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TEMPORAL–SPATIAL CHARACTERISTICS AND KEY INFLUENCING FACTORS OF $PM_{2.5}$ CONCENTRATIONS IN CHINA BASED ON STIRPAT MODEL AND KUZNETS CURVE

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Abstract

China's tremendous economic developments are achieved at the expense of environmental deterioration. In recent years, $PM_{2.5}$ pollution has become increasingly serious in China, attracting widespread attention from the citizens and the government. This study aims to investigate the temporal–spatial characteristics of $PM_{2.5}$ in China in 1998–2012, fully considering the potential influencing factors of $PM_{2.5}$. The satellite remote sensing data compensate for the deficiency of surface monitoring data in China, such as minimising bias from data contamination, broad coverage and representing long-term temporal–spatial resolution data. A largely expanded list of potential impacting factors is selected based on environmental Kuznets curve (EKC) theory and Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) framework. Moran's I tests are used to examine the spatial correlation of $PM_{2.5}$, and the pooled regression, spatial lag and time-fixed effects spatial lag models are used and compared to explore the influencing factors of $PM_{2.5}$. The thresholded first-order inverse distance spatial weight matrix can measure the spatial spillover effect of $PM_{2.5}$ more accurately by fully considering the effect of distance on spatial influence level. Several important findings are derived. Firstly, China's $PM_{2.5}$ shows a distinct positive spatial correlation. The local Moran's I test shows that the significant high–high $PM_{2.5}$ agglomeration regions include Beijing–Tianjin–Hebei region, Yangtze River Delta and central China, connecting the two economic urban agglomerations. Secondly, the regression results of the time-fixed effects spatial lag model indicate that that $PM_{2.5}$ of a given region increases by 0.362% if the $PM_{2.5}$ of its ambient region increases by 1%. Thirdly, factors from all perspectives of STIRPAT model are very effective in explaining $PM_{2.5}$. Fourthly, no inverted "U" shape EKC is found between the overall economic development level and the $PM_{2.5}$ concentration in China in 1998-2012.

Key words: $PM_{2.5}$, EKC, influencing factors, spatial econometric model, spatial autocorrelation, STIRPAT model

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1. Introduction

Since the reform and opening policies promulgated in 1978, China's economy has achieved remarkable development. However, these tremendous developments are achieved at the expense of the environmental deterioration (Wei et al., 2015a; Wei et al., 2015b; Xing et al., 2017). According to the Global Urban Pollution Database published by the World Health Organization (WHO) on May 12, 2016, 30 of the top 100 cities with the highest annual average $PM_{2.5}$ concentration in the world are from China (Qi and Yan, 2017). China still has problems, such as excessive pressure on the resources and environment,

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unreasonable production structure and insufficient environmental protection, thereby resulting in the decline in China's environmental quality and frequent environmental pollution problems (Li et al., 2017; Li et al., 2018a; Liu and Xie, 2016; Wei et al., 2019a; Wei et., 2019b).

$PM_{2.5}$, also known as the fine particulate matter, refers to a particle with a diameter less than or equal to 2.5 microns in the atmosphere. Since 2013, the smog pollution with $PM_{2.5}$ as the main component has become increasingly serious in China, thereby threatening the health and daily life of the residents. For example, the large-scale, continuous smog pollution that broke out in January 2013 affected more than 8 million people and is considered the most serious air pollution incident in China since the last century (Wang et al., 2014).

Scholars have conducted extensive research on $PM_{2.5}$ pollution, and the hotspot topics include the spatial distribution characteristics of $PM_{2.5}$ (Dimitriou et al., 2015; Donkelaar et al., 2015; Farah et al., 2018; Huang et al., 2018; Li et al., 2017b; Li et al., 2018b; Li et al., 2018c; Li et al., 2019), chemical compositions (Fanizza et al., 2025; Lee et al., 2011; Zikova et al., 2016) and pollution sources (Bove et al., 2014; Chen et al., 2019; Choi et al., 2013; Ding et al., 2019; Wei et al., 2018; Zhang and Jiang, 2018; Zhang et al., 2019). Numerous studies have been conducted on $PM_{2.5}$ pollution in China, but these studies still have some shortcomings, as follows: (1) $PM_{2.5}$ pollution data prior to 2012 are lacking. However, China had begun setting up surface monitoring stations throughout the country as late as in 2012 to officially monitor $PM_{2.5}$. The current studies on $PM_{2.5}$ pollution are largely limited by the continuity and reliability of data and cannot reflect the temporal–spatial evolution characteristics of $PM_{2.5}$ in a long time span. For example, Li (2016), Liu and Jiang (2017) and Yang and Wang (2017) adopted $PM_{2.5}$ data measured by China's surface monitoring stations in 2014 or 2015 to conduct studies. However, $PM_{2.5}$ data measured by US research institutes through satellite remote sensing technology are rarely adopted to carry out systematic research on nationwide temporal–spatial evolution of $PM_{2.5}$ during a long time span between 1998 and 2012. (2) Cheng et al. (2017) and Huang et al. (2018) pointed out that some studies did not consider the spatial correlation of $PM_{2.5}$ concentration, including those of Li et al. (2014), Sun and Zhong (2015) and Li and Yin (2017). In fact, when the research data are obtained from different regions, a correlation, which is defined as 'spatial correlation', often exists among the data in the regions. This assumption is contrary to that about the sample independence of classical statistical analysis, such as the ordinary least squares (OLS) model and the generalised least squares (GLS) model. In the research on pollutants with strong transborder flow characteristics in $PM_{2.5}$ pollution, the accuracy of the research results will be contaminated if the classical statistical analysis that does not consider spatial factor is adopted. (3) Some studies considered the spatial correlation of $PM_{2.5}$, but the setting of spatial weight matrix is not sufficiently reasonable. For example, Ma and Zhang (2014), Liu and Jiang (2017) and Ma and Xiao (2017) used Queen spatial weight matrix, defined as co-edge or co-point adjacency, where value 1 is assigned to adjacent areas, and value 0 is assigned to non-adjacent areas. This method did not consider the distance because the impact of $PM_{2.5}$ varies with the distance between regions. According to Tobler's First Law of Geography, the interaction of $PM_{2.5}$ pollution should be smaller in distant regions (Tobler, 1970). (4) In addition, the $PM_{2.5}$ influencing factors considered by other studies are incomprehensive, and the underlying rationales of factor selection are unreliable. $PM_{2.5}$ pollution formation is not only closely related to nature particularly meteorological factors, such as relative humidity, temperature and precipitation, but also closely influenced by economic, population, technological and social factors. However, these factors are rarely integrated for research at present, and the indicator selection lacks theoretical underpinnings.

The present study aims to investigate the temporal-spatial characteristics of $PM_{2.5}$ in China in 1998-2012, fully considering the key influencing factors of $PM_{2.5}$ pollution. The specific research processes to overcome these shortcomings include the following: (1) using geographic information system (GIS) techniques to analyse $PM_{2.5}$ raster data measured by NASA with satellite remote sensing in 1998–2012; (2) establishing a theoretical analysis framework for $PM_{2.5}$ pollutions based on Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model and environmental Kuznets curve (EKC) and determining the corresponding independent variables; (3) studying the temporal–spatial characteristics and evolution process of $PM_{2.5}$ in China through global Moran's I test and local Moran's I test based on thresholded first-order inverse distance spatial weight matrix; (4) selecting spatial econometric model through Lagrange Multiplier (LM) test, Likelihood Ratio (LR) test and Hausman test, analysing the main influencing factors that led to $PM_{2.5}$ pollution through regression coefficients of spatial econometric model and verifying the existence of EKC between economic development and provincial $PM_{2.5}$ pollution in China; (5) providing policy suggestions for $PM_{2.5}$ pollution control on the basis of the research findings.

This study contributes to the literature in following aspects:

1) The satellite remote sensing data compensate for the deficiency of surface monitoring data in China.

Although surface monitoring stations collect high temporal resolution data, the spatial coverage are greatly undermined by some impediment factors, such as physical, financial and technical factors (Pope and Wu, 2014). A total of 338 air quality surface monitoring stations that can measure $PM_{2.5}$ concentration in China, according to the Ministry of Environmental Protection (http://www.zhb.gov.cn/), were set up by July 2018. The locations of these monitoring networks are depicted in Fig. 1.

