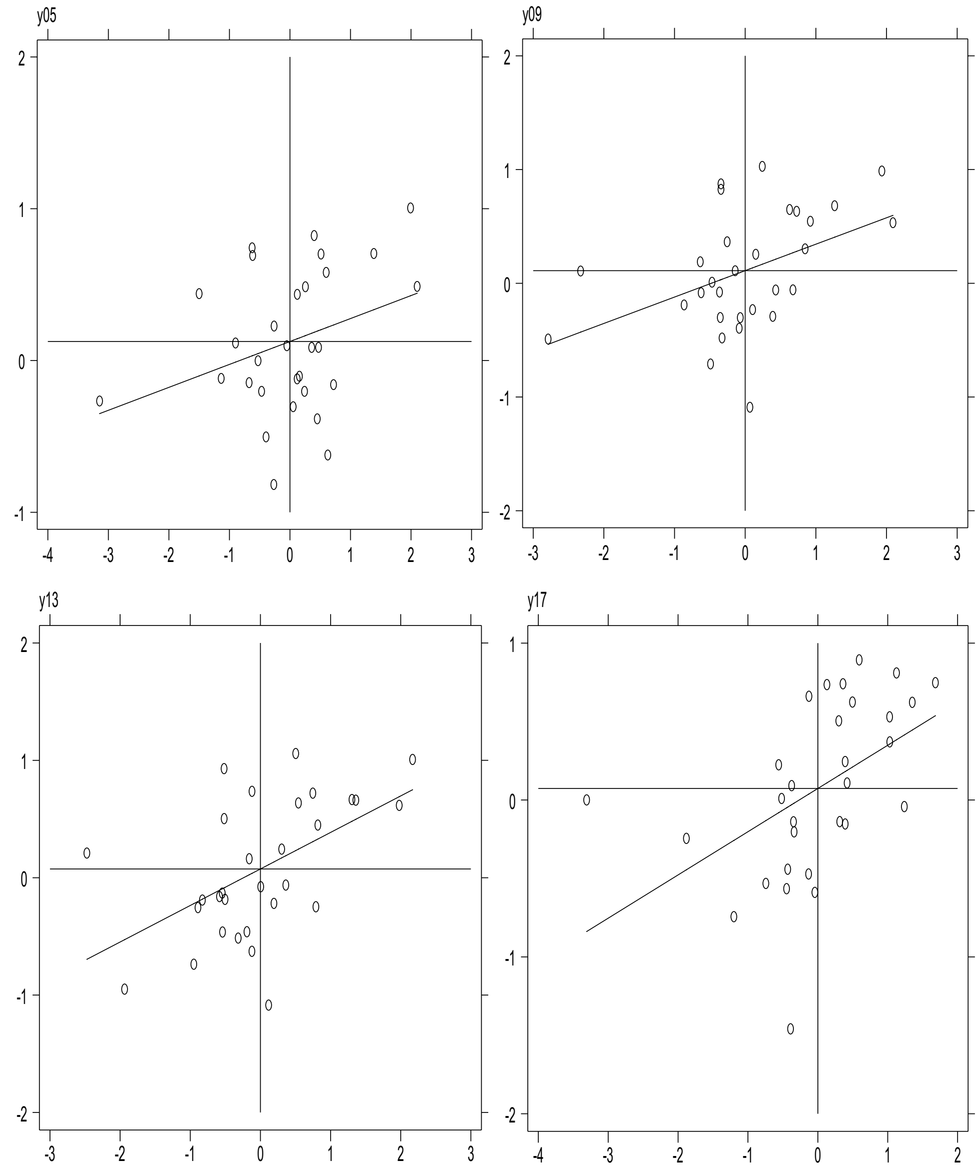


Fig. 3 Scatter plots of SO_2 emissions

W_2, suggesting that growth in environmental emissions of adjacent regions increases the local environmental emissions. This result implies that spatial spillover effects are significant on environmental emissions in thirty provinces of China. Thus, it is vital for performing spatial econometric models, considering spatial effects, to analyze the driving factors affecting environmental emissions and to examine the spatial spillover effects.

