Science of the Total Environment 740 (2020) 140155

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Effects of socioeconomic and natural factors on air pollution in China: A spatial panel data analysis

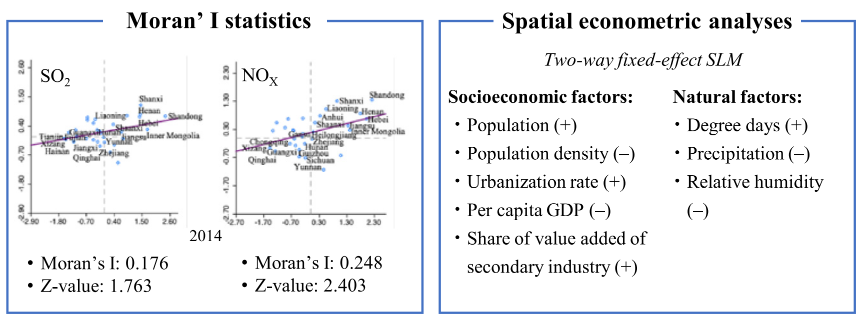
Lina Ren [a], Ken'ichi Matsumoto [a,b,*]

[a] Graduate School of Fisheries and Environmental Sciences, Nagasaki University, 1-14 Bunkyo-machi, Nagasaki 852-8521, Japan
[b] Research Institute for Global Change, Japan Agency for Marine-Earth Science and Technology, 3173-25 Showa-machi, Kanazawa-ku, Yokohama 236-0001, Japan

HIGHLIGHTS

- We conducted spatial autocorrelation and special panel regression analyses.
- Panel data for 31 provinces from 2011 to 2017 in China were used.
- Significantly positive spatial autocorrelation was shown for SO_2 and NO_X emissions.
- Both social and natural factors affect positively/negatively air pollution.
- Promotion of regional cooperation is necessary to further reduce air pollution.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 3 April 2020
Received in revised form 10 June 2020
Accepted 10 June 2020
Available online 15 June 2020

Editor: Pavlos Kassomenos

Keywords:
Sulfur dioxide emissions
Nitrogen oxides emissions
Socioeconomic factors
Natural factors
Spatial econometric analysis

ABSTRACT

China's energy use has increased significantly in recent years with the country's rapid economic growth and large-scale urbanization. Therefore, air pollution has become a major issue. In this study, we conducted spatial autocorrelation and spatial panel regression analyses of sulfur dioxide (SO_2) and nitrogen oxide (NO_X) emissions using the panel data of 31 provincial-level administrative units in China during the period 2011–2017 to comprehensively understand the factors affecting air pollutant emissions. This study contributes to the literature by considering comprehensive factors and spatial effects in the panel-data econometric framework of the whole country of China. The analysis of spatial characteristics shows that during the study period, pollutant emissions in China declined, although emissions in northern regions were still relatively high. Furthermore, SO_2 and NO_X emissions showed significant positive spatial autocorrelations. The results of a fixed-effect spatial lag model showed that both socioeconomic and natural factors were statistically significant for air pollutant emissions, although the degree differed by the type of pollutant. The population, the urbanization rate, the share of added value of secondary industry, and heating and cooling degree days positively affected emissions, while population density, per-capita gross regional product, precipitation, and relative humidity negatively affected emissions. Based on these results, we have put forward suggestions to address the issue of air pollution and achieve environmental sustainability, such as the promotion of regional cooperation and a transition of the economic structure.

1. Introduction

China's energy use has significantly increased over the past few decades with the country's rapid economic growth and large-scale urbanization. This has led to a corresponding increase in air pollutant emissions. Persistent large-scale air pollution has not only hindered China's economic development but has also adversely affected people's health and quality of life (Li and Zhang, 2014). The effective control of air pollution and the consequent improvement of urban ambient air quality have proven to be one of the most important goals for social and economic transformation and development in China (Wang et al.,

* Corresponding author at: Graduate School of Fisheries and Environmental Sciences, Nagasaki University, 1-14 Bunkyo-machi, Nagasaki 852-8521, Japan.
E-mail address: kenichimatsu@nagasaki-u.ac.jp (K. Matsumoto).

https://doi.org/10.1016/j.scitotenv.2020.140155
0048-9697/

2014). Although the Chinese government has been working to alleviate this problem, air pollution has long been a known and pressing problem in the country. In its Twelfth Five-Year Plan (2011–2015), a strategy to control emissions of nitrogen oxides (NO_X), sulfur dioxide (SO_2), and major particulate matter (PM) was implemented nationwide (Ding et al., 2017). This strategy has been amended many times, but the situation has not significantly improved. Indeed, in 2017, only 99 of 338 (29.3%) prefecture-level cities nationwide met national ambient air-quality standards (Chinese Ministry of Ecology and Environmental Protection, 2017).

The factors influencing air pollution are extensive and complex, and many studies have been implemented to explore the causes of changes in air pollutant emissions and concentrations (e.g., SO_2, NO_X, and PM) and in the air quality index (AQI). Table 1 summarizes the literature on the potential factors (socioeconomic and natural) influencing air pollution in China. Different studies have focused on different factors.

Regarding socioeconomic factors, population (e.g., Wang et al., 2016; S. Zhao et al., 2018), population density (e.g., Hao and Liu, 2016; Huang, 2018; Zhao et al., 2019), economic conditions (e.g., Hao and Liu, 2016; Wang et al., 2016), secondary industry activity (e.g., Huang, 2018; Zeng et al., 2019; Han et al., 2019), and urbanization (e.g., Han et al., 2014; Liu et al., 2017; Hao et al., 2020) are often considered the important determinants of air pollution.[1] The two population-related factors affect air pollution differently. Population is basically a factor that accelerates air pollution. Using a semi-parametric panel model with provincial-level data, Wang et al. (2016) found that population was a factor that increases SO_2 emissions. Zhao et al. (2019) used regression models with the data for 269 Chinese cities to evaluate the relationship between $PM_{2.5}$ concentrations and socioeconomic factors from 2015 to 2016 and found that population positively affected the $PM_{2.5}$ concentrations due to the acceleration of urbanization. S. Zhao et al. (2018) applied structural equation modeling with the data of 200 Chinese cities in 2015 to analyze the driving forces of NO_X pollution and found that the resident population indirectly and positively affected NO_X pollution.

In contrast to population, the impact of population density on air pollution is somewhat complicated. On one hand, a higher population density leads to a higher degree of urbanization and industrialization, which may increase urban $PM_{2.5}$ concentrations (Hao and Liu, 2016). On the other hand, a high population density enables the intensive use of energy, which reduces total pollutant emissions and is therefore beneficial to the environment (Hao and Liu, 2016). Huang (2018) also pointed out that a high population density can degrade the air quality due to a crowd effect or improve the air quality due to a civilization effect. In analyzing the relationship between SO_2 emissions and socioeconomic factors using panel spatial Durbin models in 30 provinces in China, Huang (2018) showed that population density could reduce SO_2 emissions because the civilization effect was greater than the crowd effect. However, Zhao et al. (2019) concluded that population density would increase the $PM_{2.5}$ concentration level.

Various economic factors have also been evaluated in the literature, and their impacts on air pollution also varied. Per-capita gross domestic product (GDP) or per-capita gross regional product (GRP), which indicate the wealth of countries or regions, are variables often investigated in the literature. Yang et al. (2017b) employed various panel-data regression models in 30 cities in China and found that per-capita GDP negatively affected SO_2 concentrations. However, a global analysis with country-level data and spatial panel econometric models by Fu and Li (2020) revealed that per-capita GDP was a positive factor for $PM_{2.5}$ concentrations. Other studies had mixed findings. For example, Wang et al. (2016) found an inverted U-shaped relationship between SO_2 emissions and per capita GDP. Hao and Liu (2016) evaluated the socioeconomic factors affecting $PM_{2.5}$ concentrations and the AQI for 73 Chinese cities in 2013 using spatial econometric models and found a similar relationship. These studies indicate that air pollution can be worse during the initial stage of economic growth and can be improved after economic levels have reached a certain point.

