The hazards of PM2.5 pollution: Empirical evidence from perinatal mortality in China

guangqin Li (zjfcligq@126.com)
Anhui University of Finance and Economics https://orcid.org/0000-0002-2938-5392

Lingyu Li
Shanghai University of Finance and Economics

Dan Liu
University of Technology Sydney

Research

Keywords: PM2.5, Perinatal Mortality Rates, Spatial Econometrics, SDM

Posted Date: February 25th, 2020

DOI: https://doi.org/10.21203/rs.2.24425/v1

Title

The hazards of $PM_{2.5}$ pollution: Empirical evidence from the perinatal mortality in China

Authors' information

Guangqin Li [1], Lingyu Li [2], Dan Liu [3]

[1] College of International Economics and Trade, Anhui University of Finance and Economics, Bengbu, Anhui, PR China （zjfcligq@126.com）
[2] Institute of Finance and Economics Research, Shanghai University of Finance and Economics, Shanghai, PR China （75375989@qq.com）
[3] Centre for Health Economics Research and Evaluation, University of Technology Sydney, Sydney, Australia （Dan.Liu@uts.edu.au）

Corresponding Author: Guangqin Li
Email: zjfcligq@126.com
Address: College of International Economics and Trade, Anhui University of Finance and Economics, Bengbu, Anhui, PR China

Abstract

Background: Although the adverse effects of air pollution on health have aroused widespread concern in academia, there is little evidence about the impact of PM2.5 on perinatal mortality rates.

Methods: Using the spatial analysis function of ArcGIS, we get the haze pollution data from the satellite remote sensing data. We adopt fixed effects model, spatial Durbin model (SDM) and the instrument variable method to investigate the causality between PM2.5 and perinatal mortality rates.

Results: We find that PM2.5 has a significantly positive effect on perinatal mortality rates. A 1% increase of log-transformed average concentrations and maximum concentrations of PM2.5 result in 1.76‰ and 2.31‰ increase of perinatal mortality rates, respectively. In spatial econometrics analysis, we find PM2.5 has significant spatial autocorrelation characteristics. A 1% increase of concentrations of log-transformed average and maximum PM2.5 lead to a 2.49‰ and 2.19‰ increase of perinatal mortality rates, respectively. Using instrument variable method to deal with the endogeneity, the result is similar. The potential mechanism through which air pollution has an impact on perinatal mortality rates is infant weight.

Conclusions: PM2.5 pollution has a significant and positive effect on perinatal mortality. The results show that environmental pollution control should be strengthened

and the exposure of pregnant women in polluted air should be reduced.
KEYWORDS:

$PM_{2.5}$; Perinatal Mortality Rates; Spatial Econometrics; SDM

JEL CLASSIFICATION: I15; F64; K32

The hazards of $PM_{2.5}$ pollution: Empirical evidence from the perinatal mortality in China

1. Background

With the rapid growth of the economy, the environment pollution has become a serious issue in China. According to data from the Ministry of Environmental Protection, the average fine particulate matter ($PM_{2.5}$) concentrations reached 72μg/m^3 in 2013. As a result, 99% of the China's population lived in areas exceeding the World Health Organization (WHO) Air Quality Guideline of 10μg/m^3 $PM_{2.5}$ [1, 2]. According to the Asian Development Bank (ADB) Annual Report 2012, less than 1% of China's 500 biggest cities is up to the WHO standards, and seven cities in China list among the ten most polluted cities in the world [3]. China has become one of the countries with the highest environmental burden of disease in the world [4]. The Institute for Health Metrics and Evaluation Global of Disease estimates that outdoor air pollution contributes to 1.20 million premature deaths in China, and air pollution is the fourth leading cause of premature deaths in 67 risk factors [5]. In addition, outdoor air pollution in China is responsible for 12.34 million deaths and 25 million healthy life-years lost per year. The frequency of severe air pollution events has spurred widespread concern about the environment among citizens and scholars.

A great number of studies find a significant and negative relationship between air pollution and health. Samet et al. [6] find that the levels of $PM_{2.5}$ in the air are associated with the risk of deaths from all causes. Dominici et al. [7] analyze a national database of air pollution and mortality for the 88 largest U.S. cities for the period of 1987-1994. They conclude that previous-day PM_{10} concentrations are positively associated with total mortality in most locations, with a 0.5% increment for a 10 μg/m^3 increase in PM_{10}. Wong et al. [8] and Fang et al. [9] study the effects of air pollution on mortality in Asia and China, respectively. They find similar results. Using prefectural panel data from China, Chen and Chen [10] test the impact of air pollution on public health, and find that a 1% increase in gas emission leads to an increase in the number of deaths from respiratory diseases and lung cancer by 0.05‰ and 0.03‰, respectively. Pope et al. [11] find that fine particulate and sulfur oxide-related pollution are associated with all-cause, lung cancer and cardiopulmonary mortality. Each 10 μg/m^3 elevation in fine particulate air pollution is associated with approximately a 4%, 6%, and 8% increased risk of all-cause, cardiopulmonary and lung cancer mortality, respectively.

The carrier of air pollutants such as $PM_{2.5}$ has been linked to lung and

cardiovascular diseases, which increase mortality rates [12, 13, 14, 15, 16]. A number of studies investigate mechanisms through which air pollution causes diseases. Kampa and Castanas [17] find air pollution has both acute and chronic effects on human health by affecting a number of different systems and organs. Tallon et al. [18] find that exposures to long-term $PM_{2.5}$ and NO_2 are associated with decreased cognitive function in a cohort of older Americans. Individuals who experience a stroke or elevated anxiety are more susceptible to the effects of $PM_{2.5}$ on cognition.

Different groups of individuals are affected by air pollution in various ways. Vulnerable population, such as children, are more susceptible to the adverse effects of exposure to air pollution than others are. A number of studies examine the adverse health effects of ambient air pollution on kids. Chay and Greenstone [19] take the significant drop in the level of air pollution caused by the U.S. economic recession of 1981-1982 as an external shock. They conclude that a 1% reduction in total suspended particulates (TSPs) leads to a 0.35% decline in the infant mortality rate at the county level, implying that 2,500 fewer infants died during 1980–1982 than would have in the absence of the TSPs reductions. Chay and Greenstone [20] focus on the impact of improved air quality on infant health due to the implementation of the 1970 Clean Air Act (CAAA) in the U.S. They find that the infant mortality rate dropped by 0.5% after the implementation of the CAAA. Currie and Neidell [21] examine the impact of three criteria pollutants on infant death in California over the 1990s. Reductions in carbon monoxide over the 1990s saved approximately 1000 infant lives in California. Currie et al. [22] find negative effects of exposure to CO on infant health.

If a mother during pregnancy is exposed to increased environmental stressors, it could result in an increased risk of fetal growth restriction or a preterm birth, which are strong predictors for infant mortality and morbidity [23, 24]. DeFranco et al. [25] find that exposure to high levels of $PM_{2.5}$ in the third trimester of pregnancy is associated with a 42% increase in stillbirth risk. Faiz et al. [26] find that the relative odds of stillbirth is associated with interquartile range increases in the mean pollutant concentrations on lag day 2 and lag days 2-6 before delivery.