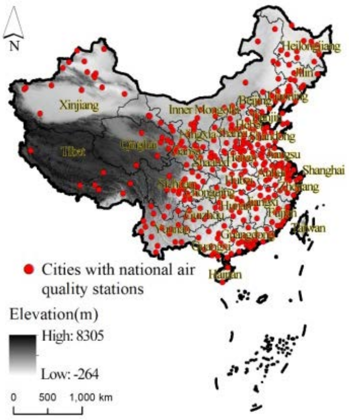

Fig. 1. Spatial distribution of China's 338 $PM_{2.5}$ surface monitoring stations in 2018

Liu et al. (2017b) pointed out that the monitoring stations were only distributed in 161 cities by October 2014. Although the amount of surface air quality monitoring stations has doubled in recent years (Fig. 1), the monitoring stations were mainly distributed in eastern China. Some parts of Northeastern and Southwestern China as well as most parts of western and Northwestern China are still uncovered, especially Inner Mongolia, Qinghai, Xinjiang and Tibet. Therefore, the $PM_{2.5}$ concentration calculated based on China's surface monitoring stations cannot comprehensively measure the condition of provincial $PM_{2.5}$ pollution, thereby generating severe bias. Donkelaar et al. (2015) pointed out that the satellite sensing data have three vital advantages. However, 1) the goal of worldwide monitoring can be realised by a single satellite when it orbits the earth, greatly reducing artefacts that may result from regional differences in surface monitoring network design and operation; 2) concentration values in areas not covered by surface monitoring stations can be detected to more accurately and comprehensively reflect air pollution levels; 3) remote sensing data by satellites also provide one of the few observationally based sources for long-term $PM_{2.5}$ concentrations that can represent long-term exposure and detect important changes in many parts of the world. In recent years, satellite-based observations covering broad regions have become increasingly available; thus, the remote sensing data are a powerful tool for research (Tao et al., 2012).

China has gradually set up monitoring stations throughout the country to monitor $PM_{2.5}$ only since 2012. In the research on $PM_{2.5}$ pollution in China in 1998–2012, significant gaps in information exists on surface monitoring data; thus, the data measured by NASA with satellite remote sensing are a powerful tool for research.

2) Considerable potential $PM_{2.5}$ influencing indicators are selected on the basis of EKC theory and STIRPAT framework, which are basic theoretical and analytical frameworks in environmental economics (Cheng et al., 2017; Ding et al., 2019). A largely expanded list of potential impacting factors is selected from the perspectives of economy, population, technology, society and nature, and the main influencing factors of $PM_{2.5}$ are investigated comprehensively.

3) A great deal of related studies, such as those of Li et al. (2014), Zhang et al. (2016) and Li and Zhang (2016), used traditional statistical methods, such as OLS and GLS. Compared with these studies, the spatial lag model and the time-fixed effects spatial lag model used in the present study can fully consider the spatial correlation effect of $PM_{2.5}$ at provincial level and investigate whether the environmental performance in a region is affected by the nearby regions. Estimation bias results from ignoring the spatial correlation of $PM_{2.5}$ can be avoided, thereby improving the accuracy and scientific implication of the regression model. Meanwhile, compared with the Queen spatial weight matrix, which is widely used by most scholars, the thresholded first-order inverse distance spatial weight matrix used in this study can measure the spatial spillover effect of $PM_{2.5}$ more accurately by fully considering the effect of distance on spatial influence level.

The remainder of this paper is organised as follows. Section 2 introduces the research methods and data source. Section 3 presents the temporal–spatial characteristics of China's $PM_{2.5}$. Section 4 shows the results of spatial econometric model analysis on the influencing factors of $PM_{2.5}$ in China. Section 5 summarises the conclusion of this paper and proposes suggestions for $PM_{2.5}$ governance.

2. Materials and method

2.1. Research methods

2.1.1. Test of spatial characteristic

The spatial correlation test of $PM_{2.5}$ should be performed separately for the global and local areas to explore the spatial characteristics of $PM_{2.5}$.

The global spatial correlation test should use global Moran's I index (Eq. 1), as follows:

$$\mathrm{I} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(A_i - \bar{A})(A_j - \bar{A})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} \quad (1)$$

In Eq. 1, I is the global Moran's I index, measuring the integral spatial correlation of the$PM_{2.5}$ of all regions; $S^2 = \frac{1}{n}\sum_{i=1}^{n}(A_i - \bar{A})^2$, $\bar{A} = \frac{1}{n}\sum_{i=1}^{n} A_i$, where A_i and A_j are the $PM_{2.5}$ concentration of i-th and j-th regions, respectively; W is the spatial weight matrix; n is the total number of regions. The range of global Moran's I index is from -1 to 1; $I > 0$ represents a positive spatial correlation; $I < 0$ represents a negative spatial correlation; $I = 0$ indicates that the distribution of $PM_{2.5}$ is random and that no spatial correlation exists. Statistics Z is used to examine the significance of global Moran's I index. The formula of Z is as shown in Eq. (2), as follows:

$$Z = \frac{I - E[I]}{\sqrt{V[I]}} \tag{2}$$

In Eq. (2), $E[I]$ and $V[I]$ represent the theoretical mean and variance of I, respectively (Eq. 3);

$$E[I] = \frac{-1}{n-1} \text{ and } V[I] = E[I^2] - E[I]^2 \tag{3}$$

The global Moran's I index reflects the integrated spatial characteristic of $PM_{2.5}$. However, Anselin (1995) indicated that the global evaluation ignores the spatial characteristics of local areas. Local Indicators of Spatial Association (LISA) must be used to explore the specific spatial relationships in local areas and determine whether significant agglomeration phenomenon exists. The local Moran's I index is applied to measure LISA, and it is calculated in Eq. (4), as follows:

$$I_i = \frac{(A_i - \bar{A})}{S^2} \sum_{j=1}^{n} W_{ij}(A_j - \bar{A}) \tag{4}$$

In Eq. (4), $A_i, \bar{A}, n, W, S^2$ are consistent with Eq. 1; A_j is the $PM_{2.5}$ concentration of j-th region; I_i is the local Moran's I index of i-th region, reflecting the spatial correlation extent of i-th region with its surrounding regions; $I_i > 0$ indicates that the i-th region is positively related to its surrounding regions; $I_i < 0$ indicates that the i-th region is negatively related to its surrounding regions.

The Moran scatterplot and LISA cluster map are widely used to visualise the local spatial characteristics of data clearly and intuitively. The Moran scatterplot (Fig. 4) can divide all regions into four quadrant agglomeration patterns to identify the relationship between a region and its surrounding regions. The horizontal axis denotes the standard score of i-th region's $PM_{2.5}$ concentration, whose value is $\frac{A_i-\bar{A}}{S}$; the vertical axis denotes the standard score of the other regions' $PM_{2.5}$ concentration, whose value is $\frac{\sum_{j=1}^{n} W_{ij}(A_j-\bar{A})}{S}$. The first quadrant indicates that a high $PM_{2.5}$ region is encompassed by other high $PM_{2.5}$ regions (high–high agglomeration). The second quadrant indicates that a low $PM_{2.5}$ region is encompassed by high $PM_{2.5}$ regions (low–high agglomeration). The third quadrant indicates that a low $PM_{2.5}$ region is encompassed by low $PM_{2.5}$ regions (low–low agglomeration). The fourth quadrant indicates that a high $PM_{2.5}$ region is encompassed by high $PM_{2.5}$ regions (high–low agglomeration).

The calculation of the significance of local Moran's I index has the same structure as global Moran's I index (Eq. 2). The significance results can be clearly illustrated by a LISA cluster map (Fig. 5).

In the Moran's tests and spatial economics model, spatial weight matrix W is defined to illustrate the spatial relationship amongst areas. Common spatial weight matrix includes Rook spatial weight matrix (co-edge adjacency), Queen spatial weight matrix (co-edge or co-point adjacency), K-nearest spatial weight matrix (nearest K regions adjacency) and inverse distance spatial weight matrix. In this study, thresholded first-order inverse distance spatial weight matrix, which can fully consider the effect of distance on spatial spillover interaction, is used. Its form is shown in Eq. (5), as follows:

$$W_{ij} = \left\{ \begin{matrix} \dfrac{1}{d[i,j]} \\ 0 \end{matrix} \right\} \begin{matrix} i \neq j, d_{[i,j]} \leq 1100km \\ else \end{matrix} \tag{5}$$

In Eq. 5, $d_{[i,j]}$ is the distance between the geographical centres of i-th region and j-th region, measured by ArcGIS 10.2. Meanwhile, each region with at least one adjacent region is considered the standard, and the maximum threshold distance is set to 1100 km. When the distance between the geographical centres of the two regions exceeds this threshold, the spatial mutual influence of $PM_{2.5}$ between these regions can be ignored.

2.1.2. Spatial econometric model

After examining the $PM_{2.5}$'s spatial effects, a spatial econometric model should be adopted to analyse the key influencing factors of $PM_{2.5}$. The spatial econometric models are firstly proposed by Cliff and Ord (1981) and is a very effective method to deal with spatially related data. The applications of the spatial econometric models are relatively mature. The spatial lag model (SLM) and spatial error model (SEM) will be mainly introduced in this study.