Another important economic variable is the activity of secondary industry (e.g., the value added or GDP of secondary industry, or the ratio of the value added of secondary industry to GDP), which is the main emitter of air pollutants. Zeng et al. (2019) employed spatial econometric models with China's 31 provincial-level administrative units to empirically estimate the effects of energy policies and socioeconomic variables on PM_{10}, $PM_{2.5}$, and SO_2 emissions. The results indicated that the GDP of secondary industry positively affected PM_{10} and SO_2 emissions. Huang (2018) also found that provinces with higher proportions of secondary industries to total GRP emitted more SO_2. This finding can be explained by the fact that the development of secondary industry stimulates energy use and greatly increases air pollution (Jiao et al., 2017).

Finally, urbanization is another important factor affecting air pollution. Liu et al. (2017) used various spatial econometric models and the data of 289 prefecture-level cities in 2014, and found that urbanization positively affects AQI. Hao et al. (2020) used a dynamic threshold panel model with the data for 29 provinces for the period 1998–2015 and found that per-capita pollutant emissions increased with increasing urbanization. As these studies have revealed, urbanization usually positively affects air pollution because it causes an increase in energy consumption, crowding, traffic congestion, and vehicle emissions (Liu et al., 2017; Wu et al., 2019).

Although these studies help us understand the causes of air pollution from socioeconomic perspectives, natural factors (meteorological variations and conditions), such as temperature (e.g., Yang et al., 2017a; Feng et al., 2019), precipitation (e.g., Li et al., 2014; Bai et al., 2019; Liu et al., 2019), and humidity (e.g., Li et al., 2014; Chen et al., 2016; Bai et al., 2019), are also important factors that affect air pollution.[2] Yang et al. (2017a) used a series of regression models and data from 113 major cities in China in 2014 to evaluate the impact of natural factors on SO_2 concentrations. They found that temperature had a positive effect on SO_2 concentrations and precipitation had a negative effect. Feng et al. (2019) examined global datasets and found that $PM_{2.5}$ concentrations were positively correlated with temperature but negatively correlated with precipitation. Li et al. (2014) evaluated the relationship between air quality and various meteorological factors using correlation analysis and data for the period 2001–2011 in Guangzhou, and found that precipitation and relative humidity were negatively correlated with air quality. These findings were confirmed by Chen et al. (2016), who evaluated the factors affecting $PM_{2.5}$ concentrations in the Chinese city of Nanjing from 2013 to 2015. Precipitation contributes to the diffusion of atmospheric pollutants, and relative humidity increases the size and volume of the pollutant particles, thus lowering pollution levels (Li et al., 2014; Lu et al., 2017; Bai et al., 2019).

Many studies have mainly focused on either socioeconomic or natural factors, but a few have considered both socioeconomic and natural factors in their analyses (Table 1), although it is important to include all possible influencing factors (i.e., socioeconomic and natural factors here) in regression models to remove the possible omitted variable bias. Liu et al. (2017) found that factors such as urbanization, industrialization, urban population aggregation, and temperature had a significantly positive impact on the AQI, while all the natural factors besides temperature had a negative impact. Han et al. (2019) studied the factors affecting the AQI in China using the data of 152 cities using global and local regression models. They found that the increase in the industrial structures and the number of civilian vehicles led to an increase in the AQI, but the impact of precipitation was reversed.

The purpose of this study is to explore the spatial effects and factors affecting air pollution using provincial-level data in China for the period

[1] There are other socioeconomic factors that can affect air pollution, as shown in Table 1. However, the literature review here focused on the factors evaluated in this study.

[2] There are other natural factors that can affect air pollution as shown in Table 1. However, the literature review here focused on the factors evaluated in this study.

Table 1
Summary of the selected literature analyzing the factors influencing air pollution in China using regression models.

Factors	Source	Region	Period	Main method	Variables
Socioeconomic factors	Hao and Liu (2016)	73 cities	2013	Spatial lag model (SLM), spatial error model (SEM)	Dependent variables: Air Quality Index (AQI) and $PM_{2.5}$ concentrations Independent variables: per-capita gross domestic product (GDP), industrial structure, vehicle population, population density
	Wang et al. (2016)	Provinces (the number is not specified)	1990–2012	Parametric and semi-parametric panel fixed-effect models	Dependent variable: SO_2 emissions Independent variables: population, energy use, per-capita GDP, percentage of urban population
	Huang (2018)	30 provinces	2008–2013	Panel spatial Durbin model	Dependent variable: SO_2 emissions Independent variables: provincial spending on environmental protection, gross regional product (GRP), foreign direct investment, population density, share of trade to GRP, heat supply, private investment of pollution treatment, share of product of secondary industry to GRP
	D. Zhao et al. (2018)	Five hot spots (Yangtze River Delta, Bohai Rim, Pan–Pearl River Delta, Central region, Western region)	2004–2012	Stochastic impacts by regression on population, affluence, and technology model (panel regression model)	Dependent variable: $PM_{2.5}$ pollution intensity Independent variables: population density, per-capita GDP, per-capita energy consumption, private cars
	S. Zhao et al. (2018)	85 cities (1996) and 200 cities (2015)	1996, 2015	Structural equation modeling	Dependent variables: SO_2 and NO_X concentrations Independent variables: household electricity consumption, civilian vehicles, urban built-up area, resident population, secondary industry GDP, tertiary industry GDP, power generation, urban heated area
	Zhou et al. (2018)	190 cities	2014	Ordinary least squares (OLS) regression, SEM	Dependent variables: $PM_{2.5}$ concentrations Independent variables: Per capita GDP, population density, urban secondary industry share, industrial soot emissions, road density, ratio of foreign direct investment to GDP, electricity consumption
	Zeng et al. (2019)	27 provinces and four direct-controlled municipalities	2003–2016	OLS regression, spatial autoregressive model, SEM	Dependent variables: PM_{10}, $PM_{2.5}$, and SO_2 emissions Independent variables: emission reduction policies, renewable energy policies, GDP of secondary industry, consumption expenditure, educational level, population density, private vehicle discharge level, waste gas emissions, industry pollution source treatment, investment in anti-pollution projects
	Zhao et al. (2019)	269 cities	2015–2016	OLS regression	Dependent variable: $PM_{2.5}$ concentration Independent variables: population, built-up areas, GDP, population density, share of secondary industry, private vehicles, per-capita disposable income
	Hao et al. (2020)	29 provinces	1998–2015	Dynamic threshold panel model incorporating generalized method of moments	Dependent variable: per-capita SO_2, industrial soot, and industrial waste gas emissions Independent variables: urbanization, per-capita GDP, ratio of secondary industry to GDP, ratio of tertiary industry to GDP, ratio of trade to GDP, per-capita education years, energy intensity
Natural factors	Yang et al. (2017a)	113 cities	2014	OLS, SLM, and SEM, geographic weighted regression model	Dependent variable: SO_2 concentration Independent variables: precipitation, temperature, wind speed, relative humidity
Socioeconomic and natural factors	Liu et al. (2017)	289 prefecture-level cities	2014	SLM, SEM, Spatial Durbin model	Dependent variable: AQI Socioeconomic variables: total population, urban population, GDP, urban land, share of value added of secondary industry, population density, per-capita GDP, private car density Natural variables: temperature, precipitation, normalized difference vegetation index, atmospheric pressure, relative humidity, wind speed, elevation, green ratio
	Yang et al. (2017b)	30 cities	1995–2016	Pooled regression models, variable intercepts and constant coefficients models, variable intercepts and variable coefficients models	Dependent variable: SO_2 concentration Socioeconomic variables: population density, per-capita GDP, secondary industry share Natural variables: precipitation, temperature, wind speed, relative humidity
	Hu et al. (2019)	29 provinces	2002–2014	Stochastic frontier analysis, error correction model	Dependent variable: SO_2 emissions Socioeconomic variables: price index, GDP, population, household size, vehicles, share of industry and service sectors, Natural variable: heating and cooling degree days
	Han et al. (2019)	152 cities	2016	Global and local regression model	Dependent variable: AQI Socioeconomic variables: secondary industry GDP, industrial structure, population density, per-capita GDP, urbanization rate, civil vehicles, traffic mileage Natural variables: temperature, precipitation, atmospheric pressure, wind speed, elevation, green ratio