The above studies demonstrate the relationship between air pollution and infant mortality. There is also some literature on the relationship between air pollution and perinatal mortality. For example, Woodruff et al. [27] use 4 million infants born between 1989 and 1991 in the 86 metropolitan statistical areas in the United States. They find that the particulate matter is associated with risk of post neonatal mortality. De Medeiros et al. [28] investigate the relationship between traffic-induced air pollution and perinatal mortality rates through case studies. Hackley et al. [29] study the impact of exposure to air pollution on health of pregnant women and offer suggestions on how to minimize exposures.

In this study, we aim to test the hypothesis that exposure to higher level of $PM_{2.5}$ in

the air during pregnancy is associated with higher risk of perinatal mortality. Perinatal mortality is an indicator of mother and child health and may reflect the conditions of reproductive health [30, 31]. Using data of China's provincial level $PM_{2.5}$ concentrations from 2002 to 2015, we adopt both fixed effects model and spatial Dubin model (SDM) to investigate the relationship between $PM_{2.5}$ and the perinatal mortality rates. This paper contributes to the literature in several respects. First, many studies on China examine the association between some pollutants, such as CO, PM_{10}, SO_2 and health; however, few studies investigate the effect of $PM_{2.5}$ on mortality. Second, we contribute to literature that examines the effects of air pollution on perinatal death rates. The prenatal stage of life is a very sensitive period such that exposure to $PM_{2.5}$ pollution might have an adverse effect on the development of fetuses. Third, we adopt spatial panel model to analyze the spatial autocorrelation of $PM_{2.5}$ pollution among Chinese provinces and demonstrate time and space lag effects of the $PM_{2.5}$ pollution on health.

The paper is organized as follows. Section 2 explains our methodology. Section 3 describes the data. Section 4 presents regression results. Section 5 is the discussion.

2. Methodology

We use fixed effects model and spatial econometrics model to estimate the relationship between PM2.5 and infant mortality rates.

2.1. Fixed Effects Model

We use the following baseline econometric model:

$$mortality_{i,t} = \alpha + \beta\left(\ln PM_{2.5}\right)_{i,t-1} + X'_{i,t}\gamma + province_i + year_t + \varepsilon_{i,t} \tag{1}$$

In the above, i and t indicate the region i and year t, respectively; $mortality$ is the perinatal mortality rates; province is the province fixed effects; year represents year fixed effects; and ε is the random disturbance term (In empirical research, we use clustered standard errors at the province level. $\left(\ln PM_{2.5}\right)_{i,t-1}$ is the natural logarithms of one-year-lagged $PM_{2.5}$. β is the estimated coefficient of interest. X' represents a vector of control variables, including the total number of health agencies per 10,000 population, the total number of health beds per 10,000 population and gross domestic product (GDP) per capita.

2.2. Spatial Econometrics Model

Shao et al. [34] show that $PM_{2.5}$ pollution has significant spatial autocorrelation characteristics, which indicates that the perinatal mortality rates are affected not only by the local $PM_{2.5}$ pollution, but also the neighborhood $PM_{2.5}$ pollution. Therefore, we

use a spatial econometric approach to investigate the relationship between $PM_{2.5}$ and the perinatal mortality rates.

The most commonly used spatial econometric models in applied research are the spatial lag model (SLM), the spatial error model (SEM) and the SDM model [35]. The SDM model includes spatial lag terms from dependent variables and independent variables to capture the spillover effects deriving from different variables, which is used widely in environment research [36, 37].

We estimate the following SDM specification:

$$\begin{aligned} mortality_{i,t} &= \alpha + \rho Wmortality_{i,t} + \beta\left(\ln PM_{2.5}\right)_{i,t-1} + \varphi W\left(\ln PM_{2.5}\right)_{i,t-1} \\ &+ X'_{i,t}\gamma + WX'_{i,t}\phi + province_i + year_t + \varepsilon_{i,t} \quad \varepsilon_{i,t} \square (0,\theta^2) \end{aligned} \tag{2}$$

where W is the spatial weighting matrix; $Wmortality$ represents perinatal mortality rates in neighboring areas; $W\left(\ln PM_{2.5}\right)_{i,t-1}$ represents the natural logarithms of one-year-lagged $PM_{2.5}$ in neighboring areas; WX' is a vector of control variables in neighboring areas; ρ is the spatial autoregressive parameter; φ is the coefficient of $W\left(\ln PM_{2.5}\right)_{i,t-1}$; γ and ϕ are the parameters of the two matrices, respectively; and ε obeys normal distribution with standard deviation of θ.

To study the spatial distribution of perinatal mortality rates in 31 province-level regions, the spatial weight matrix W needs to be defined first. There are many specifications for spatial weighting matrix, such as spatial contiguity weights, inverse distance matrix and socio-economic distance matrix, but the most commonly used one is the binary contiguity matrix. In this study, we choose the specification of binary contiguity to create the spatial weight matrix W. The elements of spatial weight matrix W are defined as W_{ij}=1 if location i is adjacent to location j. It is convenient to normalize spatial weights to remove dependence on extraneous scale factors. Therefore, row-normalized weight matrices are used in the study.

To investigate the spatial clustering pattern of the $PM_{2.5}$ and perinatal mortality rates, we calculate Moran's I index, which is the correlation coefficient of observed values and spatial lagged variables. The value of Moran's I index is between -1 and 1, with positive values implying positive spatial autocorrelation, negative values implying negative spatial autocorrelation and a zero-value indicating a random spatial pattern. The formula for calculating Moran's I index is as follows:

$$Moran's\ \mathrm{I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{3}$$

Where $S^2 = \sum_{i=1}^{n}(x_i - \bar{x})^2 / N$, $\bar{x} = \sum_{i=1}^{n} x_i / N$; x_i represents mortality rates of

region i; N is the number of sample; and W_{ij} is the spatial weighting matrix.

2.3. Instrumental variables

Our estimation might be biased due to omitted variables, such as genetic factors. For this concern, we employ instruments based on geographical features. In the 1950s, with the help of the Soviet Union, China was prepared to provide winter heating to urban residents. However, due to limited heating equipment, the Chinese government decided to provide heating only in cities north of the Huai River-Qin Mountains line in winter. This line is the geographical divining line between Northern and Southern China. This heating policy has been used to the present. The winter heating is mainly relying on coal power. Therefore, Northern provinces suffer from serious air pollution, especially $PM_{2.5}$ pollution. The heating policy results in dramatic variations in air quality within China [38, 39]. Geographic characteristics are related to air pollution, but they do not have an impact on perinatal mortality rates and are not correlated with omitted variables. Thus, we employ two geographical characteristics as our instrumental variables. The first one is a dummy variable (*north)*, which equals to 1 if provinces are located in the north of the line, and equals to 0 otherwise. Given that, $PM_{2.5}$ pollution will be more serious with the increase of distance from Northern provinces to the line, we choose the distance from the line as another instrumental variable (*distance*. It is calculated as the shortest vertical distance from the center of provincial capital cities to the line using ArcGIS. The value of the distance is positive if the provinces located in the north of the line, and negative otherwise.