(1) SLM

Compared with ordinary linear model, SLM has an extra spatial lag term Wy, which fully considers the spatial interaction of dependent variables. The general form of SLM is shown in Eq. (6), as follows:

$$y = \rho wy + x\beta + \varepsilon \tag{6}$$

In Eq. 6, y is the dependent variable; X is the matrix of explanatory variables; W is the spatial weight matrix, also a square matrix of order n; Wy is the spatial lag term; ρ is the spatial correlation coefficient that signifies the extent to which the explanatory variables spatially interact with one another. The value of ρ ranges from −1 to 1, and a large ρ value indicates a significant spatial interaction. The spatial spillover effect is stronger when ρ is larger. β is the parameter vector; ε is the random error that fits in the normal distribution with 0 as its mean value.

(2) SEM

SEM decomposes the random error term, which especially considers the spatial correlation due to missing variables. The general form of SEM is shown in Eq. (7), as follows:

$$y = x\beta + \varepsilon, \varepsilon = \lambda w\varepsilon + \mu \tag{7}$$

In Eq. 7, the sets of y, X, W and β are the same as that in Eq. 5. $W\varepsilon$ is the spatial error lag term, whose coefficient is λ. A significant λ indicates that a spatial autocorrelation effect of the random error term exists; μ is the random error after decomposition, assuming it obeys a normal distribution with 0 as its mean value.

2.1.3. Panel data processing method

This study used panel data with two dimensions of cross-section (31 regions) and time (13-year groups). Individual heterogeneity and commonality should be considered when processing panel data. Individual effects model assumes that each individual's regression equation has the same slope, but the intercept can be different (Chen, 2010). The individual effects model is shown in Eq. (8), as follows:

$$y_{it} = x_{it}^{'}\beta + z_{i}^{'}\delta + u_i + \varepsilon_{it} (i = 1,2,...,n; t = 1,2,...,T) \tag{8}$$

In Eq. (8), y_{it} is the dependent variable; x_{it} is the explanatory variable; z_i represents individual characteristics, which remain unchanged with time, such as gender; disturbance term consists of u_i and ε_{it}, where u_i is the intercept item that represents individual heterogeneity, and ε_{it} is the stochastic disturbance term, assuming that ε_{it} is independent, obedient to the same distribution and irrelevant to u_i.

(1) Pooled regression model

Assuming that all individuals have the same regression equation, then Eq. (8) can be written as shown in Eq. (9), as follows:

$$y_{it} = \alpha + x_{it}^{'}\beta + z_{i}^{'}\delta + \varepsilon_{it} (i = 1,2,...,n; t = 1,2,...,T) \tag{9}$$

In Eq. 9, α is the intercept, and x_{it} does not include constant terms. Therefore, the panel data can be combined regardless of individual and time period, and OLS regression can be performed similar to dealing with cross-section data.

(2) Fixed effects model

In Eq. 8, if u_i is correlated with an explanatory variable, then the equation is further called the individual-fixed effects model. The fixed effects model also has other two forms, namely, time-fixed effects model and time-individual fixed effects model. These two modelscontain time tendency term γt, which changes with time but does not change with individual.

The time-fixed effects model is shown in Eq. 10, as follows:

$$y_{it} = x_{it}^{'}\beta + z_{i}^{'}\delta + \gamma t + \varepsilon_{it} (i = 1,2,...,n; t = 1,2,...,T) \tag{10}$$

The time-individual fixed effects model is shown in Eq. (11), as follows:

$$y_{it} = x_{it}^{'}\beta + z_{i}^{'}\delta + \gamma t + ui + \varepsilon_{it} (i = 1,2,...,n; t = 1,2,...,T) \tag{11}$$

Whether individual effects or time effects exist can be determined by likelihood ratio (LR) test. The basic idea of LR test is that if a parameter constraint is effective, then adding such a constraint should not cause a significant decrease in the maximum value of the likelihood function. The likelihood function maxima are initially calculated under constraint condition and without constraint, and then whether the ratio of the two likelihood maxima values is significant at a given level is tested. The null hypothesis of LR test is that no individual effects or time effects constraint exists.

(3) Random effects model (RE)

In Eq. 7, the RE model assumes that u_i is irrelevant to all explanatory variables (x_{it}, z_i). The estimator of the RE model is marked as $\hat{\beta}_{RE}$, which can be estimated by GLS.

Hausman test can be used to determine whether the model applies to 'fixed effects' or 'random effects'. Hausman test holds the null hypothesis that u_i is irrelevant to all explanatory variables (x_{it}, z_i). Under this condition, the assumptions of the RE model are satisfied, making the RE model more effective than the FE model. If the null hypothesis of Hausman test is false, then the RE model cannot obtain a consistent estimation of the parameters.

The statistics of Hausman test is calculated using Eq. (12), as follows:

$$\left(\hat{\beta}_{FE} - \hat{\beta}_{RE}\right)^{'}[Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})]^{-1}\left(\hat{\beta}_{FE} - \hat{\beta}_{RE}\right) \approx X^2(K) \tag{12}$$

In Eq. (12), $\hat{\beta}_{FE}$ is the estimator of the FE model; K is the dimension of $\hat{\beta}_{FE}$ or the number of explanatory variables. When the Hausman statistics is greater than the critical value at a given confidence level, the null hypothesis is rejected. Thus, the FE model should be selected.

2.1.4. Theory of STIRPAT

When selecting the potential influencing factors of $PM_{2.5}$, STIRPAT theory and EKC theory are adopted. The supplementary explanation is provided here. The prototype of STIRPAT model is IPAT model, whose form is $I = PAT$ (Ehrlich and Holdren, 1971). The IPAT model reveals that the environment is determined by the multiplicative combination of population, affluence and technology levels. York et al. (2003) pointed out that although the IPAT model is concise and practical, it is only a mathematical identity and is unable to perform hypothesis testing. Meanwhile, the IPAT model cannot identify the importance of each environmental impact factor. Dietz and Rosa (1994) developed the IPAT model into the STIRPAT model to overcome these disadvantages. The original formula of STIRPAT model is shown in Eq. (13), as follows:

$$I_i = \alpha P_i^b A_i^c T_i^d u_i \tag{13}$$

Natural logarithms (Eq. 14) are performed on both sides of Eq. (13):

$$\ln I_i = \alpha + b(\ln P_i) + c(\ln A_i) + d(\ln T_i) + u_i \tag{14}$$

In Eq. (14), a is the constant term; u_i is the random error term; subscript i indicates the individual object in the research; b, c and d are coefficients that can be obtained by regression. The STIRPAT model can not only measure the importance of the environmental influencing factors by estimating the parameters, but also decompose the relevant influencing factors according to the purpose of the research. Furthermore, other factors that affect the environment can be added through research and analysis (Chen et al., 2014).

2.1.5. Theory of EKC

American economist Grossman and Krueger (1991) demonstrated that the relationship between economic development and environmental quality generally follows the EKC. This curve indicates the presence of a general process, where environmental quality and economic development interact with each other. Economic development at initial stages leads to environmental degradation, which in turn inhibits economic development and causes it to slow down. Committed efforts are required to control pollution and improve the ecological environment. As the environment recovers, the economy regains its high development speed. This hypothesis lays the foundation for exploring the connection between economic development and environment quality (Ding et al., 2019; Li et al., 2016a; Lin et al., 2016; Jebli and Youssef, 2015).

In general, when interpreting an environmental dependent variable index Y (such as $PM_{2.5}$, SO_2, and NO_2), for an economic index independent variable X (such as constant price per capita GDP and per capita household income), if the regression coefficient of $\ln X$ is positive and the regression coefficient of $(\ln X)^2$ is negative, then an inverted U-shaped relationship exists between Y and X, thereby indicating that the EKC hypothesis holds for the research variable (Li, 2016; Ma and Zhang, 2014; Qi and Yan, 2017).

2.2 Research data

2.2.1. PM2.5 data

The $PM_{2.5}$ data in this research are obtained from Global Annual $PM_{2.5}$ Grids of MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) and v1 (1998–2012) data set issued by American NASA's Socioeconomic Data and Applications Centre (http://beta.sedac.ciesin.columbia.edu/). Such data are obtained by measuring the AOD with a satellite sensor, and a three-year sliding average is used to reduce the annual data noise measured by the satellite. Meanwhile, such data are subject to population weighting, which provides full consideration to the condition that the exposure level in densely populated areas is stronger than in sparsely populated areas under the same $PM_{2.5}$ environment conditions. The data set used in this study has longer time range and higher accuracy and resolution than the remote sensing data in 2001–2010 issued by Battelle Institute and applied by Ma and Zhang (2014) et al. This research uses the divisional statistics function of ArcGIS 10.2 software to analyse the raw raster data and obtains the mean value of $PM_{2.5}$ sliding in 13 groups from 1998–2000 to 2010–2012 with the unit of μg/m^3. The subjects of this research are 31 provinces, autonomous regions and municipalities in China (excluding Hong Kong and Macao); thus, 13 * 31 = 403 sample points are available.