2011–2017. The study focuses on SO_2 and NO_X emissions as the target air pollutants because they are primary sources of air pollution. Although China significantly reduced SO_2 emissions between 2007 and 2016 (from 36.6 Mt. to 8.4 Mt.), it is still the world's second largest emitter (Hu et al., 2019), with over 70% of SO_2 emissions derived from industrial sources (Zhang and Crooks, 2012). Furthermore, China produces about 25% of the world's NO_X emissions (Cui et al., 2013), mainly from the burning of fossil fuels and the production of explosives, dyes, nitric acid, and nitrogenous fertilizer (Lee et al., 1997; Cui et al., 2013). Therefore, SO_2 and NO_X emissions are still the main causes of air pollution in China. Few studies have been conducted on the emission of various pollutants, and further research will improve our understanding of the effectiveness of air pollution mitigation efforts and strategies. In regard to the research model, we employed spatial econometric models, in particular fixed-effect spatial panel regression models. Spatial econometric models are suitable for this study considering that regional air pollutant discharge has the characteristics of spatial spillover and spatial diffusion (i.e., flows from one province to the adjacent provinces). Furthermore, panel data regression models can increase the number of observations, and the province fixed effect can capture unobserved factors in a province, whereas the year fixed effect can capture the factors that affect pollutant emissions equally across a province in each year. Recent studies by Liu et al. (2017) and Yang et al. (2017b) have evaluated both socioeconomic and natural aspects that affect air pollution, similar to this study. However, Liu et al. (2017) only used single-year data, which is weak for evaluating causality, while Yang et al. (2017b) did not consider spatial effects. In addition, these studies focused on limited geographical areas. The city-level analysis is more detailed in terms of geographical resolution, but given China's vast area and socioeconomic diversity, studies of specific areas lack the necessary generalizability for an overall assessment of China. Therefore, our approach is more appropriate to explore the various factors affecting air pollution. Considering our literature review, the main contributions of this study are that we consider (1) comprehensive factors (i.e., multiple socioeconomic and natural factors) and multiple air pollutants, (2) the whole country with its multiple regions, (3) spatial effects, and (4) panel data for a relatively long period.

2. Data and methodology

This section describes the variables, data, and models used to analyze the factors affecting air pollutant emissions.

2.1. Variable selection and data

In this study, we used SO_2 and NO_X emissions as the dependent variables. From the literature review in Section 1, it is clear that not only socioeconomic but also natural factors can affect air pollution. Considering the literature review and the data availability, we chose eight factors (i.e., five socioeconomic factors—population (*POP*), population density (*PD*), urbanization (*URB*), per-capita GRP (*PCGRP*), and added value of secondary industry divided by GRP (*SDA_GRP*)—and three natural factors—degree days (*DD*), precipitation (*PRE*), and relative humidity (*RHU*)[3]) to examine. Definitions and descriptive statistics are provided in Table 2.

For the temperature-related variable, this study used degree days, the sum of heating degree days (*HDD*) and cooling degree days (*CDD*), which were calculated based on daily temperature.[4] In the literature, temperature is often used as an independent variable. However, it is not possible to capture cold winter and hot summer, when more energy is consumed, with a linear modeling framework if temperature is used. Therefore, we used degree days. The base temperatures used for *HDD* and *CDD* were 18 °C and 26 °C, respectively (Shi et al., 2016). Eqs. (1) and (2) are used to calculate the degree days where D is the number of days in the year, T_d is the daily mean temperature for day d, and rd is equal to 1 if T_d is lower than 18 (Eq. (1)) or higher than 26 (Eq. (2)) and is equal to 0 otherwise.

$$HDD = \sum_{d=1}^{D} rd(18-T_d) \tag{1}$$

$$CDD = \sum_{d=1}^{D} rd(T_d-26) \tag{2}$$

Considering availability and comprehensiveness, the annual data of the 31 provincial-level administrative units (hereafter, provinces) during the period 2011–2017 were employed (the total observation was 217). The data for SO_2 and NO_X emissions and socioeconomic factors were taken from the National Bureau of Statistics for each province.[5] Degree days were calculated based on daily temperatures taken from Meteomanz.com,[6] and the annual average precipitation and relative humidity were taken from the China Statistical Yearbook.[7] The data from a major city of each province[8] were used as representatives with regard to the natural factors.

2.2. Empirical framework

In this study, a spatial autocorrelation analysis using Moran's I and scatter plots was performed first, followed by spatial econometric estimations. To choose suitable models, we conducted the Hausman and Lagrange multiplier (LM) tests.

2.2.1. Spatial autocorrelation analysis

Spatial dependence is a geographical phenomenon. Regional air pollutant discharge has the characteristics of spatial spillover and spatial diffusion, with a great impact on the air pollution of neighboring areas. Here, the most commonly used Moran's I was selected to measure the spatial correlation of SO_2 and NO_X. The Moran's I is defined as Eq. (3), where N is the number of spatial units indexed by locations (provinces in this study) i and j, W_{ij} is a spatial weight matrix with zeroes on the diagonal, x_i and x_j refer to the observations of i and j, respectively, and $\bar{x}$ refers to the mean of x.

$$I = \frac{\sum_{i=1}^{N}\sum_{j\neq i}^{N} W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\left(\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}\right)} = \frac{\sum\limits_{i=1}^{N}\sum\limits_{j\neq i}^{N} W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\left(\sum\limits_{i=1}^{N}\sum\limits_{j\neq i}^{N} W_{ij}\right)\sum\limits_{i=1}^{N}(x_i-\bar{x})^2} \tag{3}$$

A spatial weight matrix is necessary when implementing spatial econometric analysis, as it provides spatial-structure information between adjacent areas and how they interact with each other. The choice of the spatial weight matrix is the premise for the analysis. There are two types of spatial weight matrices, which are based on either

[3] The natural factors are not constant and vary every year, and the degree of change differs by province. Therefore, fixed effects cannot capture the effect of the natural factors. Consequently, it is reasonable to include them as independent variables.

[4] Heating degree days refers to the cumulative daily temperatures below a base temperature in a year, and cooling degree days refers to the cumulative daily average temperatures above a base temperature. Because *HDD* and *CDD* are both temperature-related variables and are highly correlated, we applied *DD* not *HDD* and *CDD* in our analyses.

[5] The data are available at http://data.stats.gov.cn/easyquery.htm?cn=E0103.

[6] The data are available at http://www.meteomanz.com/.

[7] The data are available at http://www.stats.gov.cn/tjsj/ndsj/.

[8] The selected major cities are: Hefei (Anhui), Beijing, Chongqing, Fuzhou (Fujian), Yuzhong (Gansu), Guangzhou (Guangdong), Nanning (Guangxi), Guiyang (Guizhou), Haikou (Hainan), Shijiazhuang (Hebei), Harbin (Heilongjiang), Zhengzhou (Henan), Wuhan (Hubei), Changsha (Hunan), Nanjing (Jiangsu), Nanchang (Jiangxi), Changchun (Jilin), Shenyang (Liaoning), Hohhot (Inner Mongolia), Yinchuan (Ningxia), Xining (Qinghai), Jinghe (Shaanxi), Jinan (Shandong), Baoshan (Shanghai), Taiyuan (Shanxi), Wenjiang (Sichuan), Tianjin, Urumqi (Xinjiang), Lhasa (Xizang), Kunming (Yunnan), and Hangzhou (Zhejiang).

Table 2
Definitions and descriptive statistics of variables.

Factors	Variables	Definition	Mean	S.D.	Min.	Max.
Air pollution	*SO_2*	Annual SO_2 emissions (ton)	561,809.18	398,404.16	3462.81	1,827,397.20
	NO_X	Annual NO_X emissions (ton)	624,496.03	424,650.87	30,153.52	1,801,138.33
Socioeconomic factors	*POP*	Population at the end of the year (10^4 person)	4398.61	2769.82	303.00	11,169.00
	PD	Population density (person/km^2)	2796.94	1164.11	515.00	5821.00
	URB	Urbanization rate (%)	55.58	13.38	22.73	89.61
	PCGRP	Per-capita GRP (Yuan/person)	50,049.28	23,388.45	16,436.55	129,041.64
	SDA_GRP	Ratio of added value of secondary industry to GRP	0.45	0.08	0.19	0.59
Natural factors	*DD*	Sum of heating degree days and cooling degree days in a major city of each province (°C-day)	2393.17	1223.03	557.30	5477.10
	PRE	Annual precipitation of a major city in each province (mm)	942.51	565.85	148.80	2939.70
	RHU	Annual average relative humidity of a major city in each province (%)	65.30	11.94	33.50	84.58

contiguity or distance. Here, the widely used contiguity spatial weight matrix has been adopted. The spatial weight matrix is defined as **W**, with elements W_{ij} indicating whether or not observations *i* and *j* are spatially close. If units *i* and *j* (≠ *i*) are neighbors, the spatial weight is 1; otherwise, it is 0. W_{ij} can be written as Eq. (4).

$$W_{ij} = \begin{cases} 1 & \text{if } i \text{ is contiguous to } j \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The value of Moran's I ranges from −1 to 1. When the value is close to −1, the spatial distribution shows a discrete trend. In contrast, when the value is close to 1, a clustering trend appears in the spatial distribution. If the value is close to 0, there is no correlation. The results of Moran's I are not only displayed numerically but also shown through the Moran scatter plot. The slope of the linear smooth line of the scatter plot is consistent with the Moran's I value. In this study, we used GeoDa 1.14 to calculate the Moran's I and to draw the Moran scatter plots. Contiguity of provinces is set based on Fig. S1 and Table S1 in the Supplementary Material.