As seen in Table 2, TEC exerts a negative impact on environmental emissions with matrices W_1 and W_2, indicating that a higher technological level will result in less environmental emissions. One possible reason, as suggested by the finding of Liu and Lin (2019), argues that the improvement of technology can alleviate environmental emissions. However, the coefficient of W*TEC is significantly positive with matrices W_1 and W_2, suggesting that the development of technology in other regions increases environmental emissions in the local region. The coefficient of UR is both significantly positive with matrices W_1 and W_2, indicating that a higher proportion of the urban population will result in more environmental emissions. However, the coefficient of W*UR is significantly negative with matrix W_1, suggesting that the increase of local urbanization reduces environmental emissions. Meanwhile, the impact of FDI is significantly negative with matrix W_2, indicating that the increase of foreign direct investment exerts a negative impact on local environmental emissions. Also, the coefficient of W*lnFDI negatively influenced environmental emissions with matrix W_1, indicating that an increase in FDI of adjacent provinces decreases the local environmental emissions. Moreover, the influence of RE is not significant with matrices W_1 and W_2, indicating that the increase of environmental regulation exerts no

Table 2 Regression results with SDM

	Variable	Coefficient	Variable	Coefficient
W_1	lnFDI	−0.0301 (−1.4299)	W*lnFDI	−0.0831** (−2.4427)
	lnPGDP	4.7437*** (4.4900)	W*lnPGDP	0.5074 (0.3305)
	lnPGDP^2	−0.2215*** (−4.4024)	W*lnPGDP^2	−0.0018 (−0.0239)
	TEC	−0.0171*** (−5.1707)	W*TEC	0.0116** (2.4463)
	lnRE	0.0219 (1.0561)	W*lnRE	0.0492 (1.4686)
	UR	0.0588*** (7.1967)	W*UR	−0.1223*** (−9.1295)
	lnP	2.3352*** (4.4240)	W*lnP	−3.4210*** (−3.8119)
	ρ	0.5630*** (12.4754)	R^2	0.9465
W_2	lnFDI	−0.0460** (−2.0911)	W*lnFDI	0.3042* (1.9564)
	lnPGDP	2.7065** (2.3234)	W*lnPGDP	15.5573*** (2.7566)
	lnPGDP^2	−0.1418** (−2.5192)	W*lnPGDP^2	−0.8398* (−2.5552)
	TEC	−0.0244*** (−7.6341)	W*TEC	0.0968*** (3.6649)
	lnRE	0.0261 (1.2394)	W*lnRE	0.1506** (−2.1240)
	UR	0.0425*** (4.9106)	W*UR	0.0280 (0.4717)
	lnP	−0.3755 (−0.8232)	W*lnP	−7.8034 (−1.3559)
	ρ	0.6110*** (9.0118)	R^2	0.9448

*, **, and *** respectively represent significance at 10%, 5%, and 1%. *T*-statistics in parentheses

remarkable impact on local environmental emissions. Furthermore, the impact of population size is significantly positive with matrix W_1, indicating that the increase of population size exerts a positive impact on local environmental emissions. However, the coefficient of W*lnP negatively influenced environmental emissions with matrix W_1, indicating that an increase in population size of adjacent provinces decreases the local environmental emissions. The coefficients of PGDP and squared PGDP are significantly positive and negative with matrices W_1 and W_2, respectively. It indicates an inverted U nexus between environmental emissions and economic growth. Besides, W*lnPGDP positively influenced environmental emissions with matrix W_2, suggesting that higher economic growth of adjacent provinces could increase the local environmental emissions.

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 environmental emissions, but also affect the increase of environmental emissions 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 effect 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 environmental emissions, whereas the indirect effect suggests the influences of factors on other regions' environmental emissions. The decomposition effects are calculated in Table 3.

As listed in Table 3, the first column displays the direct effects. The direct effect of TEC is significantly negative with matrices W_1 and W_2. This indicates that the technology is further improved; the industrial structure has been gradually upgraded and optimized, and thus reducing the environmental emissions. By using innovative clean technologies, the cost of producing and using clean energy is greatly reduced. Therefore, wider use of clean energy may be possible, which significantly decreases environmental emissions. The direct effects of PGDP and UR are significantly positive with matrices W_1 and W_2, indicating that the development of economic and urbanization increase environmental emissions. However, the direct effect of FDI is significant with matrix W_1 whereas not significant with matrix W_2. The direct effect of RE is not significant with matrices W_1 and W_2. Moreover, the direct effect of lnP is significantly positive with matrix W_1, indicating that the development of population size increases environmental emissions.