2.2.2. Independent variables

Based on STIRPAT model, the following model is constructed in combination with the influencing factors selected by an extensive literature review on $PM_{2.5}$ pollution (Eq. 15):

$$lnI_i = a + b(lnP_i) + c(lnA_i) + d(lnT_i) + e(lnS_i) + f(lnN_i) + u_i \tag{15}$$

In Eq. (15), i represents the research individual object, I is the three-year average $PM_{2.5}$ concentration, P represents population factors, A represents affluence factors, T represents technology factors, S represents social factors, and N represents natural factors. Each class includes the selected subdivision index. The existing research and the selected argument indexes are shown in Table 1.

In addition to the original data of the three indicators, namely, temperature, humidity and precipitation obtained from the Statistical Yearbook of China, the original data of other independent variables are derived from the National Bureau of Statistics of China (http://www.stats.gov.cn/). The annual default values are supplemented by the sliding average of two adjacent years. All independent variables will be subjected to a three-year sliding average processing in the same approach to maintain consistency with the dependent variables.

3. Results of temporal-spatial characteristics of PM2.5

3.1. Temporal distribution characteristics of PM2.5

The Ambient Air Quality Standards (GB 3095-2012) issued by the Ministry of Environmental Protection of China specified that the standard limits for Grade I and Grade II annual average $PM_{2.5}$ concentration are 15 and 35 μg/m^3, respectively.

Table 1. Independent variables

Primary Indicators	***Secondary Indicators***	***Three-level Indicators***	***Specific Indicators***	***References***
Affluence Factor	Economic development	GDP	per capita GDP of constant price	Li et al. (2016a); Qi and Yan (2017).
	Economic structure	Industrial structure	ratio of the secondary industry to GDP	Ma and Xiao (2017); Yang and Wang (2017).
			ratio of the tertiary industry to GDP	Lu et al. (2017); Sun and Zhong (2015).
		Price structure	producer price index	Ma and Xiao (2017).
		Foreign economic relation	ratio of total investment of foreign-invested enterprises to GDP	Cheng et al. (2017); Ma and Xiao (2017).
Population Factor	Population density	Population density	urban population density	Wang et al. (2017).
	Family size	Family size	average number of people per household	Balakrishnan et al. (2013); Fabian et al. (2012).
	Population structure	Population age structure	proportion of working age population	Chen and Xu (2016).
			proportion of elderly population	Chen and Xu (2016).
		Population urbanisation structure	urbanisation rate	Li et al. (2016b); Liu and Jiang (2017); Liu et al. (2017a).
		Population education structure	proportion of college graduates and above	Chen and Xu (2016).
Technology Factor	Technology progress	Energy consumption intensity	coal consumption per unit of GDP	Li and Yin (2017); Zhou et al. (2017).
		Government investment	scientific and technological expenditure per GDP	Qi and Yan (2017).
Social Factor	Social security	Low insured population	proportion of minimum living security for urban residents	Both (2012); Both et al. (2011).
	Transportation situation	Development of transportation, storage and postal industry	ratio of the added value of transportation, storage and postal industry to GDP	Sun and Zhong (2017).
	Infrastructure	Construction area	construction area of construction industry	Ma and Xiao (2017).
		Greening level	forest cover rate	Zheng et al. (2018).
			green coverage of built-up areas	Lu et al. (2017); Qi and Yan (2017).
		Heating condition	area of central heating	Cheng et al. (2017); Jiang et al. (2018).
	Government investment	Government environmental protection investment	environmental protection investment per unit of GDP	Qi and Yan (2017).
Natural Factor	Natural conditions	Temperature	annual average temperature	Liu et al. (2017a); Lu et al. (2017); Zhang and Cao (2015).
		Humidity	annual average relative humidity	Liu et al. (2017a); Lu et al. (2017); Zhou et al. (2017).
		Precipitation	annual precipitation	Li (2016); Liu et al. (2017a); Lu et al. (2017).

However, the standard limit for average annual concentration of fine particulate matter pollution with respect to population weighting suggested by WHO is 10 μg/m³. Therefore, the $PM_{2.5}$ concentration value is divided into four grades, as follows: 0–10 μg/m³, 10–15 μg/m³, 15-35 μg/m³ and 35μg/m³ and above.

Fig. 2 shows the ratio of $PM_{2.5}$ concentrations in various provinces of China in different years and grades in 1998-2012. The regions with the highest ratio of $PM_{2.5}$ concentration in China (above 35 μg/m³) account for 52.11% of the total areas, and the peaks are registered in 2005-2007, 2007-2009, 2008-2010, 2009–2011 and 2010–2012. In each year group, the $PM_{2.5}$ concentration of 18 provinces (58.06% of total provinces) exceeds 35 μg/m³, and the ratio is on the rise over time during the investigation, thereby indicating a worsened situation of $PM_{2.5}$ pollution in China. Meanwhile, the regions with 15–35 μg/m³ $PM_{2.5}$ concentration in China account for 34.74% of the total area, those with 10–15 μg/m³ account for 8.93%, and the other regions with $PM_{2.5}$ concentration below the standard of WHO only account for 4.22%. Therefore, China currently faces a daunting reality of $PM_{2.5}$ pollution.

3.2. Spatial distribution characteristics of PM2.5

Fig. 3 shows that, in the 31 provinces/municipalities, the $PM_{2.5}$ average of 15 districts exceeds the standard limit of the annual average $PM_{2.5}$ concentration for Grade II as specified by the national standard (35 μg/m^3), and the $PM_{2.5}$ average of 26 districts exceeds that of the annual average $PM_{2.5}$ concentration for Grade I (15 μg/m^3). The three provinces/municipalities subject to the most serious $PM_{2.5}$ pollution are Henan (73.77 μg/m³), Tianjin (71.46 μg/m³) and Shandong (67.7 μg/m³). Among these data, the most serious pollution is $PM_{2.5}$ pollution in Tianjin in 2009-2011, reaching 85.069 μg/m³, which is 8.5 times of the healthy level according to WHO. In summary, among the regions in China, only the $PM_{2.5}$ concentrations of Tibet (4.51 μg/m³) and Qinghai (5.47 μg/m³) are within the health-level range provided by WHO.

3.3. Spatial correlation analysis of PM2.5

3.3.1 Global Moran's I test

Table 2 presents the global Moran's I index values for $PM_{2.5}$ in 31 provinces of China in each year group. The Table shows that all the global Moran's I index values are significantly positive at the confidence level of 1%, which indicates that a strong positive spatial correlation of the $PM_{2.5}$ concentration distribution exists in China.

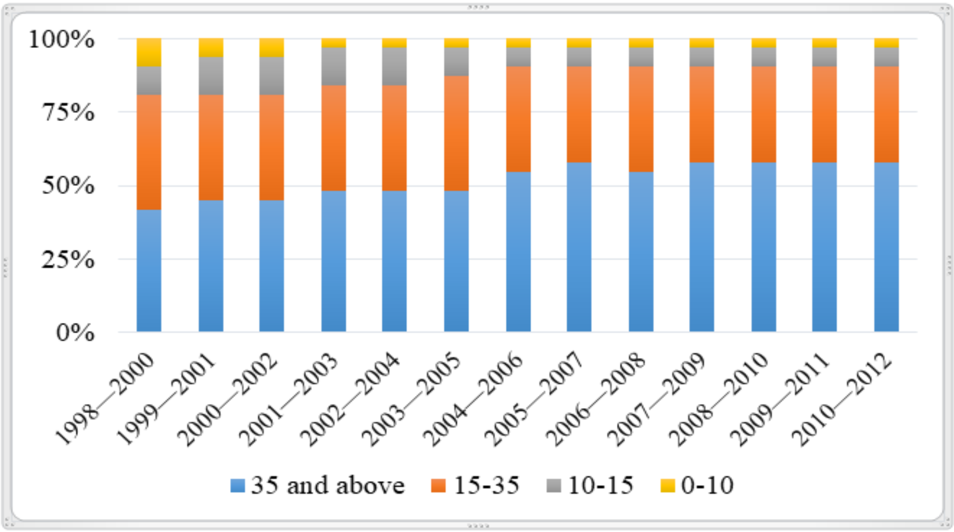

Fig. 2. Cumulative percentage map of different $PM_{2.5}$ segments in China from 1998 to 2012