2.2.2. Spatial panel models

The spatial econometric model primarily analyzes the interaction and interdependence of spatial regions. First, a simple pooled regression model with space-specific effects but without spatial interaction effects was considered (Elhorst, 2010). The simple pooled linear regression model can be written as Eq. (5), where *t* is an index for the time dimension (years in this study), with $t = 1, \ldots, T$. y_{it} is the dependent variable (SO_2 or NO_X emissions in this study) at *i* and *t*, x_{it} represents the vector of the independent variables at *i* and *t*, and β represents the coefficient vector. u_i denotes a spatial-specific effect for *i*, while ε_{it} is an error term for *i* and *t*.

$$y_{it} = \beta x_{it} + u_i + \varepsilon_{it} \tag{5}$$

The standard reasoning behind spatial-specific effects is that they control all space-specific time-invariant variables, the omission of which could bias the estimates of a typical cross-sectional study.

The spatial econometric model can effectively solve the spatial dependence problem. In order to examine and measure possible spatial effects, two types of spatial econometric models were considered—the spatial lag model (SLM) and the spatial error model (SEM). The SLM can be interpreted as containing endogenous interaction effects among the dependent variables and can be expressed as Eq. (6), where δ is the spatial autoregressive coefficient and W_{ij}' is the row-standardized spatial weight matrix (W_{ij}).

$$y_{it} = \delta \sum_{j=1}^{N} W_{ij}' y_{jt} + \beta x_{it} + u_i + \varepsilon_{it} \tag{6}$$

The SEM considers that the dependent variable depends on a set of observed local characteristics and that the error terms are correlated across space. The SEM can be written as Eq. (7), where $\sum_{j=1}^{N} W_{ij}' \phi_{it}$ denotes the interaction effects among the disturbance terms of the different units and λ refers to the spatial autocorrelation coefficient. ϕ_{it} reflects the spatially autocorrelated error term.

$$\begin{aligned} y_{it} &= \beta x_{it} + u_i + \phi_{it} \\ \phi_{it} &= \lambda \sum_{j=1}^{N} W_{ij}' \phi_{it} + \varepsilon_{it} \end{aligned} \tag{7}$$

2.2.3. Model selection

As fixed-effect and random-effect models are often used for panel data analysis, it is necessary to choose a suitable model. Here, a series of Hausman tests was performed to identify the presence of endogeneity in the explanatory variables in order to effectively estimate random and fixed effects.

After the one model was chosen, the LM test was applied for further model selection (SLM or SEM). The four tests pertaining thereto were the LM-lag, LM-error, robust LM-lag, and robust LM-error tests. When the standard versions (i.e., LM-lag or LM-error) were both significant, the robust versions were conducted. We used R 3.6.1 and Stata 16 for panel spatial regression analyses and the related tests.

3. Results

3.1. Temporal and spatial distribution of air pollution

According to the China Statistical Yearbook,[9] in China the total national emissions of SO_2 decreased from 22.18 Mt. in 2011 to 8.75 Mt. in 2017, and those of NO_x decreased from 24.04 Mt. in 2011 to 12.59 Mt. in 2017. These figures show that national pollutant emissions have gradually receded in recent years. As shown in Fig. 1, which details the spatial distribution of air pollutant emissions, the emissions have also been decreased over the years throughout the country. Comparing regions, the emissions in the central and southern parts of China have largely decreased, but emissions are still relatively high in the northern part of China.

3.2. Spatial autocorrelation

The Moran's I statistics were used to test the spatial autocorrelation of air pollutants in China. Table 3 lists the Moran's I statistics for SO_2 and NO_X emissions in China from 2011 to 2017. As shown in the table, the Moran's I values were positive and statistically significant at the 5% or 10% level for almost every year. Comparing the two emissions, the

[9] The data are available at http://www.stats.gov.cn/tjsj/ndsj/.

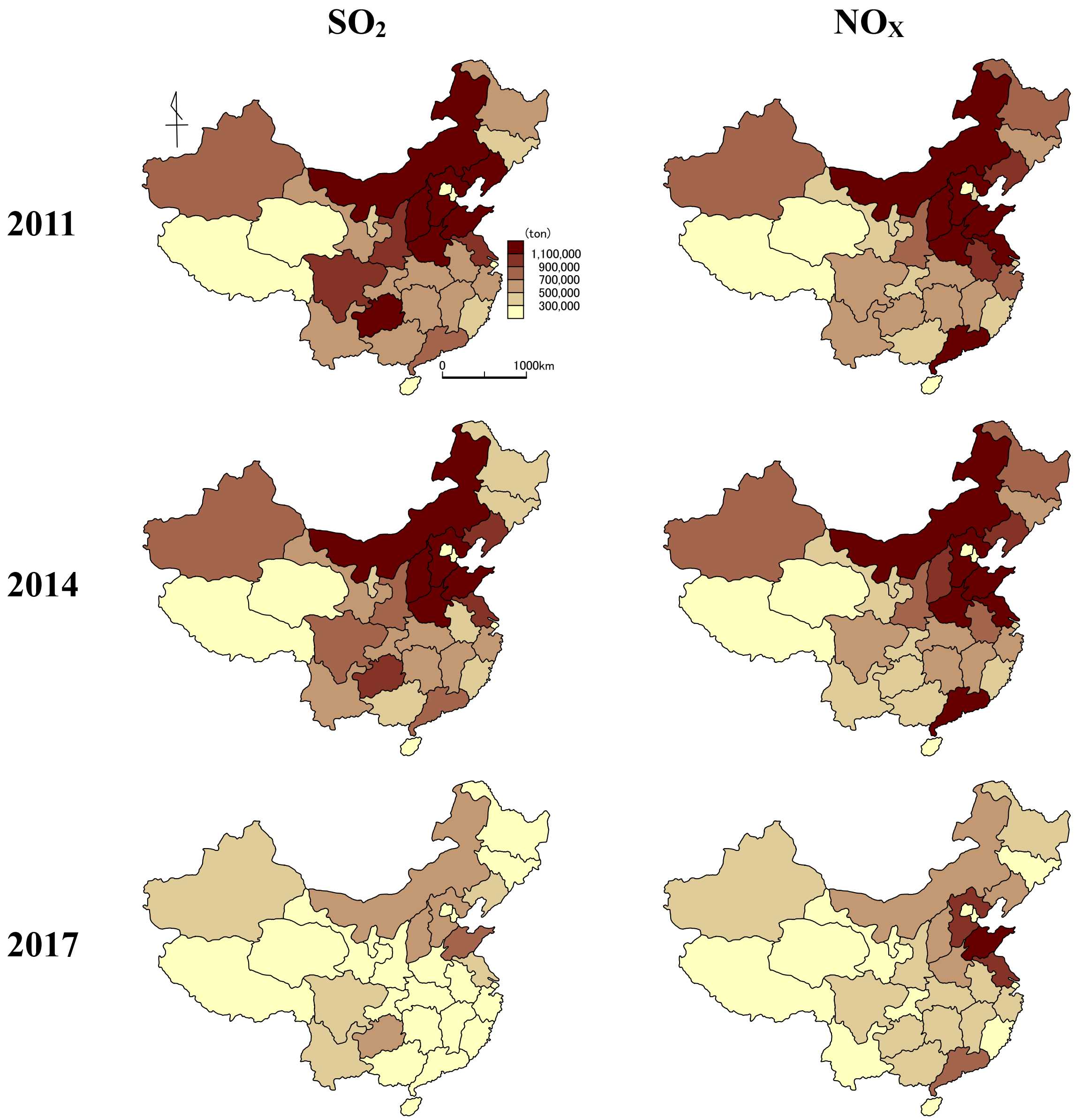


Fig. 1. Spatial distribution of two air pollutant emissions in mainland China in the selected years.

positive autocorrelation is stronger for NO_X. These results indicate that there were positive spatial autocorrelations for SO_2 and NO_X, which in turn indicate that areas with high emissions tend to cluster together.