3. Data

3.1. Perinatal mortality rates

In this paper, the definition of perinatal mortality rate is the ratio of neonatal mortality (including stillbirths) from 28 weeks of gestation to 7 days after delivery to live births (unit is ‰. Data on perinatal mortality rates is from *China Health and Family Planning Statistical Yearbook*.

3.2. Main explanatory variable ($PM_{2.5}$)

In China, the main sources of air pollution data are data on (TSPs) (before 2013 and Air Quality Index (AQI) after 2013. The TSP is a comprehensive index, with only a few cities as monitoring cities. The AQI level is based on the level of six atmospheric pollutants, which covers most major cities in China, but no data is available before 2013. We use $PM_{2.5}$ concentration data from the Socioeconomic Data and Applications Center, hosted by the Center for International Earth Science Information Network (CIESIN) at Columbia University. The dataset contains information on three-year running mean of

$PM_{2.5}$ concentration for 0.01°×0.01° grids since 1998. Adjacent grid points are approximately 10 kilometers apart. We use ArcGIS software to extract $PM_{2.5}$ concentration data of years from 2002 to 2015. For each province-year observation, we calculate the average and maximum $PM_{2.5}$ concentration using the data of the grid points that fall within the province [40, 41, 42]. We take the average value of $PM_{2.5}$ concentration as province's annual air pollution level. It should be pointed out that the satellite data in the monitoring process will be affected by meteorological factors, which is slightly lower than the actual ground monitoring data. However, compared to the ground monitoring using "point to surface" measure, the satellite data is relatively reasonable. Therefore, we perform a robustness test using maximum $PM_{2.5}$ concentration as the air pollution measure.

3.3. Other explanatory variables

According to literature [43], we control the following variables.

Regional medical conditions. We control for the number of hospital beds per ten thousand persons and the number of hospital agencies per ten thousand persons at the province level, which represent the availability of health care.

Regional economic development level. Regional economy provides the necessary material and nonmaterial support for decreasing perinatal mortality. We assume the higher the level of regional economic development is, the larger the health care spend is. So, a negative relationship between regional economic development and perinatal mortality is expected. In this paper, per capita actual gross domestic product (GDP) is used as a proxy for regional economic development, which is inflation-adjusted by constant 2002 prices.

Urbanization rate. It is the proportion of population in urban areas in a province. It is related to the social economic status (SES) of citizens, such as economic status and education. The higher the urban rate is, the higher the SES of citizens is, and the more attention will be paid to health, resulting in lower perinatal mortality rates. However, higher urban rate will also lead to serious air pollution, which might have a negative effect on perinatal mortality rates.

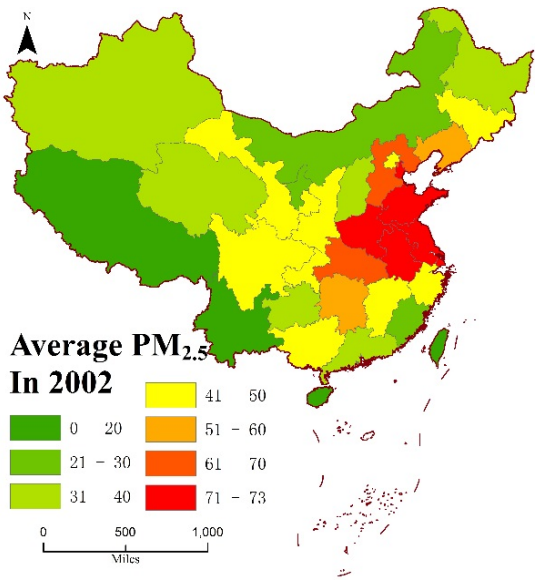
The above data are available from *China Statistical Yearbook*, *China Health and Family Planning Statistical Yearbook, China Urban Statistical Yearbook* and *China Regional Economic Statistical Yearbook*.

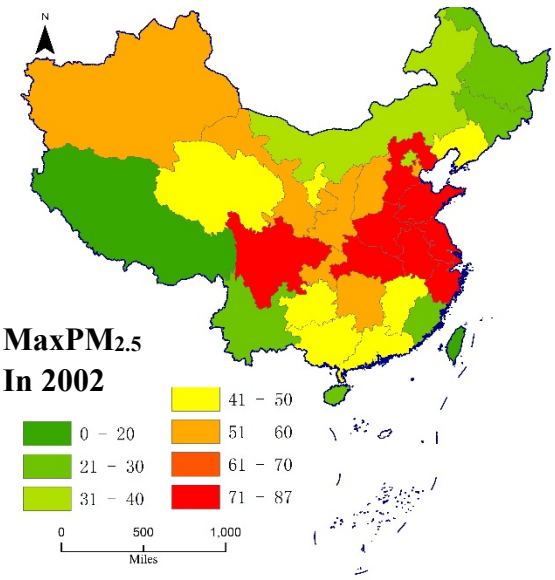
3.4. Descriptive statistics

We construct data of China's 31 provinces from 2002 to 2015. The descriptive statistics of data is provided in Table 1. Figure 1 shows the spatial distribution of $PM_{2.5}$ in 2002 and 2015 ($\mu g/m^3$). The maximum and average value of $PM_{2.5}$ are higher than Air Quality Guideline ($10\mu g/m^3$) of the WHO.

Table 1 Descriptive statistics for the variables

Variable	Grouping	Mean	SD	Min	Max	Observations
Perinatal	overall	9.129	4.547	2.150	25.800	N=434
mortality rates	between		3.618	2.876	20.935	n=31
(‰)	within		2.824	2.215	20.538	T=14
Average $PM_{2.5}$	overall	3.745	0.484	2.183	4.519	N=434
(log)	between		0.479	2.351	4.391	n=31
	within		0.108	3.186	4.208	T=14
Max $PM_{2.5}$	overall	3.987	0.416	2.666	4.718	N=434
(log)	between		0.405	2.890	4.544	n=31
	within		0.117	3.430	4.578	T=14
GDP per	overall	4.701	0.672	2.790	6.107	N=434
capita(log)	between		0.478	3.813	5.671	n=31
	within		0.480	3.492	5.618	T=14
No. of hospital	overall	35.675	10.809	15.318	63.671	N=434
beds per	between		6.171	27.839	49.940	n=31
10,000 persons	within		8.939	21.434	61.823	T=14
No. of	overall	5.038	3.446	1.231	21.789	N=434
hospitals per	between		1.957	1.697	12.439	n=31
10,000 persons	within		2.856	-2.860	14.388	T=14
Urbanization	overall	48.327	15.252	13.890	89.600	N=434
rate (%)	between		13.112	22.351	84.071	n=31
	within		8.115	-11.190	85.220	T=14