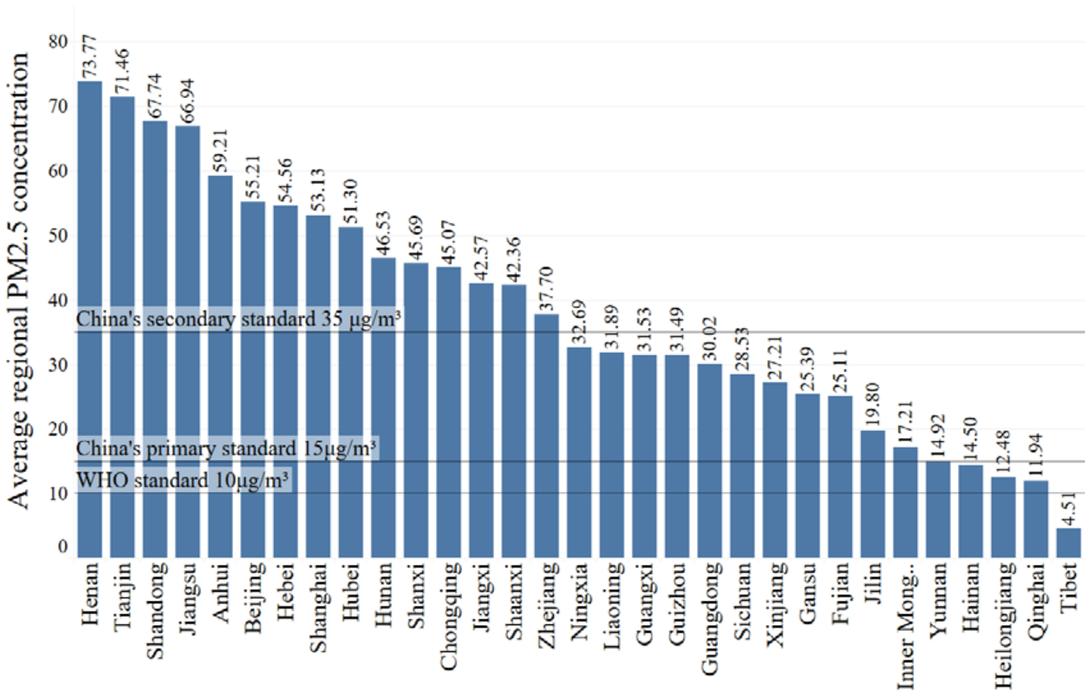

Fig. 3. Average Regional $PM_{2.5}$ Concentration of China from 1998 to 2012

Such positive spatial correlation of $PM_{2.5}$ in China fluctuated at approximately 0.35-0.40 in 1998-2012 and reached the peak in 2001–2003, indicating that such positive correlation has been maintained at a high level for a long-term. The spatial econometric model can be applied to the research on $PM_{2.5}$ pollution.

3.3.2. Local Moran's I test

Fig. 4 shows the Moran scatterplot of $PM_{2.5}$ in 2001–2003. The corresponding Moran scatterplots in other years are similar to those in 2001-2003. Thus, the other Moran scatterplots will not be listed due to page limitations. The first quadrant and the third quadrant of Moran scatterplot are high–high aggregated and low-low aggregated positive correlation regions, respectively, whereas the second quadrant and the fourth quadrant are low–high aggregated and high–low aggregated negative correlation regions, respectively.

The regions in the first and the third quadrants are typical observation areas, and the regions in the second and the fourth quadrants are atypical observation areas given the significant positive correlation in the global Moran's I test. Fig. 4 shows that most of China's 31 provinces were in the typical observation areas from 2000 to 2003, with only five provinces in the low-high atypical observation areas, including Inner Mongolia, Fujian, Jilin, Ningxia and Liaoning.

The result of global Moran's I test is further verified from the internal structure distribution of Moran scatterplot, indicating the stability of the positive correlation of China's $PM_{2.5}$. The four aggregation characteristics in the local area can be clearly demonstrated through LISA cluster map (Fig. 5). The confidence level of LISA cluster map in this study is 95%, which can be obtained by 999 times of Monte Carlo simulation operation with Geoda1.6.7 software.

Table 2. Results of Global Moran's I Test

Year	*Moran's I index*	*E(I)*	*Sd(I)*	*Z-value*	*P-value*
1998-2000	0.3643	-0.0333	0.0813	4.9165	0.001
1999-2001	0.3826	-0.0333	0.0805	5.1979	0.001
2000-2002	0.3958	-0.0333	0.0817	5.2611	0.001
2001-2003	0.3982	-0.0333	0.0837	5.1785	0.001
2002-2004	0.3928	-0.0333	0.0803	5.2659	0.001
2003-2005	0.3859	-0.0333	0.0814	5.1658	0.001
2004-2006	0.3691	-0.0333	0.0819	4.9186	0.001
2005-2007	0.3691	-0.0333	0.0809	4.9744	0.001
2006-2008	0.3784	-0.0333	0.0803	5.0991	0.001
2007-2009	0.3756	-0.0333	0.0827	4.9747	0.001
2008–2010	0.3562	-0.0333	0.0798	4.9263	0.001
2009-2011	0.3480	-0.0333	0.0840	4.5927	0.001
2010-2012	0.3523	-0.0333	0.0800	4.8676	0.001