The spatial clustering and heterogeneity were further confirmed by the Moran scatter plots (Fig. 2). Most provinces are located in the first and third quadrants, which reveal a positive spatial autocorrelation of the SO_2 and NO_X emissions. The scatter plots show that provinces with high SO_2 and NO_X emissions (Hebei, Henan, Shanxi, Inner Mongolia, and Shandong) and those with low pollutant emissions (Zhejiang, Hainan, Xizang, and Qinghai) are located in the first and third quadrants.

Table 3
Moran's I statistics for SO_2 and NO_X emissions from 2011 to 2017.

	SO_2			NO_X		
Year	Moran's I	z-value	*p*-Value	Moran's I	z-value	*p*-Value
2011	0.242	2.333	0.018	0.280	2.650	0.011
2012	0.193	1.916	0.042	0.267	2.544	0.013
2013	0.187	1.859	0.046	0.249	2.402	0.019
2014	0.176	1.763	0.050	0.248	2.403	0.018
2015	0.193	1.919	0.042	0.260	2.502	0.014
2016	0.117	1.325	0.097	0.155	1.606	0.055
2017	0.096	0.112	0.136	0.185	1.878	0.042

3.3. Spatial econometric analysis

To select appropriate models (fixed-effect or random-effect), the Hausman test was conducted. The *p* values of the Hausman test were close to zero for both SO_2 and NO_X. Therefore, fixed-effect models were selected.

LM tests were then conducted to select the appropriate spatial model. The results of the LM-lag and LM-error tests for SO_2 and NOx were close to zero (Table 4), meaning that all models passed the significance level of 1%. Therefore, we conducted the robust LM tests. The *p* values for the robust LM-lag tests passed the significance level of 1%, while the robust LM-error tests did not (Table 4). Therefore, the SLM is more suitable for both SO_2 and NOx emissions. Based on the Hausman tests and LM tests, the fixed-effect SLM was selected for all specifications.

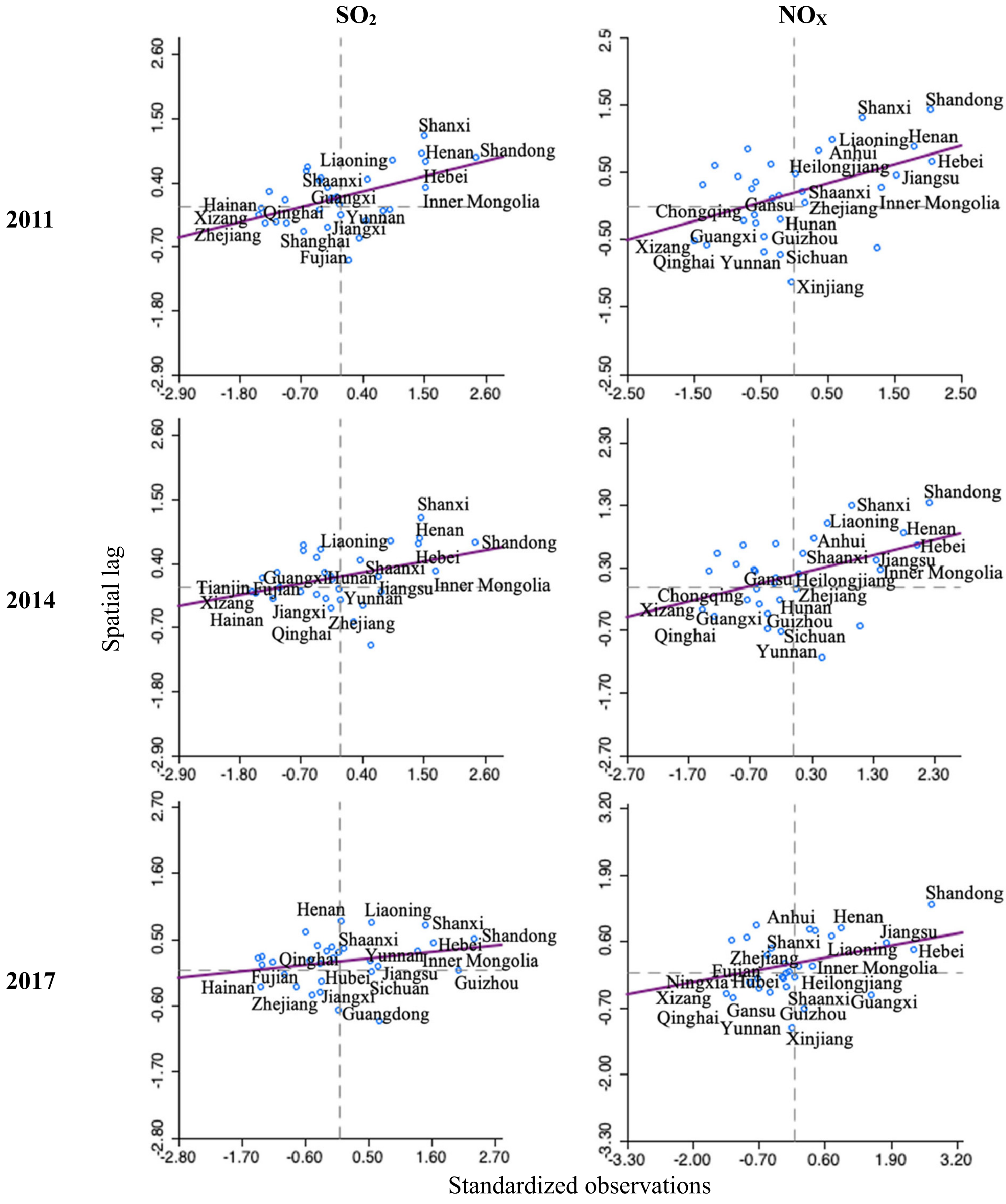


Fig. 2. Moran scatter plots for two air pollutant emissions in the selected years.

Table 5 presents the results for non-spatial fixed-effect estimates (not considering spatial effect) and the fixed-effect SLM. The models were estimated taking into consideration the fixed effects of cross-section only (individual) and both cross-section and year (two-way). The study also used the fixed-effect SEM (see Table S2 in Supplementary Material).[10] Note that as the spatial autocorrelation exists for SO_2 and NO_X emissions, as shown in Section 3.2, the fixed-effect SLM is the appropriate model for this study. Therefore, the results are explained based on that model (with a two-way fixed effect).

With regard to socioeconomic factors, the results show that the coefficients for *POP* were positive and statistically significant at the 1% level for

Table 4
LM test results.

	SO_2	NO_X
LM-lag test	2.08×10^{-11}	2.20×10^{-16}
LM-error test	2.57×10^{-6}	3.50×10^{-9}
Robust LM-lag test	5.39×10^{-7}	1.66×10^{-10}
Robust LM-error test	0.13	0.99

[10] The results of the fixed-effect SLM and the fixed-effect SEM were similar.

Table 5
Results of fixed-effect model without spatial effect and SLM for two air pollutants.