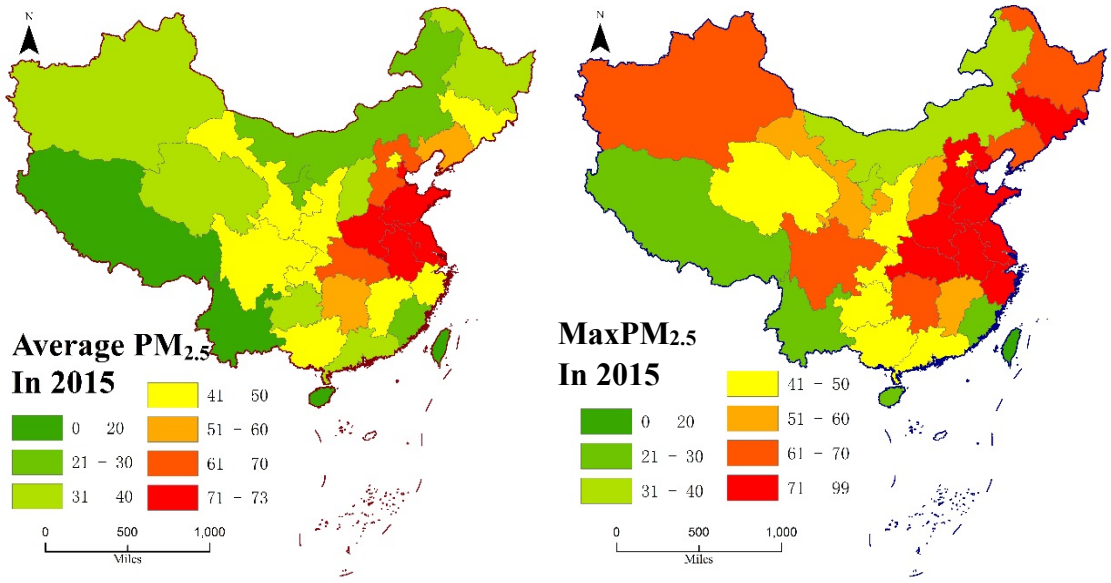


Fig.1 Spatial distribution of $PM_{2.5}$ in 2002 and 2015 (μg/m^3), respectively. The left two maps are the spatial distribution maps of average $PM_{2.5}$ pollution concentration in 31 provinces in 2002 and 2015,respectively, and the right two maps are the spatial distribution maps of maximum $PM_{2.5}$ pollution depth in 31 provinces in 2002 and 2015, respectively.

4. Results

4.1. Fixed effects model

4.1.1. Baseline model

Fixed effects model is used based on the Hausman test. Table 2 displays the results of the baseline model (Column (1) and Column (2)) reports the results of the impacts of average concentrations of $PM_{2.5}$ on perinatal mortality rates controlling for only province fixed effects or both province and year fixed effects. Column (3) and (4) include all controls on the basis of the first two columns. The estimate coefficients of the log value of $PM_{2.5}$ are 2.439, 2.759, 1.644 and 1.76, respectively, which are positive and significant. Column (4) is our referred model, which shows the perinatal mortality rate will increase by 1.76‰ for every 1% increase in $PM_{2.5}$ (log) pollution.

The coefficient of the GDP (log) per capita is -5.161 in Column (4), which is negative at the 1% significance level, meaning that a 1% increase of the log value of GDP per capita results in 5.16‰ increase of perinatal mortality rates. The coefficient of the number of hospital beds per ten thousand persons and the number of hospital agencies per ten thousand persons are -0.076 and -0.106 respective, which means they are negatively related to perinatal mortality rates (shown in Column (4)), as the improvement of access to healthcare is conducive to reducing mortality rates. The

coefficients of urbanization rates are insignificant.

Table 2 The impacts of average $PM_{2.5}$ concentrations on perinatal mortality rates

Explanatory Variable	**Explained Variable: *Perinatal mortality***			
	(1)	(2)	(3)	(4)
Average $PM_{2.5}$ (log)	2.439***	2.759***	1.644**	1.760**
	(0.749)	(0.957)	(0.751)	(0.886)
GDP per capita(log)			-3.644***	-5.161***
			(0.389)	(1.100)
No. of hospital beds per 10,000 persons			-0.073***	-0.076***
			(0.018)	(0.027)
No. of hospitals per 10,000 persons			-0.065	-0.106*
			(0.041)	(0.054)
Urbanization			0.006	-0.001
			(0.013)	(0.013)
Constant	24.009***	34.874***	22.769***	28.819***
	(2.650)	(4.885)	(2.632)	(5.233)
Year fixed effects	N	Y	N	Y
Province fixed effects	Y	Y	Y	Y
Within R-squared	0.685	0.691	0.702	0.700
Observations	434	434	434	434

Notes: Clustered standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.1.2. Robustness check

One concern of our baseline finding is that the effect of average $PM_{2.5}$ concentrations on perinatal mortality might be underestimated because of measurement error. Therefore, we define maximum concentrations of $PM_{2.5}$ as a measure of $PM_{2.5}$ pollution for robustness check. The results are presented in Table 3. Column (1) and column (2) report the results controlling for only province, and both province and year fixed effects, respectively. The results show that maximum concentrations of $PM_{2.5}$ have a significant and positive impact on perinatal mortality rates. Similarly, after controlling covariates, the results in column (3) and column (4) show that maximum concentrations of $PM_{2.5}$ have a significant and positive impact on perinatal mortality rates. Our preferred model in column (4) indicates that a 1% increase of the log value of maximum concentrations of $PM_{2.5}$ results in 2.312‰ increase of perinatal mortality rates. The maximum $PM_{2.5}$ has greater impact on perinatal mortality than average $PM_{2.5}$.

Table 3 The impacts of maximum $PM_{2.5}$ concentrations on perinatal mortality rates

Explanatory Variable	Explained Variable: *Perinatal mortality*			
	(1)	(2)	(3)	(4)
Max $PM_{2.5}$ (log)	2.650***	2.412***	2.066***	2.312***
	(0.675)	(0.769)	(0.671)	(0.770)
GDP per capita(log)			-3.695***	-5.050***
			(0.380)	(1.094)
No. of hospital beds per 10,000 persons			-0.072***	-0.073***
			(0.017)	(0.027)
No. of hospitals per 10,000 persons			-0.065	-0.110**
			(0.041)	(0.054)
Urbanization			0.006	0.001
			(0.012)	(0.013)
Constant	22.602***	32.102***	20.852***	25.696***
	(2.576)	(4.756)	(2.566)	(5.127)
Year fixed effects	N	Y	N	Y
Province fixed effects	Y	Y	Y	Y
Within R-squared	0.688	0.695	0.705	0.704
Observations	434	434	434	434

Notes. Standard in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Spatial Analysis

4.2.1. Moran's I index

Table 4 lists the results of the Moran's I test for overall spatial correlation of perinatal mortality rates and regional $PM_{2.5}$. The values of Moran's I for mortality rates are more than 0.3 and pass the 1% significance test, which indicates that there exists significant and positive autocorrelation among regional perinatal mortality rates in the geographical space. There also exists significant positive autocorrelation among regional $PM_{2.5}$.