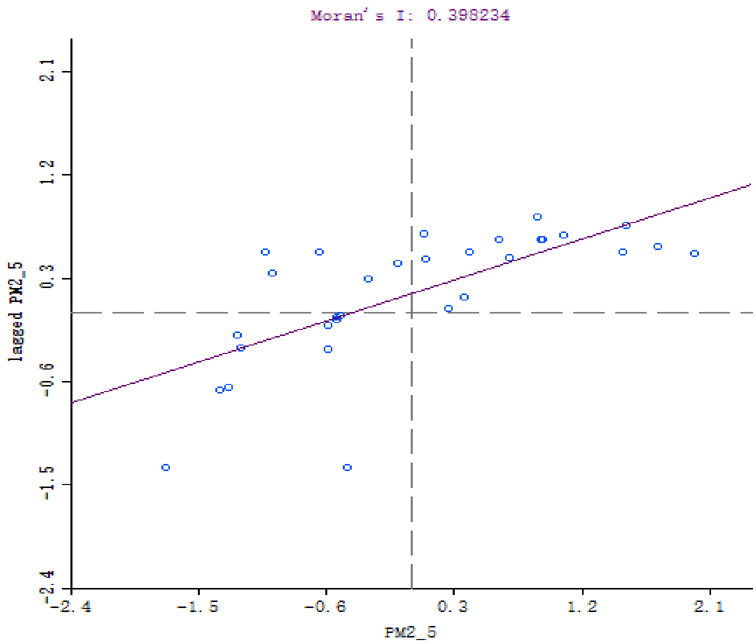

Fig. 4. Moran Scatterplot of 2001-2003

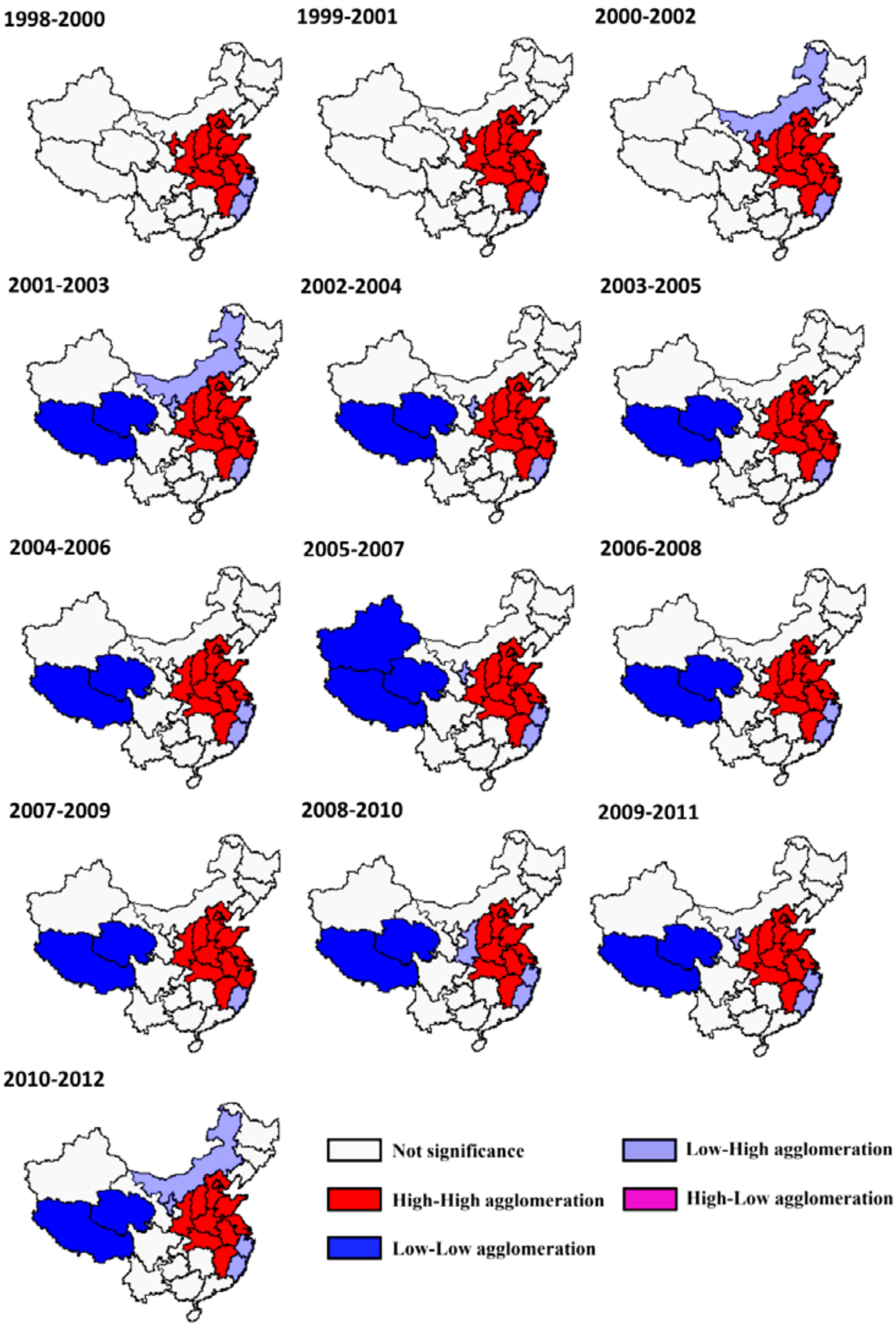

Fig. 5. LISA Cluster Map of $PM_{2.5}$ from 1998 to 2012

The results show that low–low type aggregations are mainly distributed in Tibet and Qinghai; low–high type aggregations are mainly distributed in Inner Mongolia, Fujian and Ningxia; high–high type aggregations are mainly distributed in Beijing-Tianjin-Hebei region, Yangtze River Delta and central China, connecting the two economic urban agglomerations. In addition, the spatial clustering effect in these areas is significant and in long-term stable state. Moreover, Zhejiang and Ningxia gradually change from high–high aggregation areas to low-high aggregation areas, indicating that Zhejiang and Ningxia's $PM_{2.5}$ pollution conditions have improved over time during the investigation period.

4. Results of spatial econometric model analysis on influencing factors of PM2.5 in China

4.1. Pooled regression model and spatial lag model

The specification of the pooled regression model is as follows, assuming that all individuals have the same regression equation (Eq. 16):

$$\ln(PM_{2.5\,it}) = a + b\ln(per\ capita\ GDP\ of\ constant\ price_{it}) + c[\ln(per\ capita\ GDP\ of\ constant\ price_{it})]^2 + d\ln(ratio\ of\ the\ secondary\ industry\ to\ GDP_{it}) + e\ln(ratio\ of\ the\ tertiary\ industry\ to\ GDP_{it}) + f\ln(urbanization\ rate_{it}) + g\ln(producer\ price\ index_{it}) + h\ln(urban\ population\ density_{it}) + i\ln(ratio\ of\ the\ added\ value\ of\ transportion,\ storage\ and\ postal\ industry\ to\ GDP_{it}) + j\ln(average\ number\ of\ people\ per\ household_{it}) + k\ln(proportion\ of\ colleage\ graduates\ and\ above_{it}) + l\ln(proportion\ of\ elderly\ population_{it}) + m\ln(proportion\ of\ college\ graduates\ and\ above_{it}) + n\ln(green\ coverage\ of\ built-up\ areas_{it}) + o\ln(annual\ average\ relative\ humidity_{it}) + p\ln(ratio\ of\ total\ investment\ of\ foreign-invested\ enterprises\ to\ GDP_{it}) + q\ln(forest\ cover\ rate_{it}) + r\ln(proportion\ of\ minimum\ living\ security\ for\ urban\ residents_{it}) + s\ln(annual\ average\ temperature)_{it} + t\ln(scientific\ and\ technological\ expenditure\ per\ GDP_{it}) + u\ln(annual\ precipitation_{it}) + v\ln(coal\ consumption\ per\ unit\ of\ GDP_{it}) + w\ln(construction\ area\ of\ construction\ industry_{it}) + x\ln(environmental\ protection\ investment\ per\ unit\ of\ GDP_{it}) + y\ln(area\ of\ central\ heating_{it}) + \varepsilon_{it} \quad (16)$$

Subsequently, LM test and Robust LM test are performed to trade-off between SLM and SEM. The result is shown in Table 3. * is specified as follows: *** represents a significant test at the confidence level of 1%, ** represents a significant test at the confidence level of 5%, and * represents a significant test at the confidence level of 10%.

The LM-lag and Robust LM-lag tests showed passing results, whereas the LM-error and Robust LM-error showed failed results, indicating that SLM is more suitable for this research. In SLM, spatial lag item Wy is added on the basis of Eq. 15, and its coefficient is ρ. The elastic coefficient regression is performed for the pooled regression model with OLS method, and the elastic coefficient regression is performed for SLM with maximum likelihood method. The results are compared and displayed in Table 4.

The regression coefficients and statistical test results of mixed regression model and SLM are mostly consistent, indicating that the model results are stable and reliable and that most of the indexes have passed the significance test. The R^2 of SLM is 0.873, which is slightly higher than that of the pooled region model ($R^2 = 0.840$), when the spatial effect for $PM_{2.5}$ in SLM is considered.

Table 3. Results of LM Test, LR Test and Hausman Test

	Statistics	*p-value*	*LR chi2 (26)*	*Prob > chi2*
LM-lag	99.035***	0.000	-	-
Robust LM-lag	101.912***	0.000	-	-
LM-error	0.697	0.404	-	-
Robust LM-error	3.574	0.059	-	-
Individual effects	-	-	1.62	1.000
Time effects	-	-	1080.14	0.000
Hausman Test	862.13***	0.000	-	-

Table 4. Results of pooled regression model and SLM

Independent variables	*Pooled regression model*		*Spatial lag model*		*Time-fixed spatial lag model*	
	Coefficient	t-value	Coefficient	z-value	Coefficient	z-value
(Intercept)	0.00	0.00	-0.29***	-16.02	-	-
LN (per capita GDP of constant price)	-4.66***	-5.16	-2.88***	-3.71	-3.44***	-3.89
LN (per capita GDP of constant price)^2	4.26***	4.63	2.43***	3.06	3.06***	3.42
LN (ratio of the secondary industry to GDP)	0.133***	3.38	0.09**	2.54	0.05	1.05
LN (ratio of the tertiary industry to GDP)	-0.03	-0.56	-0.07	-1.51	-0.08	-1.47
LN (producer price index)	0.04	1.58	0.04**	2.05	0.04**	2.01
LN (ratio of total investment of foreign-invested enterprises to GDP)	-0.15***	-3.08	-0.08*	-1.80	-0.17***	-3.56
LN (urban population density)	0.08***	3.09	0.08***	3.39	0.07**	2.52
LN (average number of people per household)	-0.02	-0.33	0.01	0.14	0.04	0.63
LN (proportion of working age population)	-0.01	-0.13	-0.10*	-1.81	-0.06	-1.07
LN (proportion of elderly population)	0.26***	4.71	0.17***	3.63	0.13**	2.38
LN (proportion of college graduates and above)	0.20**	3.03	0.28***	4.98	0.33***	5.03
LN (urbanisation rate)	0.22***	3.02	0.25***	3.90	0.23***	3.18
LN (coal consumption per unit of GDP)	0.19***	4.92	0.13***	4.08	0.13**	2.51
LN (scientific and technological expenditure per GDP)	-0.10**	-2.61	0.00	0.10	-0.06*	-1.77

LN (proportion of minimum living security for urban residents)	-0.07	-1.31	0.06	1.37	0.01	0.27
LN (ratio of the added value of transportation, storage and postal industry to GDP)	0.09***	3.01	0.02	0.85	0.07**	2.32
LN (construction area of construction industry)	0.29***	5.12	0.41***	8.31	0.45***	7.08
LN (forest cover rate)	-0.34***	-8.89	-0.25***	-7.56	-0.36***	-9.89
LN (green coverage of built-up areas)	0.21***	5.15	0.05	1.38	0.11***	2.59
LN (area of central heating)	0.31***	7.24	0.18***	4.92	0.28***	6.57
LN (environmental protection investment per unit of GDP)	-0.12***	-2.75	-0.12***	-3.16	-0.17***	-3.69
LN (annual average temperature)	0.62***	11.41	0.45***	9.66	0.50***	8.75
LN (annual average relative humidity)	0.08	1.26	0.11**	2.20	0.19***	3.09
LN (annual precipitation)	-0.16**	-2.57	-0.15***	2.93	-0.19***	-3.26
R^2	0.840		0.873		-	
ρ	-		0.00257		0.362***	
R^2 (within)	-		-		0.447	
R^2 (between)	-		-		0.922	
R^2 (overall)	-		-		0.828	

4.2. Time-fixed effects spatial lag model

The coefficient ρ of the spatial lag item *Wy* in SLM is 0.00257, approaching zero, which indicates that SLM cannot effectively reflect the spatial effect of $PM_{2.5}$. Thus, the model is degraded into pooled regression model because the data used in the research are panel data, with time dimension (13-year groups) and cross-section dimension (31 regions) at the same time and are different from time series data and cross-section data. The existence of individual effects and time effects must be considered.