	Non-spatial fixed-effect model				Fixed-effect SLM			
	SO_2		NO_X		SO_2		NO_X	
	Individual FE	Two-way FE	Individual FE	Two-way FE	Individual FE	Two-way FE	Individual FE	Two-way FE
POP	−859.14***	−778.77***	−589.96***	−511.94**	84.08***	79.15***	107.39***	98.63***
	(176.74)	(178.61)	(131.85)	(135.35)	(8.39)	(9.46)	(7.07)	(7.77)
PD	35.28	21.54	13.35	−7.41	−68.04***	−74.09***	−40.42***	−50.47***
	(28.38)	(21.31)	(201.4)	(20.67)	(16.82)	(16.86)	(13.90)	(13.86)
URB (×1000)	−26.37***	−19.62**	−18.92***	−6.13	3.09	1.79	5.82**	5.9**
	(4.89)	(9.42)	(3.90)	(8.03)	(3.30)	(3.64)	(2.73)	(2.99)
PCGRP	1.91	3.93	0.64	4.25	−4.30**	−3.35*	−3.86**	−2.89*
	(1.70)	(2.87)	(1.38)	(2.73)	(1.90)	(2.01)	(1.57)	(1.65)
SDA_GRP (×100,000)	19.42***	15.16**	19.56***	11.47**	9.82***	12.28***	12.64***	16.38***
	(4.19)	(4.65)	(3.34)	(4.57)	(2.50)	(2.79)	(2.05)	(2.30)
DD	−53.39	30.13	−24.38	8.91	33.95	46.47*	51.75***	50.09**
	(40.28)	(28.01)	(26.13)	(24.07)	(22.74)	(24.70)	(18.83)	(20.30)
PRE	16.09	−4.22	−32.72	−39.56	−146.45***	−129.68**	−33.03	−40.22
	(40.76)	(30.74)	(32.91)	(32.24)	(56.79)	(59.48)	(46.67)	(48.85)
RHU (×1000)	−1.68	−3.03	−2.57	−3.37	−4.62*	−6.23**	−8.26***	−10.11***
	(2.99)	(3.03)	(2.69)	(2.81)	(2.59)	(2.68)	(2.13)	(2.20)
Adjusted R^2	0.91	0.94	0.94	0.95	–	–	–	–
Log likelihood	–	–	–	–	−3005.07	−2997.32	−2962.44	−2954.53

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. Non-spatial fixed-effect models do not consider the spatial effects. The number of observations is 217 for all analyses.

both SO_2 and NO_X. This suggests that SO_2 and NO_X emissions increase with increasing population. Furthermore, the coefficient for *URB* was also positive and statistically significant for NO_X, which means that NO_X emissions increase with increasing urbanization. Similarly, the coefficients for *SDA_GRP* were positive and statistically significant for SO_2 and NO_X; the higher the ratio of the added value of secondary industry to GRP, the more SO_2 and NO_X will be emitted. However, the effects of *PD* on SO_2 and NO_X emissions were negative and statistically significant at the 1% level. Similarly, the estimated effect of *PCGRP* was also negative and statistically significant for both emissions. These results suggest that increases in population density and per-capita GRP decrease SO_2 and NO_X emissions.

For natural factors, the coefficients for *DD* were positive and significant for SO_2 and NO_X emissions. In contrast, *PRE* and *RHU* were negative and statistically significant for SO_2 or NO_X emissions. Therefore, increases in the temperature-related variable, in terms of degree days, increase pollutant emissions, while increases in precipitation and relative humidity reduce emissions.

4. Discussion

The results of the spatial autocorrelations and the influencing factors in Section 3 are important in developing environmental policies. Here, we discuss the results based on the Moran's I statistics and the two-way fixed-effect SLM.

The Moran's I statistics and the Moran scatter plots for the SO_2 and NO_X emissions indicated there were positive and statistically significant spatial autocorrelations in most years. These results suggest clustering trends. Therefore, to improve air pollution neighboring provinces should strengthen cooperation and formulate local control measures, in addition to the efforts of individual provinces.

With regard to the SLM estimates, of the socioeconomic factors population was positive and statistically significant for both SO_2 and NO_X emissions. Increasing population growth and energy demand (including fossil fuels) eventually cause an increase in air pollutants. In other words, the more people the more serious the pollution will be. This is consistent with the findings in the literature (e.g., Liu et al., 2017). Regarding the urbanization rate and the ratio of value added of secondary industry, they were positive and statistically significant for SO_2 and NO_X. Urbanization is associated with increases in people, traffic, industry, and energy consumption (S. Zhao et al., 2018). Similarly, energy-intensive secondary industry stimulates the use of fossil fuels. Therefore, these factors both cause an increase in air pollution, which is consistent with the findings of previous studies (Liu et al., 2017; Huang, 2018; Hao et al., 2020). In this study, we verified that the ratio of value added of the secondary industry was significantly positive not only for SO_2 emissions (Huang, 2018) but also for NO_X emissions. Regarding population density, this study showed it had a negative and statistically significant effect on SO_2 and NO_X emissions. Population density can effect either a decrease or an increase in air pollution (Brajer et al., 2011; Hao and Liu, 2016; Huang, 2018). An increase can occur due to a higher degree of urbanization and industrialization, and a crowd effect (Hao and Liu, 2016; Huang, 2018). In contrast, a decrease can occur due to the intensive use of energy and a civilization effect (Hao and Liu, 2016; Huang, 2018). Furthermore, big cities have advantages in improving the level of public administration, and a higher population density can improve the urban environment in various ways (Stone, 2008; Cheng et al., 2017). Although both positive and negative effects are possible, the negative effect was stronger in this study, as it was in Huang (2018). Different from Huang (2018), who evaluated the impact on SO_2 emissions, we found that population density reduced NO_X emissions. These results suggest that while considering population accumulation, we should continuously improve the efficiency of resource utilization and the environmental literacy of citizens to effectively alleviate air pollution. Finally, per-capita GRP was negative and statistically significant for both SO_2 and NO_X emissions. This indicates that with China's economic growth and increasing wealth, the air pollution situation has improved. This may be due to citizens' consciousness and eco-friendly behaviors (Duroy, 2008). In addition, as technology advances, the emission of pollutants per unit of production decreases as income increases (Park and Lee, 2011). Such a relationship between pollutants and per-capita GRP is consistent with the findings of previous studies (e.g., Yang et al., 2017b; Zhou et al., 2018). However, Wang et al. (2016) found an inverted U-shaped relationship between SO_2 emissions and per-capita GRP, often called the environmental Kuznets curve. With the non-spatial fixed-effect model, we also found a similar relationship to that found by Wang et al. (2016) (see Table S3 in Supplementary Material). However, this relationship disappeared by including spatial effects in this study (i.e., fixed-effect SLM). This is almost consistent with Hao and Liu (2016).[11] Based on the results of the Moran's I statistics and the Moran scatter plots, it is essential to consider the spatial effects in analyzing

[11] Hao and Liu (2016) indicated the possibility of an inverted U-shaped relationship between $PM_{2.5}$/AQI and per-capita GDP with their OLS and SEM estimations. However, such results were seldom shown with the SLM estimations, which this study employed.

SO_2 and NO_X emissions. Furthermore, the fixed-effect SLM model was selected based on the statistical tests. Because the other variables were identical among the models employed in this study, such relationships may only appear because the spatial effects were considered. The other differences in the results between non-spatial and SLM models (Table 5) are also considered due to the existence of the spatial effects.

In addition to the socioeconomic factors, the impact of natural factors on air pollution cannot be ignored. As shown in Table 5, the coefficients for degree days were positive and statistically significant for both the pollutant emissions. This is related to China's energy consumption during the heating and cooling seasons, particularly the heating season when coal is extensively used for heating. This study used the degree days instead of temperature, which is often used in the literature (Yang et al., 2017a; Feng et al., 2019), as the independent variable. This is because temperature cannot express the effect of cold winters and hot summers when heating and cooling demands increase with a linear modeling framework. Although the impact of temperature on air pollution has been evaluated in the literature, this study found that degree days were an important factor in determining the level of air pollution. This is because energy demand is significantly influenced by temperature (Wan et al., 2011; De Cian et al., 2013; Cui et al., 2017). Finally, precipitation and relative humidity both had a negative and statistically significant effect on the air pollutant emissions. Precipitation and humidity can regulate the temperature and cause pollutants to settle and dissolve (Li et al., 2014; Whiteman et al., 2014; Yang et al., 2017a; Bai et al., 2019), which consequently reduces the pollution levels.

Although the significant factors and the degrees differ to some extent by the type of air pollutant, this study comprehensively confirmed the factors affecting multiple air pollutants. The results in this study were mostly consistent with those of most previous studies, as discussed above. As stated in Section 1, this study improved the estimation methods (i.e., spatial panel econometric models) with multiple air pollutants and both socioeconomic and natural factors. With more appropriate and comprehensive estimation methods, this study helped improve understanding of the determinants of air pollution discharge. Furthermore, the findings provide effective information for determining air pollution control measures in China.