Table 4 The Moran's I test for spatial correlation

Year	Perinatal mortality		Average PM2.5 (log)		Max $PM_{2.5}$ (log)	
	Moran's I	P-value	Moran's I	P-value	Moran's I	P-value
2002	0.426	0.000	0.484	0.000	0.337	0.002
2003	0.463	0.000	0.505	0.000	0.384	0.001
2004	0.558	0.000	0.497	0.000	0.327	0.003
2005	0.623	0.000	0.506	0.000	0.352	0.001
2006	0.600	0.000	0.505	0.000	0.371	0.001

2007	0.560	0.000	0.558	0.000	0.458	0.000
2008	0.477	0.000	0.512	0.000	0.330	0.003
2009	0.396	0.000	0.484	0.000	0.393	0.000
2010	0.414	0.000	0.481	0.000	0.339	0.002
2011	0.478	0.000	0.520	0.000	0.389	0.000
2012	0.348	0.000	0.481	0.000	0.351	0.001
2013	0.386	0.000	0.525	0.000	0.425	0.000
2014	0.392	0.000	0.504	0.000	0.360	0.001
2015	0.403	0.000	0.546	0.000	0.496	0.000
Average	0.466	0.000	0.508	0.000	0.379	0.001

4.2.2. Results of Spatial analysis

Table 5 reports the results of formula (2. The spatial lag coefficients of perinatal mortality rates are significant and negative in four models, indicating that it is competitive in improving health among neighboring provinces; that is, the decrease of mortality rates in the surrounding provinces would promote the decrease of mortality rate in the region. Column (1) and column (2) present the result using the average concentrations of $PM_{2.5}$. Column (3) and column (4) present the corresponding results using maximum concentrations of $PM_{2.5}$. Column (1) and column (3) are the result only controlling for the province fixed effects. Column (2) and column (4) further control the year fixed effects. The difference between the coefficients of $PM_{2.5}$ in four model is very small, which are all significant at the 5% level.

The spatial lag of $PM_{2.5}$ pollution is not significant. The lag of GDP per capita is significantly positive, indicating that the higher the level of economic development in neighboring areas, the higher the perinatal mortality rate in this region. The reason may be that the higher the economic development level, the more serious the pollution, which leads to the higher perinatal mortality in the region, which is also the reason why the spatial lag of $PM_{2.5}$ pollution is no longer significant. The spatial lag coefficients of the two medical conditions variables are significantly negative in column (2) and (4), indicating that the increase of medical level in the neighboring areas could improve the perinatal mortality rates in the region, because residents could choose to go to the neighboring areas for medical treatment.

Table 5 Results with spatial Durbin Model

Explanatory Variable	**Explained Variable: *Perinatal mortality***			
	(1)	(2)	(3)	(4)
W*Mortality	-0.125*	-0.248***	-0.137*	-0.263***
	(0.072)	(0.074)	(0.072)	(0.074)
Average $PM_{2.5}$ (log)	2.454**	2.491**		

	(1.161)	(1.112)		
Max PM2.5 (log)			2.293**	2.186**
			(0.893)	(0.856)
GDP per capita(log)	-6.270***	-5.150***	-6.165***	-5.003***
	(0.890)	(0.997)	(0.887)	(0.992)
No. of hospital beds per	-0.055**	-0.055*	-0.055**	-0.056**
10,000 persons	(0.028)	(0.029)	(0.028)	(0.028)
No. of hospitals per	-0.035	-0.044	-0.044	-0.051
10,000 persons	(0.051)	(0.053)	(0.051)	(0.053)
Urbanization	-0.000	0.006	0.000	0.007
	(0.012)	(0.012)	(0.012)	(0.012)
W*Average $PM_{2.5}$ (log)	-1.864	-1.622		
	(1.542)	(1.687)		
W* Max PM2.5 (log)			-0.967	0.014
			(1.247)	(1.379)
W* GDP per	2.300**	7.673***	2.014**	7.398***
capita(log)	(0.993)	(1.829)	(0.990)	(1.821)
W* No. of hospital	-0.038	-0.207***	-0.035	-0.196***
beds per 10,000 persons	(0.034)	(0.059)	(0.034)	(0.058)
W* No. of hospitals per	-0.087	-0.420***	-0.077	-0.409***
10,000 persons	(0.062)	(0.099)	(0.062)	(0.098)
W* Urbanization	0.040	0.024	0.040	0.028
	(0.029)	(0.030)	(0.029)	(0.030)
Year fixed effects	N	Y	N	Y
Province fixed effects	Y	Y	Y	Y
Within R-squared	0.735	0.543	0.736	0.527
Observations	434	434	434	434

Notes. Clustered standard in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Spatial effects can be further decomposed into direct effect, indirect effect (spillover effects) and total effect with reference to the research result of LeSage and Pace (2009). The indirect effects represent the independent variables' influence on the dependent variable in all other regions through spatial interactions. Therefore, we verify the existence of spillover effects by using partial matrix analysis. Table 6 illustrates the direct effect, indirect effect and total effect of the variables in SDM model. The results show that the estimated coefficient of $PM_{2.5}$' direct effect have the same direction as the estimated coefficients of SDM model in Table 5. But the estimated coefficient of $PM_{2.5}$' indirect effect is negative and insignificant.

When it comes to the estimated coefficients of controlled variables, we find that not all the spatial spillover effects of variables are significant. Overall, the GDP per capita have direct and indirect influence on perinatal mortality. The number of hospital beds per thousand persons has the significant direct effect, while the indirect effect is insignificant.

Table 6 Decomposition of direct effect, indirect effect, and total effect

Explanatory Variable	**Explained Variable: *Perinatal mortality***			
	(1)	(2)	(3)	(4)
Direct Effect				
Average $PM_{2.5}$ (log)	2.483**	2.580**		
	(1.183)	(1.174)		
Max PM2.5 (log)			2.308**	2.194**
			(0.912)	(0.903)
GDP per capita(log)	-6.360***	-5.643***	-6.258***	-5.512***
	(0.915)	(1.022)	(0.912)	(1.019)
No. of hospital beds	-0.053*	-0.044	-0.054**	-0.045
per 10,000 persons	(0.028)	(0.029)	(0.027)	(0.029)
No. of hospitals per	-0.035	-0.023	-0.043	-0.030
10,000 persons	(0.051)	(0.055)	(0.052)	(0.056)
Urbanization	-0.001	0.005	-0.001	0.006
	(0.013)	(0.013)	(0.013)	(0.013)
Indirect Effect				
Average $PM_{2.5}$ (log)	-1.960	-1.885		
	(1.509)	(1.601)		
Max PM2.5 (log)			-1.147	-0.459
			(1.216)	(1.290)
GDP per capita(log)	2.846***	7.716***	2.623***	7.460***
	(0.978)	(1.533)	(0.973)	(1.515)
No. of hospital beds	-0.031	-0.169***	-0.026	-0.157***
per 10,000 persons	(0.033)	(0.050)	(0.032)	(0.049)
No. of hospitals per	-0.075	-0.349***	-0.063	-0.336***
10,000 persons	(0.061)	(0.084)	(0.061)	(0.083)
Urbanization	0.037	0.019	0.036	0.022
	(0.027)	(0.026)	(0.026)	(0.026)
Total Effect				
$\ln PM_{2.5}$	0.523	0.695		
	(0.854)	(0.969)		