Initially, the LR test is used under fixed effect to examine whether individual effects or time effects exist. The test outcomes are illustrated in Table 3. The likelihood ratio test results indicate that the null hypothesis of 'Inexistence of individual effects' should be accepted, whereas the null hypothesis of 'Inexistence of time effects' should be strongly rejected.

Further, Hausman test is conducted to determine which of the fixed effect or the random effect fits this research effectively, and the results are as shown in Table 3. The null hypothesis with superior random effect model is strongly rejected because the p-value of the Hausman test is 0.000, less than 0.01. The fixed effect model should be used because the consistency estimate cannot be realised by the random effect model at this time.

Thus far, all the models have been selected, and the time-fixed effect SLM should be used. The regression results are shown in Table 4.

As shown in Table 4, the time-fixed effect SLM should focus on investigating R^2 (between) = 0.922 among groups, which shall correspond to the likelihood ratio test, and should indicate the existence of significant time effects in the data. The fitting effect of time-fixed effects SLM is better than that of pooled regression model (R^2 = 0.840) and SLM (R^2 = 0.873)

The time-fixed effects SLM has a ρ = 0.362, which is significant at the confidence level of 0.01. Compared with the pooled regression model and SLM, the time-fixed effects SLM can better reflect the spatial autocorrelation of $PM_{2.5}$ pollution, corresponding to the result of global Moran's I test. It further illustrates that the apparent spatial overflow effect existed in the $PM_{2.5}$ pollution in China in 1998-2012. For a given province, every one percentage point increase in the $PM_{2.5}$ concentration of its surrounding provinces will lead to 0.362 percentage point increase in the $PM_{2.5}$ concentration of the given province.

From the overall view of the three models, the economic, population, technical, social and natural factors in the STIRPAT model are convincing for $PM_{2.5}$, and most of the indicators pass the significance test at the confidence level of 0.1, thereby indicating the rationality of the indicator selection.

4.3. Discussion of the key factors of PM2.5 pollution

Then, the pooled regression model, SLM, and the time-fixed effects SLM are combined to analyse all the independent variables.

4.3.1. Affluence factors

(1) Per capita GDP of constant price: in the three models, the elastic coefficients of LN (per capita GDP of constant price) are negative, the elastic coefficients of its quadratic item are positive, and all of them have passed Z test with confidence level of 0.01. From 1998 to 2012, the relationship between $PM_{2.5}$ pollution and economic development in China is opposite to the EKC, which has positive U-shaped relationship. As the per capita GDP of constant price increases constantly, the provincial $PM_{2.5}$ concentration presents a continuous rising state after a short drop, consistent with the research results of Ma and Zhang (2014) and Liu and Jiang (2017) et al. In the present study, the empirical results show that China's overall economic development level is far from the inflection point for improvement occurrence, and $PM_{2.5}$ pollution will continue to deteriorate with the rapid development of China's economy. China's haze governance still requires substantial effort. (2) Ratio of the secondary industry to GDP: the coefficients are positive in the three models and are significant in the pooled regression model and SLM. The secondary industry is the main consumer of energy and the main discharger of pollutants. For a

region, higher secondary industry proportion will lead to higher direct and indirect energy consumption and pollutant discharge, as well as greater contribution to $PM_{2.5}$ pollution. (3) Ratio of the tertiary industry to GDP: the elastic coefficients are negative but insignificant in the three models. (4) Producer price index: in the SLM and time-fixed effects SLM, the elastic coefficients are positive and significant. A higher producer price index indicates more vigorous production, higher pollution discharge level and more serious $PM_{2.5}$. (5) Ratio of total investment of foreign-invested enterprises to GDP: the elastic coefficients are negative and significant. The environmental protection measures and concept of the foreign enterprises are generally higher than those of the domestic enterprises, and a higher level of opening up is conducive to introducing advanced foreign environmental protection technology and equipment, as well as increasing the input of foreign merchants to the Chinese environmental protection industry, thereby reducing the $PM_{2.5}$ level in the region (Ma and Xiao, 2017).

4.3.2. Population factors

(1) Urban population density: the elastic coefficients are positive and significant in the three models. When the urban population is densely populated, the consumption of various energy sources, such as electricity and gasoline, is increased, the requirements for house construction area of the building industry are improved and transportation tools, such as automobiles and buses, are highly required, which are the main sources of $PM_{2.5}$. (2) Proportion of working age population: the coefficients are insignificant. (3) Proportion of elderly population: the elastic coefficients are positive and significant. The high proportion of elderly population generally indicates higher medical and health level in local area, better economic development status and greater energy demand in the entire region, indirectly causing the increase in $PM_{2.5}$ pollution level, such as Shanghai, Jiangsu and Tianjin. (4) Average number of people per household: the coefficients are insignificant. (5) Proportion of college graduates and higher levels: the elastic coefficients are positive and significant. High proportion of college degree and above indicates higher education level of local people, indicating a good economic development status, such as in Beijing and Shanghai. These areas have greater resource and energy demand and produce relatively large amount of air pollutants. At the same time, the highly educated population tends to have higher standard of living (Liao et al., 2012) and greater demand of energy and material consumption, resulting in $PM_{2.5}$ pollution. (6) Urbanisation rate: the elastic coefficients are positive and significant. In the process of urbanisation, the mass rural population transfers from the countryside to the city, greatly increasing the urban energy and land demand, such as power consumption, coal consumption and steel production. At the same time, urbanisation has freed the rural population from the primary industry, and more population occupies the other industries, thereby producing more energy consumption and pollution discharge (Wei et al., 2014; Wei et al., 2016).

4.3.3. Technology factors

(1) Coal consumption per unit of GDP: the elastic coefficients are positive and significant. Coal consumption per unit of GDP can reflect the local production structure and technical level. In general, higher coal consumption per unit of GDP indicates higher secondary industry share to GDP and less advanced production technology. Burning coals can release mass $PM_{2.5}$ pollutants into the environment. Thus, high coal consumption per unit of GDP leads to serious $PM_{2.5}$ pollution. (2) Scientific and technological expenditure per GDP: the elastic coefficients are negative and significant in the pooled regression model and time-fixed effects SLM. Higher science and technology expenditure in a region will lead to more advanced production technology and discharge purification technology of the enterprise, remarkably reducing $PM_{2.5}$ pollutants produced and discharged during the production.

4.3.4. Social factors

(1) Proportion of minimum living security for urban residents: the coefficients are insignificant. (2) Ratio of the added value of transportation, storage and postal industry to GDP: the elastic coefficients are positive and significant in the pooled regression model and the time-fixed effects SLM. Transportation, storage and postal services are industries that are closely related to motor vehicles. Motor vehicle density and operating intensity increase with the boom of these industries, and automobile exhaust is an important source of $PM_{2.5}$ (Ma and Xiao, 2017). (3) Construction area of construction industry: the elastic coefficients are positive and significant. During the construction of new houses, the demolition and renovation of old houses and the transportation of construction materials, tons of smoke and dust will be produced. Moreover, because the construction sites are mostly outdoor operations, these dusts are discharged into the air in large quantities and become the ‘prime culprit’ of aggravated haze (Ma and Xiao, 2017). (4) Forest coverage rate: the elastic coefficients are negative and significant. The forest has evident purification effect on the pollutants in the air environment. On the one hand, as the wind blows through the forest, it rubs against the lush branches and leaves of the forest, reducing the wind speed and causing fine particles in the air to settle; on the other hand, the trees can secrete juices to absorb gaseous inorganic pollutants, and harmful substances are continuously absorbed and fixed along with the growth and development of trees. (5) Green coverage of built-up areas: the elastic coefficients are positive and significant in the pooled regression model and time-fixed effects SLM model. The greening of the built-up areas in China has not formed a full-scale, and the purifying effect of the trees, shrubs, lawns and other urban greening vegetation in the air has not

reached the ideal effect. (6) Area of central heating: the elastic coefficients are positive and significant. Zhou et al. (2017) pointed out that urban central heating requires a large amount of energy and discharges tons of air pollutants. For example, coal burning is the main heating mode of central heating in northern China; it causes severe effect on $PM_{2.5}$ pollution. At the same time, Cheng et al. (2017) pointed out that the environmental protection equipment used for dust removal has extremely low utilisation rate and efficiency and cannot provide full purification effect on pollution filtration. Thus, the dust particles generated by coal burning are directly discharged into the atmosphere, and the concentration of the local $PM_{2.5}$ is increased. (7) Environmental protection investment per unit of GDP: the elastic coefficients are negative and significant. Environmental protection investment is conducive to supporting the environmental protection industry and cleaning industry and effectively strengthens the governance of $PM_{2.5}$ pollution.