5. Conclusions

Due to China's rapid economic growth and high levels of energy consumption, the problem of air pollution has been one of the most important environmental and social issues. In this study, we conducted spatial autocorrelation and spatial panel regression analyses for SO_2 and NO_X emissions using the panel data of 31 provinces during the period 2011–2017 to comprehensively understand the factors affecting the air pollutant emissions. Our findings can be summarized as follows. Overall, in China the emissions of the two pollutants were on a downward trend during the study period. However, the emissions in the northern part of China are still relatively high. Furthermore, the air pollution showed significant and positive spatial autocorrelation. Based on the spatial panel econometric analyses, we found that both socioeconomic factors and natural factors significantly affected the emissions. Of these factors, the population, urbanization rate, ratio of added value of secondary industry to GRP, and degree days had positive and statistically significant effects, while population density, per-capita GRP, precipitation, and relative humidity had inhibitory effects. Our analysis revealed that the models with and without spatial effects had different results. Therefore, considering the characteristics of air pollutants, it is necessary to incorporate spatial effects in the models to correctly estimate and understand the factors that affect air pollution.

Having identified the key influencing factors and spatial effects of air pollution, we believe there is an urgent need to adopt more efficient air pollution prevention and control strategies to promote sustainable development. Based on the findings of this study, we suggest the following two policy implications to reduce air pollution. As it is usually not possible to control natural factors, here we address socioeconomic aspects.

1. *Promotion of regional cooperation*: The spatial autocorrelation of the two air pollutant emissions indicated that each province and its neighbors influenced each other. However, because the geographical location, economic levels, and resources possessed differ by province, the policy goals and capabilities of each province also differ. Considering such circumstances, the efforts of individual provinces are not enough to significantly reduce air pollution. Therefore, the provinces need to strengthen regional cooperation and joint governance with neighboring provinces to further mitigate air pollution. Indeed, the joint prevention and control of air pollution in the Beijing-Tianjin-Hebei region and surrounding areas, which is a mechanism of inter-regional cooperation to overcome the issue, helped to improve regional air quality (Song et al., 2020). Therefore, expanding such efforts to other provinces (e.g., by reaching consensus on the overall interests of the region, using institutional resources to break the boundaries of administrative regions, and coordinating with each other) will be effective to further reduce emissions. Such a joint mechanism is also a cost-efficient method to reduce air pollutants (Wu et al., 2015). Furthermore, when strengthening joint prevention and control mechanisms among regions, innovative pollution control and responsibility models also need to be established, focusing on environmental planning and legislation relating to urban agglomeration planning.
2. *Socioeconomic structure change and sustainable development*: From the socioeconomic perspective, the spatial econometric analyses indicated that increasing population density would contribute to air pollution mitigation. Developing compact cities and compact urban areas is a possible way to increase population density. Because compact cities and compact urban development decrease energy demand per capita and promote energy efficiency (Fertner and Große, 2016), such approaches would contribute to the reduction of air pollutants. Our analyses also indicated that reducing the ratio of value added of secondary industry to GRP and increasing per-capita GRP would facilitate air pollution mitigation. Because air pollutants are emitted mainly as a result of the combustion of fossil fuels in the industrial point sources (Zhang and Crooks, 2012), reducing the proportion of secondary industry and increasing the proportion of tertiary industry (service industry), which emits much fewer air pollutants than secondary industry, is essential. In other words, the transition of the economic structure from secondary industry-oriented to tertiary industry-oriented should be a priority for China to effectively reduce air pollutants and solve the air pollution problem. For example, the introduction of environmental tax and preferential tax policies can promote the development of greener industry. Furthermore, servicizing is a way to promote such transition, which can also promote sustainable development (Rothenberg, 2007). This way of economic growth also increases per-capita GDP/GRP, which helps improve people's environmental awareness (Duroy, 2008) and alleviate air pollution.

As a developing country, China has been plagued by air pollution for a long time. The results of this study can provide important insights not only for Chinese domestic policymakers but also for other emerging economies. At the same time as developing countries increase industrialization and urbanization, their energy consumption needs to be recognized as an important contributor to emissions. It is suggested that developing countries should not only hasten the upgrading of industrial structures but also strengthen regional cooperation according to the actual conditions of each area.

CRediT authorship contribution statement

Lina Ren: Data curation, Methodology, Software, Investigation, Writing - original draft, Visualization. **Ken'ichi Matsumoto:**

Conceptualization, Validation, Formal analysis, Writing - review & editing, Visualization, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This study was partially supported by the Integrated Research Program for Advancing Climate Models (grant number JPMXD0717935457) at the Ministry of Education, Culture, Sports, Science and Technology, Japan and JSPS KAKENHI (grant numbers JP18K11754 and JP18K11800).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.140155.

References

Bai, L., Jiang, L., Yang, D., Liu, Y., 2019. Quantifying the spatial heterogeneity influences of natural and socioeconomic factors and their interactions on air pollution using the geographical detector method: a case study of the Yangtze River Economic Belt, China. J. Clean. Prod. 232, 692–704. https://doi.org/10.1016/j.jclepro.2019.05.342.

Brajer, V., Mead, R.W., Xiao, F., 2011. Searching for an environmental Kuznets curve in China's air pollution. China Econ. Rev. 22, 383–397. https://doi.org/10.1016/j.chieco.2011.05.001.

Chen, T., He, J., Lu, X., She, J., Guan, Z., 2016. Spatial and temporal variations of $PM_{2.5}$ and its relation to meteorological factors in the urban area of Nanjing, China. Int. J. Environ. Res. Public Health 13. https://doi.org/10.3390/ijerph13090921.

Cheng, Z., Li, L., Liu, J., 2017. Identifying the spatial effects and driving factors of urban $PM_{2.5}$ pollution in China. Ecol. Indic. 82, 61–75. https://doi.org/10.1016/j.ecolind.2017.06.043.

Chinese Ministry of Ecology and Environmental Protection, 2017. Bulletin of the state of China's eco-environment. http://www.gov.cn/guoqing/2019-04/09/content_5380689.htm, Accessed date: 30 March 2020.

Cui, S., Shi, Y., Groffman, P.M., Schlesinger, W.H., Zhu, Y.G., 2013. Centennial-scale analysis of the creation and fate of reactive nitrogen in China (1910-2010). Proc. Natl. Acad. Sci. U. S. A. 110, 2052–2057. https://doi.org/10.1073/pnas.1221638110.

Cui, Y., Yan, D., Chen, C. Fei, 2017. Exploring the factors and motivations influencing heating behavioral patterns and future energy use intentions in the hot summer and cold winter climate zone of China. Energy Build 153, 99–110. https://doi.org/10.1016/j.enbuild.2017.07.068.

De Cian, E., Lanzi, E., Roson, R., 2013. Seasonal temperature variations and energy demand: a panel cointegration analysis for climate change impact assessment. Clim. Chang. 116, 805–825. https://doi.org/10.1007/s10584-012-0514-5.

Ding, L., Liu, C., Chen, K., Huang, Y., Diao, B., 2017. Atmospheric pollution reduction effect and regional predicament: an empirical analysis based on the Chinese provincial NO_X emissions. J. Environ. Manag. 196, 178–187. https://doi.org/10.1016/j.jenvman.2017.03.016.

Duroy, Q.M.H., 2008. Testing the affluence hypothesis: a cross-cultural analysis of the determinants of environmental action. Soc. Sci. J. 45, 419–439. https://doi.org/10.1016/j.soscij.2008.07.001.

Elhorst, J.P., 2010. Spatial panel data models. In: Fischer, M.M., Getis, A. (Eds.), Handbook of Applied Spatial Analysis. Springer-Verlag, Berlin, pp. 377–407.

Feng, H., Zou, B., Wang, J., Gu, X., 2019. Dominant variables of global air pollution-climate interaction: geographic insight. Ecol. Indic. 99, 251–260. https://doi.org/10.1016/j.ecolind.2018.12.038.

Fertner, C., Große, J., 2016. Compact and resource efficient cities? Synergies and trade-offs in European cities. Eur. Spat. Res. Policy 23, 65–79. https://doi.org/10.1515/esrp-2016-0004.

Fu, Z., Li, R., 2020. The contributions of socioeconomic indicators to global $PM_{2.5}$ based on the hybrid method of spatial econometric model and geographical and temporal weighted regression. Sci. Total Environ. 703, 135481. https://doi.org/10.1016/j.scitotenv.2019.135481.

Han, L., Zhou, W., Li, W., Li, L., 2014. Impact of urbanization level on urban air quality: a case of fine particles ($PM_{2.5}$) in Chinese cities. Environ. Pollut. 194, 163–170. https://doi.org/10.1016/j.envpol.2014.07.022.