Max PM2.5 (log)			1.162	1.735*
			(0.803)	(0.892)
GDP per capita(log)	-3.514***	2.074	-3.635***	1.948
	(0.411)	(1.610)	(0.399)	(1.581)
No. of hospital beds	-0.084***	-0.212***	-0.080***	-0.202***
per 10,000 persons	(0.019)	(0.043)	(0.018)	(0.042)
No. of hospitals per	-0.109**	-0.372***	-0.106**	-0.365***
10,000 persons	(0.045)	(0.081)	(0.044)	(0.079)
Urbanization	0.036	0.024	0.036	0.028
	(0.026)	(0.026)	(0.026)	(0.026)

Notes. Clustered standard in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Instrumental Evidence

Table 7 shows the results using instrumental variable method. Column (1) and (2) uses the average concentrations of $PM_{2.5}$(log), while the column (3) and (4) uses the maximum concentrations of $PM_{2.5}$(log. The first stage estimates show that the F value is larger than 10, indicating that instrumental variables are effective. The two instrumental variables have a significant and positive impact on pollution. It shows a 1% increase of average concentrations of $PM_{2.5}$(log) results in 13‰ increase of perinatal mortality rates in both column (1) and (2. Similar results are also found in both column (3) and (4), which shows a 1% increase of average concentrations of maximum $PM_{2.5}$(log) results in 16‰ increase of perinatal mortality rates.

Table 7 Estimation results based on Instrumental Variables method

Explanatory Variable	**Explained Variable: *Perinatal mortality***			
	(1)	(2)	(3)	(4)
Average $PM_{2.5}$ (log)	13.080***	13.023***		
	(2.462)	(2.415)		
Max PM2.5 (log)			17.222***	16.350***
			(2.236)	(2.198)
GDP per capita(log)	-6.273***	-7.418***	-6.268***	-5.641***
	(0.594)	(1.204)	(0.584)	(1.135)
No. of hospital beds	0.038	0.078**	0.015	0.018
per 10,000 persons	(0.027)	(0.038)	(0.027)	(0.034)
No. of hospitals per	-0.078	-0.136	-0.083	-0.175*
10,000 persons	(0.064)	(0.092)	(0.073)	(0.099)
Urbanization	0.010	0.016	0.020*	0.027**
	(0.012)	(0.011)	(0.012)	(0.011)

Constant	-3.538	-0.359	-24.776***	-24.894***
	(7.270)	(7.784)	(7.891)	(9.076)
Within R-squared	0.812	0.834	0.760	0.809
Observation	434	434	434	434
First stage				
north	0.404***	0.618***	0.787***	0.568***
	(0.166)	(0.064)	(0.212)	(0.210)
distance	0.005***	0.029***	0.026***	0.190***
	(0.003)	(0.030)	(0.040)	(0.039)
F	103.16	75.23	60.45	50.59
P Value	(0.000)	(0.000)	(0.000)	(0.000)
Control variables	Y	Y	Y	Y
Year fixed effects	N	Y	N	Y
Province fixed effects	Y	Y	Y	Y
Within R-squared	0.958	0.970	0.930	0.947
Observation	434	434	434	434

Note. Clustered standard in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4. Mechanisms

In this section, we explore how $PM_{2.5}$ pollution affects perinatal mortality rates. The $PM_{2.5}$ pollution may affect the ratio of infants weighing less than 2.5kg. Infants weighing less than 2.5kg are considered as low birth weight, who have a higher risk of early childhood death. The proportion of infants with low birth weight in a province (*w5*) is obtained to investigate whether it is the mechanism through which $PM_{2.5}$ pollution has an impact on perinatal mortality rates. The results are presented in column (1) and (2) of table 8. An interaction of $w5*\ln PM_{2.5}$ is included column (1) and $w5*\ln maxPM_{2.5}$ is included in column (2). We find that the coefficients of the interactions are positive and statistically significant. Thus, $PM_{2.5}$ pollution not only has a direct effect on perinatal mortality, but also has an indirect effect by affecting the birth weight of infants.

Table 8 Estimated results of mechanism analysis

Explanatory Variable	**Explained Variable: Perinatal mortality**	
	(1)	(2)
Average PM2.5 (log)	1.261	
	(0.882)	
w5* Average PM2.5 (log)	0.347***	

	(0.108)	
Max PM2.5 (log)		1.765**
		(0.757)
w5* Max PM2.5 (log)		0.309***
		(0.099)
Urbanization	0.003	0.005
	(0.017)	(0.016)
GDP per capita(log)	-6.003**	-5.757**
	(2.196)	(2.163)
No. of hospital beds per	-0.017	-0.023
10,000 persons	(0.055)	(0.054)
No. of hospitals per	0.025	0.014
10,000 persons	(0.117)	(0.110)
Constant	28.831***	25.863***
	(7.829)	(8.417)
Year fixed effects	Y	Y
Province fixed effects	Y	Y
Within R-squared	0.769	0.770
Observation	434	434

Note. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions and discussion

The air quality in China, particularly the $PM_{2.5}$ level, has become an increasing public concern because of its relation to health risks. Using ArcGIS to analyze satellite raster data, this paper explores the relationship between the $PM_{2.5}$ pollution and the perinatal mortality rates in China for the years of 2002-2015. The main results are as follows: (1) The $PM_{2.5}$ pollution has a significant and positive impact on the perinatal mortality rates. A 1% increase of average or maximum concentrations of $PM_{2.5}$(log) resulting in 1.76‰ increase of perinatal mortality rates. After using instrumental variables to deal with potential endogenous problems, the conclusion is still valid. These conclusions are similar to those of the study on air pollution and infant mortality rate and child mortality rate [27, 28, 29]. (2) The $PM_{2.5}$ pollution has strong spatial dependence after analyzing Moran's I index of the $PM_{2.5}$ pollution. Therefore, we apply SDM method and find local and neighborhood $PM_{2.5}$ pollution has a significant and positive impact on local perinatal mortality rates. A possible explanation is that pollutants move between areas due to natural conditions such as rainfalls and wind. (3) The mechanisms analysis shows that $PM_{2.5}$ pollution would affect perinatal mortality rates through the weight of newborn infants.

This paper contributes to the literature linking $PM_{2.5}$ pollution to perinatal mortality rate as there has been very little empirical evidence. It also provides policy-making basis for government to put more efforts to prevent and control $PM_{2.5}$ pollution. The policy recommendations of this paper are as follows: Firstly, the state should increase investment to control the $PM_{2.5}$ pollution, and improve the efficiency of primary energy utilization for reducing the generation of $PM_{2.5}$ pollutant emissions; Secondly, the state should promulgate relevant laws and regulations to strengthen joint prevention and control of air pollution among regions; Thirdly, pregnant women should try to be exposed to as little pollution as possible. The results show that environmental pollution control should be strengthened and the exposure of pregnant women in polluted air should be reduced.