4.3.5. Natural factors

(1) Annual average temperature: the coefficients are positive and significant. Zhang and Cao (2015) pointed out that the temperature has a catalytic effect on the chemical reactions of $PM_{2.5}$ precursor pollutants. The authors argued that the thermometer screens are mostly distributed in the urban city and less distributed in the suburb. The area with high annual average temperature is often accompanied by 'Urban heat island effect'. It refers to the phenomenon that the urban temperature is significantly higher than the suburbs as a result of many factors, such as large number of artificial heating, building wall and asphalt pavement in the urban area.

The 'Urban heat island effect' will interact with $PM_{2.5}$ pollution and enhance each other. On the one hand, various fine particulate matters, smoke and dust are suspended above the city and absorb huge long wave heat radiation, and the absorbed heat cannot diffuse and cohere because of weak circulation of urban air, thereby enlarging the heat island effect in large cities; on the other hand, when the urban heat island effect is amplified, the air at the surface and the low altitude is thermally expanded, moves upward and produces low-pressure vortex weather, thereby resulting in the accumulation of atmospheric pollutants in the urban centre and further increasing the severity of $PM_{2.5}$ pollution. (2) Annual average relative humidity: the elastic coefficients are positive and significant in SLM and time-fixed effects SLM. Under the condition that the air temperature is low in winter heating period and the weather condition is unfavourable to the diffusion of polluted gases, high relative humidity increases the rate of formation and transformation of $PM_{2.5}$, exacerbating the severity of $PM_{2.5}$ pollution. (3) Annual precipitation: the elastic coefficients are negative and significant. When the water vapour in the air condenses into rain water and falls to the ground surface, it constantly washes away air pollutants. On the one hand, the rain can precipitate particulate matter in the air; on the other hand, many air pollutants will dissolve in the rain and fall to the ground and partially dissolve in the ocean, lakes and land, having significant cleaning effect on $PM_{2.5}$.

5. Conclusions

China has been suffering from serious and widespread $PM_{2.5}$ pollution for a long period, affecting the health of the residents and the national economic development. The $PM_{2.5}$ remote sensing data are analysed, and econometric models are established according to STIRPAT model and EKC curve to explore the temporal–spatial characteristics of $PM_{2.5}$ in China from 1998 to 2012, fully considering the key influencing factors of high $PM_{2.5}$. Global Moran's I test and local Moran's I test are used to investigate the spatial correlation of $PM_{2.5}$. Lagrange multiplier test, Likelihood Ratio test and Hausman test are used for model selection. The pooled regression model, SLM and the time-fixed effects SLM are used to describe the relationship between $PM_{2.5}$ pollution and independent variables and $PM_{2.5}$ space characteristics. The following conclusions are derived and the following suggestions are put forward for the government's $PM_{2.5}$ pollution governance:

This study achieved several important findings based on the empirical results, as follows:

(1) In terms of temporal characteristics, the overall level of $PM_{2.5}$ pollution in China from 1998 to 2012 continues to increase, and the problem of $PM_{2.5}$ pollution is serious. Among the 403 $PM_{2.5}$ concentration records of all time zones and regions, 52.11% is above 35 $\mu g/m^3$, which is the national Grade II annual average $PM_{2.5}$ concentration, and only 4.22% is below the standard of WHO. In terms of regional characteristics, the three regions with the most serious $PM_{2.5}$ population weighted concentration in China are Henan, Tianjin and Shandong.

(2) In terms of spatial correlation (spillover) characteristics, the global Moran's I test indicates that $PM_{2.5}$ pollution distribution in China has a distinct positive spatial correlation. The local Moran's I test further points out that low–low type aggregations of $PM_{2.5}$ pollution in China are mainly distributed in Qinghai and Tibet; low–high type aggregations are mainly distributed in Inner Mongolia, Fujian and Ningxia; high–high type aggregations are mainly distributed in Beijing-Tianjin-Hebei region, Yangtze River Delta economic zone and the central regions, connecting the two major economic poles. In addition, the space centralisation effect in these areas is very stable during the investigation period of 1998–2012. Zhejiang and Ningxia have gradually transferred from high–high aggregation areas to low–high aggregation areas, indicating that the $PM_{2.5}$ pollution conditions of Zhejiang and Ningxia improve over time.

(3) The time-fixed effects SLM with an R-squared value of 0.922 has the best effectiveness compared with the pooled regression model and the SLM, whose R-squared values are 0.840 and 0.873,

respectively. Meanwhile, the time-fixed effects SLM better reflects the spatial correlation of $PM_{2.5}$, and the coefficient of spatial lag term is 0.362 and is significant under the confidence level of 0.01, thereby indicating that a given region's $PM_{2.5}$ increases by 0.362% if the $PM_{2.5}$ of its ambient region increases by 1%.

(4) The economic, population, technical, social and natural factors in the STIRPAT model are convincing for $PM_{2.5}$ concentration. The regression outcomes of the time-fixed effects SLM reveal that the indicators with significant positive effect on the concentration of $PM_{2.5}$ are ranked as follows according to their coefficient values: annual average temperature, construction area of construction industry, proportion of college graduates and above, area of central heating, urbanisation rate, annual average relative humidity, proportion of elderly population, coal consumption per unit of GDP, green coverage of built-up areas, urban population density, ratio of the added value of transportation, storage and postal industry to GDP, ratio of the secondary industry to GDP and producer price index. The indicators, which play a significant negative role on the concentration of $PM_{2.5}$, are ranked as follows according to their coefficient values: forest cover rate, annual precipitation, ratio of total investment of foreign invested enterprises to GDP, environmental protection investment per unit of GDP and scientific and technological expenditure per GDP.

(5) China's overall economic development level is far from the inflection point for environment improvement occurrence. From 1998 to 2012, the relationship between $PM_{2.5}$ pollution and economic development in China is opposite to the EKC, which has a U-shaped relationship. $PM_{2.5}$ concentration presents a continuous rising state after a short drop, that is, $PM_{2.5}$ pollution continues to deteriorate with the rapid development of China's economy as the constant price per capita GDP increases constantly.

Policy recommendations are put forward based on the conclusions of the empirical research, as follows:

(1) $PM_{2.5}$ pollution in China has evident spatial overflow effects. Local governments should not only focus on local pollution governance, but also establish joint anti-pollution mechanisms with surrounding areas. The superior government should impose administrative penalties on uncooperative governments to ensure the joint control of air pollution (Zhang and Li, 2018). The Beijing-Tianjin-Hebei region, which is a high–high $PM_{2.5}$ agglomeration area, is considered according to local Moran's I test. A pollution detection network system connecting Beijing, Tianjin and Hebei should be established based on polluted gas detectors and monitoring centre. The emission sources of $PM_{2.5}$ can be identified and controlled by achieving 24-hour and 360-degree monitoring. In addition, an early warning mechanism can be formed by using weather forecast data. For example, if Beijing has continuous stable and static weather, then the serious polluting factories located in the upwind direction of Beijing should reduce or stop production to proactively mitigate pollution emission.

(2) From the perspective of economic factors, promoting the transformation of China's production structure from the secondary industry to the tertiary industry is necessary to attract foreign investments and accelerate deployment of environmental protection equipment and technologies. (3) From the perspective of population factors, avoiding excessive centralisation of urban supporting resources and alleviating the present situation of population overconcentration in mega cities are necessary and building satellite cities around mega cities may be an appropriate solution; the energy consumption of urban population must be reduced through the scale effect of urban infrastructure; enterprises should make full use of the rich professional skills and knowledge of workers and take the road of refined development instead of extensive production. (4) From the perspective of technical factors, adopting advanced production technology is necessary to reduce the use of inferior coal in time, the development and utilisation of clean energy, such as solar energy and nuclear energy, must be emphasised; the government should accomplish payment transfer from well-developed regions to less-developed regions to help the economically backward regions to vigorously develop science and technology capability, such as payment transfer from Beijing to Hebei. (5) From the perspective of social factors, driving vehicles with the exhaust emission level out of limits must be strictly prohibited. Beijing, for example, prohibited vehicle with excessive exhaust emissions from driving since 2017; trees and vegetation, which are well-suited to grow in local conditions, are actively cultivated; the concept of green construction is improved, and unnecessary reconstruction works are eliminated; the heating mode and heating technology, such as using natural gas instead of coal and reducing the incineration of straw in the countryside, must be actively innovated. (6) From the perspective of natural factors, artificial heating and heat accumulator in the urban area must be reduced as much as possible; the water vapour and the residual heat generated by gas boiler during heating must be recycled to prevent the relative humidity from improving; trees must be planted to realise water retention and increase precipitation; under severe smog weather condition, artificial rainfall can be considered to reduce $PM_{2.5}$ concentration rapidly.

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