In column 2 of Table 3 shows the indirect effects. The indirect effect of PGDP is positive and significant with matrices W_1 and W_2, implying that an increase in economic growth in neighboring provinces drives up the environmental emissions. The indirect effect of RE is also positive and significant with matrices W_1 and W_2. The indirect effect of UR influences environmental emissions significantly negative with matrix W_1, indicating that urbanization negatively affected environmental emissions in neighboring regions through the spatial spillover effects. The indirect effect of FDI that influences environmental emissions is negative and

Table 3 Decomposition effects of SDM

	Variable	Direct	Indirect	Total
W_1	lnFDI	−0.0494* (−1.9422)	−0.2108** (−2.4182)	−0.2603** (−2.4793)
	lnPGDP	5.3327*** (5.1292)	6.7378** (2.4702)	12.0704*** (4.0303)
	$\ln PGDP^2$	−0.2451*** (−4.9286)	−0.2673* (−1.9337)	−0.5124*** (−3.3958)
	TEC	−0.0167*** (−4.8575)	0.0045 (0.4418)	−0.0122 (−1.0072)
	lnRE	0.0331 (1.5258)	0.1282* (1.9260)	0.161356** (2.1328)
	UR	0.0418*** (5.1380)	−0.1894*** (−7.1494)	−0.1476*** (−5.2176)
	lnP	1.9065*** (4.0652)	−4.4439*** (−2.9283)	−2.5375* (−1.7320)
W_2	lnFDI	−0.0307 (−1.1896)	0.6957* (1.7641)	0.6650 (1.6263)
	lnPGDP	3.7092** (2.6955)	44.3964*** (2.8539)	48.1056*** (2.9258)
	$\ln PGDP^2$	−0.1960*** (−2.8496)	−2.3900** (−2.6562)	−2.5860** (−2.7302)
	TEC	−0.0196*** (−5.2236)	0.2096*** (3.0714)	0.1900** (2.6940)
	lnRE	0.0354 (1.6875)	0.4258** (2.5084)	0.4612** (2.6381)
	UR	0.0462*** (4.1005)	0.1473 (0.8435)	0.1935 (1.0568)
	lnP	−0.8714 (−1.1530)	−21.2381 (−1.2547)	−22.1095 (−1.2587)

*, **, and *** respectively represent significance at 10%, 5%, and 1%. *T*-statistics in parentheses

significant with matrices W_1 and W_2. Moreover, the indirect effect of TEC is positive with matrix W_2. Furthermore, the indirect effect of lnP is negative with matrix W_1.

In column 3 of Table 3 shows the total effects. The total effect of PGDP positively influenced environmental emissions with matrices W_1 and W_2. The total effect of RE is also positive and significant with matrices W_1 and W_2. However, the total effect of UR negatively influenced environmental emissions with matrix W_1. FDI is also negative and significant with matrices W_1. lnP is also negative and significant with matrices W_1.

Discussion

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

Our results suggest that the direct effect of FDI is negative though insignificant with matrix W_2, indicating that the effect of FDI on environmental emissions is not clear yet. This is coherent with prior results from Cheng et al. (2017). On one hand, FDI can improve environmental emissions through technology spillover effects. On the other hand, FDI can exacerbate environmental emissions 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 environmental emissions, which is consistent with the finding by Sun et al. (2019). This indicates that the development of technology can remarkably decrease environmental emissions, that is, the improvement of technological progress is helpful to reduce environmental emissions. Technology brings negative impacts on environmental emissions 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 environmental emissions through direct effects, but also bring about the growth of environmental emissions in neighboring regions through spatial spillover effects and enhance the influence on local environmental emissions through feedback effects. Since the spillover effect being about much bigger than the direct effect, ultimately leads to the increase of neighboring environmental emissions. The coefficients of PGDP and squared PGDP are significantly positive and negative, respectively. It indicates an "inverted U" nexus between economic growth and environmental emissions, that is, environmental emissions rise first and then drops 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 environmental emissions. This may be because economic growth consumes more fossil energy, thus increasing environmental emissions 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 environmental emissions, possibly because higher urbanization leads to more fossil energy consumption, thus further contributes to environmental emissions in the local region. However, urbanization indirectly influences environmental emissions, suggesting that the increase of urbanization will depress the growth of environmental emissions in its neighboring regions. 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.

Conclusions

Due to the existence of spatial autocorrelation in environmental emissions across regions, the spatial dependence of units is incorporated into research. Using province-level data of 30 provinces spanning from the year 2005 to 2017, this paper explores the influencing factors on China's environmental emissions 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 strong spatial autocorrelation in China's environmental emissions. Moreover, both per capita GDP and urbanization have positive impacts on environmental emissions, but the impact of environmental regulation is insignificant. Decomposition effects indicate that urbanization has not only direct, but also indirect influence on environmental emissions. Based on these results, several corresponding policy implications are proposed.

1. Policy implementation needs 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 the 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, taking 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, 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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Declarations

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