There are still some deficiencies in this study. Firstly, China is a typical country with urban-rural dual structure. Because of the limitations of data, it is impossible to conduct analysis for urban and rural areas separately in the paper. Secondly, due to data availability, this paper uses on macro-data, but micro-data may better identify the relationship between $PM_{2.5}$ pollutant emissions and perinatal mortality rates. Thirdly, this paper only studies $PM_{2.5}$ pollution, which can be expanded about the impact of other pollutants on perinatal mortality rates.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets of PM2.5 analysed during the current study available from the corresponding author on reasonable request. All data analysed during this study are included in *China Statistical Yearbook*, *China Health and Family Planning Statistical Yearbook, China Urban Statistical Yearbook* and *China Regional Economic Statistical Yearbook*.

Competing interests

The authors declare that they have no competing interests.

Funding

Financial supports from the National Natural Science Foundation of China (No. 71934001), and the Natural Science Foundation of Zhejiang Province in China (No. LY18G030014).

Authors' contributions

Guangqin Li is responsible data processing, paper revision; Lingyu Li is in charge of data processing and is the first author of the paper; Liu Dan put forward the idea of paper revision and later embellishment of papers. All authors read and approved the final manuscript.

Acknowledgments

Thanks to Ms. Jiahong Qin for his help in ArcGIS analysis.

References

1. Brauer, M., Freedman, G., Frostad, J., et al., 2015. Ambient air pollution exposure estimation for the global burden of disease 2013. Environ. Sci. Technol., 50(1), 79-88.
2. Zheng, S., & Kahn, M. E., 2017. A new era of pollution progress in urban China? J. Econ. Perspect., 31(1), 71-92.
3. Asian Development Bank, 2012. Toward an environmentally sustainable future: Country environmental analysis of the People's Republic of China. Asian Development Bank.
4. Lozano, R., Naghavi, M., Foreman, K., Lim, S., et al., 2012. Global and regional mortality from 235 causes of death for 20 age groups in 1990 and 2010: a systematic analysis for the Global Burden of Disease Study 2010. Lancet, 380(9859), 2095-2128.
5. Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., et al., 2012. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. Lancet, 380(9859), 2224-2260.
6. Samet, J. M., Dominici, F., Curriero, F. C., Coursac, I., & Zeger, S. L., 2000. Fine particulate air pollution and mortality in 20 US cities, 1987–1994. *N. Engl. J. Med., 343*(24), 1742-1749.
7. Dominici, F., Daniels, M., Zeger, S. L., & Samet, J. M., 2002. Air pollution and mortality: estimating regional and national dose-response relationships. J. Am. Stat. Assoc., 97(457), 100-111.
8. Wong, C. M., Vichit-Vadakan, N., Kan, H., & Qian, Z., 2008. Public Health and Air Pollution in Asia (PAPA): a multicity study of short-term effects of air pollution on mortality. Environ. Health Perspect., 116(9), 1195-1202.
9. Fang, D., Wang, Q. G., Li, H., Yu, Y., Lu, Y., & Qian, X., 2016. Mortality effects assessment of ambient PM2. 5 pollution in the 74 leading cities of China. Sci. Total Environ., 569, 1545-1552.
10. Chen, S., & Chen, T., 2014. Air pollution and public health: evidence from sulfur dioxide emission of coal-fired power stations in China. Econ. Res. J., 8, 158-183.
11. Pope III, C. A., Burnett, R. T., Thun, M. J., et al., 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. J. Am. Med. Assoc., 287(9), 1132-1141.
12. Bell, M. L., Samet, J. M., & Dominici, F., 2004. Time-series studies of particulate matter. Annu. Rev. Public Health, 25, 247-280.
13. Dominici, F., Peng, R. D., Bell, M. L., Pham, L., et al., 2006. Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. *The* J. Am. Stat. Assoc*., 295*(10), 1127-1134.
14. Samoli, E., Peng, R., Ramsay, T., Pipikou, M., et al., 2008. Acute effects of ambient particulate matter on mortality in Europe and North America: results from the APHENA study. Environ. Health Perspect., 116(11), 1480-1486.
15. Chen, R., Huang, W., Wong, C. M., Wang, Z., Thach, T. Q., Chen, B., ... &

CAPES Collaborative Group., 2012. Short-term exposure to sulfur dioxide and daily mortality in 17 Chinese cities: The China air pollution and health effects study (CAPES). Environ. Res., 118, 101-106.
16. Liu, S. K., Cai, S., Chen, Y., Xiao, B., Chen, P., & Xiang, X. D., 2016. The effect of pollution haze on pulmonary function. J. Thorac. Dis., 8(1), E41.
17. Kampa, M., & Castanas, E., 2008. Human health effects of air pollution. Environ. Pollut., 151(2), 362-367.
18. Tallon, L. A., Manjourides, J., Pun, V. C., Salhi, C., & Suh, H., 2017. Cognitive impacts of ambient air pollution in the National Social Health and Aging Project (NSHAP) cohort. Environ. Int., 104, 102-109.
19. Chay, K. Y., & Greenstone, M., 2003. Air quality, infant mortality, and the Clean Air Act of 1970 (No. w10053). National Bureau of Economic Research.
20. Chay, K. Y., & Greenstone, M., 2003. The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. Q. J. Econ., 118(3), 1121-1167.
21. Currie, J., & Neidell, M., 2005. Air pollution and infant health: what can we learn from California's recent experience? Q. J. Econ., 120(3), 1003-1030.
22. Currie, J., Neidell, M., & Schmieder, J. F., 2009. Air pollution and infant health: Lessons from New Jersey. J. Health Econ., 28(3), 688-703.
23. Khoo, K. L., 2006. The haze and health: a blog about the fog. Ann. Acad. Med. Singap., 35(12), 909.
24. Hannam, K., McNamee, R., Baker, P., Sibley, C., & Agius, R., 2014. Air pollution exposure and adverse pregnancy outcomes in a large UK birth cohort: use of a novel spatio-temporal modelling technique. Scand. J. Work Environ. Health, 40(5), 518-530.
25. DeFranco, E., Hall, E., Hossain, M., Chen, A., Haynes, E. N., Jones, D., ... & Muglia, L., 2015. Air pollution and stillbirth risk: exposure to airborne particulate matter during pregnancy is associated with fetal death. PLoS One, 10(3), e0120594.
26. Faiz, A. S., Rhoads, G. G., Demissie, K., Lin, Y., Kruse, L., & Rich, D. Q., 2013. Does ambient air pollution trigger stillbirth? Epidemiol., 24(4), 538-544.
27. Woodruff, T. J., Grillo, J., & Schoendorf, K. C., 1997. The relationship between selected causes of post neonatal infant mortality and particulate air pollution in the United States. Environ. Health Perspect., 105(6), 608-612.
28. De Medeiros, A. P. P., Gouveia, N., Machado, R. P. P., et al., 2008. Traffic-related air pollution and perinatal mortality: a case–control study. Environ. Health Perspect., 117(1), 127-132.
29. Hackley, B., Feinstein, A., & Dixon, J., 2007. Air pollution: impact on maternal and perinatal health. J. Midwifery Women Health, 52(5), 435-443.
30. Jackson, D. J., Lang, J. M., & Ganiats, T. G., 1999. Epidemiological issues in perinatal outcomes research. Ped. Perin. Epidemiol., 13(4), 392-404.
31. Yu, X., Miao, Y., 2009. Analysis on Death Causes and Changes Trends in Perinatal Infants During 13 years. Matern. Child. Health Care China, 24(06), 815-817.