Han, X., Li, H., Liu, Q., Liu, F., Arif, A., 2019. Analysis of influential factors on air quality from global and local perspectives in China. Environ. Pollut. 248, 965–979. https://doi.org/10.1016/j.envpol.2019.02.096.

Hao, Y., Liu, Y.M., 2016. The influential factors of urban $PM_{2.5}$ concentrations in China: a spatial econometric analysis. J. Clean. Prod. 112, 1443–1453. https://doi.org/10.1016/j.jclepro.2015.05.005.

Hao, Y., Zheng, S., Zhao, M., Wu, H., Guo, Y., Li, Y., 2020. Reexamining the relationships among urbanization, industrial structure, and environmental pollution in China—new evidence using the dynamic threshold panel model. Energy Rep. 6, 28–39. https://doi.org/10.1016/j.egyr.2019.11.029.

Hu, B., Li, Z., Zhang, L., 2019. Long-run dynamics of sulphur dioxide emissions, economic growth, and energy efficiency in China. J. Clean. Prod. 227, 942–949. https://doi.org/10.1016/j.jclepro.2019.04.170.

Huang, J.T., 2018. Sulfur dioxide (SO_2) emissions and government spending on environmental protection in China - evidence from spatial econometric analysis. J. Clean. Prod. 175, 431–441. https://doi.org/10.1016/j.jclepro.2017.12.001.

Jiao, J., Han, X., Li, F., Bai, Y., Yu, Y., 2017. Contribution of demand shifts to industrial SO_2 emissions in a transition economy: evidence from China. J. Clean. Prod. 164, 1455–1466. https://doi.org/10.1016/j.jclepro.2017.07.060.

Lee, D.S., Köhler, I., Grobler, E., Rohrer, F., Sausen, R., Gallardo-Klenner, L., Olivier, J.G.J., Dentener, F.J., Bouwman, A.F., 1997. Estimations of global NOx emissions and their uncertainties. Atmos. Environ. 31, 1735–1749. https://doi.org/10.1016/S1352-2310(96)00327-5.

Li, M., Zhang, L., 2014. Haze in China: current and future challenges. Environ. Pollut. 189, 85–86. https://doi.org/10.1016/j.envpol.2014.02.024.

Li, L., Qian, J., Ou, C.Q., Zhou, Y.X., Guo, C., Guo, Y., 2014. Spatial and temporal analysis of Air Pollution Index and its timescale-dependent relationship with meteorological factors in Guangzhou, China, 2001-2011. Environ. Pollut. 190, 75–81. https://doi.org/10.1016/j.envpol.2014.03.020.

Liu, H., Fang, C., Zhang, X., Wang, Z., Bao, C., Li, F., 2017. The effect of natural and anthropogenic factors on haze pollution in Chinese cities: a spatial econometrics approach. J. Clean. Prod. 165, 323–333. https://doi.org/10.1016/j.jclepro.2017.07.127.

Liu, Q., Wang, S., Zhang, W., Li, J., Dong, G., 2019. The effect of natural and anthropogenic factors on $PM_{2.5}$: empirical evidence from Chinese cities with different income levels. Sci. Total Environ. 653, 157–167. https://doi.org/10.1016/j.scitotenv.2018.10.367.

Lu, D., Xu, J., Yang, D., Zhao, J., 2017. Spatio-temporal variation and influence factors of $PM_{2.5}$ concentrations in China from 1998 to 2014. Atmos. Pollut. Res. 8, 1151–1159. https://doi.org/10.1016/j.apr.2017.05.005.

Park, S., Lee, Y., 2011. Regional model of EKC for air pollution: evidence from the Republic of Korea. Energy Policy 39, 5840–5849. https://doi.org/10.1016/j.enpol.2011.06.028.

Rothenberg, S., 2007. Sustainability through servicizing. MIT Sloan Manag. Rev. 48.

Shi, Y., Gao, X., Xu, Y., Giorgi, F., Chen, D., 2016. Effects of climate change on heating and cooling degree days and potential energy demand in the household sector of China. Clim. Res. 67, 135–149. https://doi.org/10.3354/cr01360.

Song, Y., Li, Z., Yang, T., Xia, Q., 2020. Does the expansion of the joint prevention and control area improve the air quality?—evidence from China's Jing-Jin-Ji region and surrounding areas. Sci. Total Environ. 706, 136034. https://doi.org/10.1016/j.scitotenv.2019.136034.

Stone, B., 2008. Urban sprawl and air quality in large US cities. J. Environ. Manag. 86, 688–698. https://doi.org/10.1016/j.jenvman.2006.12.034.

Wan, K.K.W., Li, D.H.W., Liu, D., Lam, J.C., 2011. Future trends of building heating and cooling loads and energy consumption in different climates. Build. Environ. 46, 223–234. https://doi.org/10.1016/j.buildenv.2010.07.016.

Wang, S., Xing, J., Zhao, B., Jang, C., Hao, J., 2014. Effectiveness of national air pollution control policies on the air quality in metropolitan areas of China. J. Environ. Sci. 26, 13–22. https://doi.org/10.1016/S1001-0742(13)60381-2.

Wang, Y., Han, R., Kubota, J., 2016. Is there an environmental Kuznets curve for SO_2 emissions? A semi-parametric panel data analysis for China. Renew. Sust. Energ. Rev. 54, 1182–1188. https://doi.org/10.1016/j.rser.2015.10.143.

Whiteman, C.D., Hoch, S.W., Horel, J.D., Charland, A., 2014. Relationship between particulate air pollution and meteorological variables in Utah's Salt Lake Valley. Atmos. Environ. 94, 742–753. https://doi.org/10.1016/j.atmosenv.2014.06.012.

Wu, D., Xu, Y., Zhang, S., 2015. Will joint regional air pollution control be more cost-effective? An empirical study of China's Beijing-Tianjin-Hebei region. J. Environ. Manag. 149, 27–36. https://doi.org/10.1016/j.jenvman.2014.09.032.

Wu, H., Hao, Y., Weng, J.H., 2019. How does energy consumption affect China's urbanization? New evidence from dynamic threshold panel models. Energy Policy 127, 24–38. https://doi.org/10.1016/j.enpol.2018.11.057.

Yang, X., Wang, S., Zhang, W., Zhan, D., Li, J., 2017a. The impact of anthropogenic emissions and meteorological conditions on the spatial variation of ambient SO_2 concentrations: a panel study of 113 Chinese cities. Sci. Total Environ. 584–585, 318–328. https://doi.org/10.1016/j.scitotenv.2016.12.145.

Yang, X., Wang, S., Zhang, W., Yu, J., 2017b. Are the temporal variation and spatial variation of ambient SO_2 concentrations determined by different factors? J. Clean. Prod. 167, 824–836. https://doi.org/10.1016/j.jclepro.2017.08.215.

Zeng, J., Liu, T., Feiock, R., Li, F., 2019. The impacts of China's provincial energy policies on major air pollutants: a spatial econometric analysis. Energy Policy 132, 392–403. https://doi.org/10.1016/j.enpol.2019.05.052.

Zhang, Q., Crooks, R., 2012. Toward an Environmentally Sustainable Future: Country Environmental Analysis of the People's Republic of China. Asian Development Bank.

Zhao, D., Chen, H., Li, X., Ma, X., 2018a. Air pollution and its influential factors in China's hot spots. J. Clean. Prod. 185, 619–627. https://doi.org/10.1016/j.jclepro.2018.02.181.

Zhao, S., Liu, S., Hou, X., Cheng, F., Wu, X., Dong, S., Beazley, R., 2018b. Temporal dynamics of SO_2 and NO_X pollution and contributions of driving forces in urban areas in China. Environ. Pollut. 242, 239–248. https://doi.org/10.1016/j.envpol.2018.06.085.

Zhao, X., Zhou, W., Han, L., Locke, D., 2019. Spatiotemporal variation in $PM_{2.5}$ concentrations and their relationship with socioeconomic factors in China's major cities. Environ. Int. 133, 105145. https://doi.org/10.1016/j.envint.2019.105145.

Zhou, C., Chen, J., Wang, S., 2018. Examining the effects of socioeconomic development on fine particulate matter ($PM_{2.5}$) in China's cities using spatial regression and the geographical detector technique. Sci. Total Environ. 619–620, 436–445. https://doi.org/10.1016/j.scitotenv.2017.11.124.