32. Shao, S., Li, X., Cao, J. H., & Yang, L. L., 2016. China's economic policy choices for governing smog pollution based on spatial spillover effects. Econ. Res. J., 9, 73-88.
33. Tao, C., Yang, H., 2014. Spatial econometric model selection and its simulation analysis. Stat. Res., 31(8), 88-96.
34. Peng, W., Wu, W., & Kuang CH., 2014. the impact of environmental regulation on the spatial evolution of pollution industry: Based on the spatial panel Durbin model. World Econ. Pap., (6), 99-110.
35. Chen Z., 2016. Eco-efficiency, Urbanization and Spillover Effects: Based on Spatial Panel Durbin Model. Manage. Rev., 28(11), 66-74.
36. Chen, Y., Ebenstein, A., Greenstone, M., & Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai river policy. Proc. Natl. Acad. Sci. U. S. A., 110(32), 12936-12941.
37. Ebenstein, A., Fan, M., Greenstone, M., He, G., & Zhou, M., 2017. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. Proc. National Acad. Sci., 114(39), 10384-10389.
38. Boys, B. L., Martin, R. V., Van Donkelaar, A., et al., 2014. Fifteen-year global time series of satellite-derived fine particulate matter. Environ. Sci. Technol., 48(19), 11109-11118.
39. Van Donkelaar, A., Martin, R. V., Brauer, M., Hsu, N. C., Kahn, R. A., Levy, R. C., ... & Winker, D. M., 2016. Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors. Environ. Sci. Technol., 50(7), 3762-3772.
40. Van Donkelaar, A., Martin, R. V., Spurr, R. J., & Burnett, R. T., 2015. High-resolution satellite-derived PM2. 5 from optimal estimation and geographically weighted regression over North America. Environ. Sci. Technol., 49(17), 10482-10491.
41. Xiang, K., Song, D.Y., 2016. Spatial analysis of China province-level perinatal mortality. Iran J. Public Health, 45(5), 614.

Figures

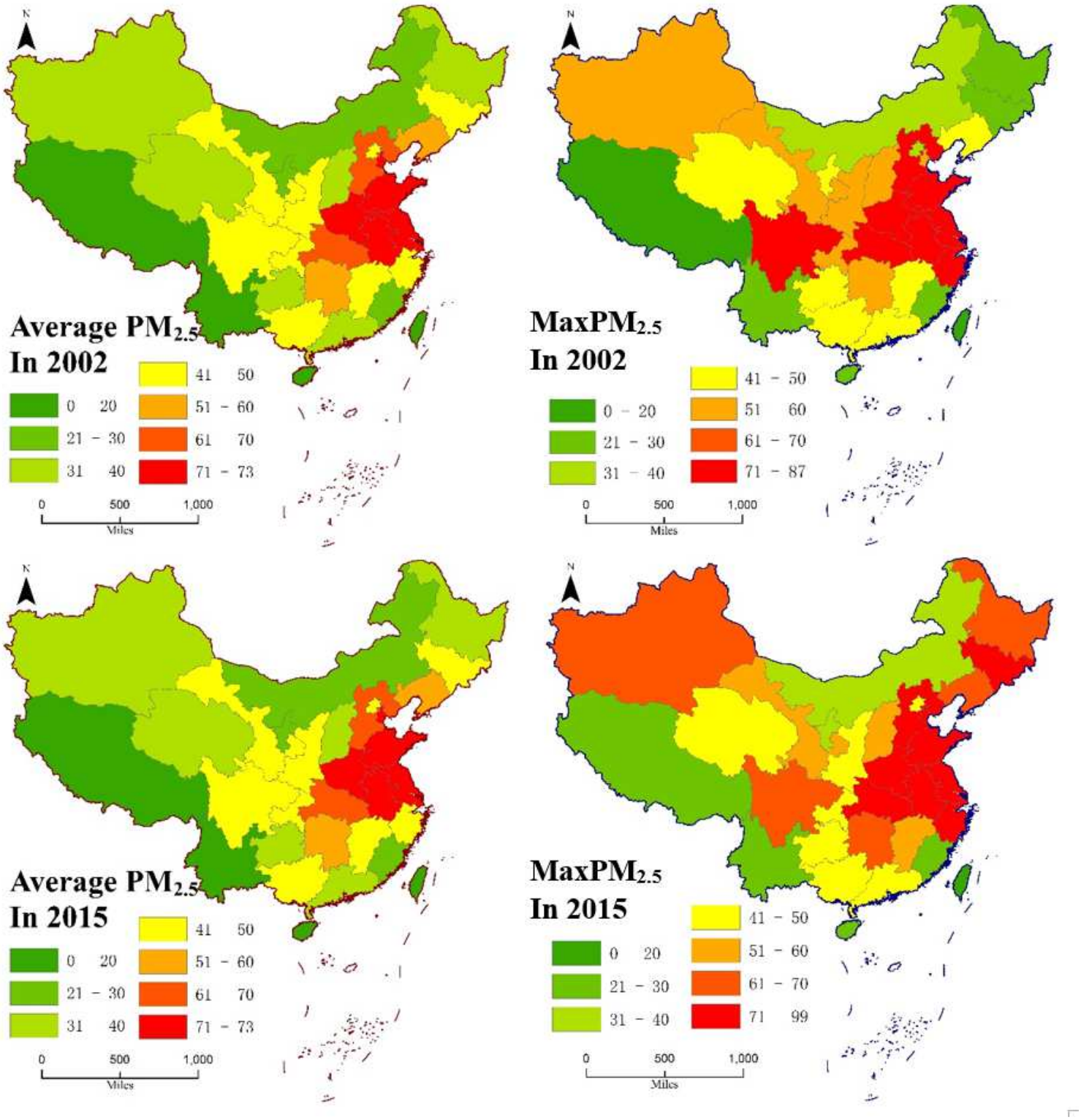


Figure 1

Spatial distribution of PM2.5 in 2002 and 2015 (μg/m3), respectively. The left two maps are the spatial distribution maps of average PM2.5 pollution concentration in 31 provinces in 2002 and 2015,respectively, and the right two maps are the spatial distribution maps of maximum PM2.5 pollution

depth in 31 provinces in 2002 and 2015, respectively. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.