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Research Article

Research of Spatial and Temporal Evolution Mechanism and Countermeasures of Haze Spatial Pattern in China: Visual Field Based on Dynamic Evolution and Spatial Agglomeration

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In this paper, spatial domain verification of the haze of dependence and the dynamic evolution process of the spatial panel data model was based on the estimation of different factors that influence on the horizon haze effect and spillover effect from the perspective of spatial economics. The study found that the provincial space is dependent on Chinese haze; the influence of haze on neighboring provinces of the spatial spillover effect factors is obvious during the period of 2000~2015; the effect of elastic coefficient of industrial structures on the haze near the space overflow area energy is high; thus the industrial structure has a significant inhibitory effect on the haze; the role of regional industrial transfer haze governance has been very fruitful; population, economic growth, financial development, and fiscal decentralization to reduce haze inhibiting the spillover effect of regional haze were increasing. In the formulation of haze-related policies and development planning, the government departments must take into account the spatial mechanism of regional haze and influencing factors and realize the overall reduction of haze amount in time dimension and spatial dimension in China.

1. Introduction

Haze has become a problem of people's livelihood. In the nineteen major reports, it is pointed out that improving the well-being of the people's livelihood is the fundamental purpose of development. The people's livelihood should be treated with iron wrist, meet the new expectations of the people, guarantee the improvement of the people's livelihood, do a good job in energy conservation, emission reduction, and environmental governance, and integrate the economic development and environmental protection policies. President Xi Jinping promised to reform the ecological civilization system, including not only the construction of the ecological environment and the development of the high-tech green industry but also the responsibility of the government to respond to the livelihood of the people. Haze is a combination of fog and haze. Fog is the product of condensation of water suspended in the air. It is the phenomenon of specific climatic effects after the continuous accumulation of fine particulates emitted from human activities beyond the carrying capacity of atmospheric circulation. Haze is composed of sulfuric acid, organic hydrocarbon, or dust in the air, resulting in atmospheric turbidity. Fog and haze is a state of air pollution. Fog and haze is a general expression of suspended particles in the atmosphere. PM2.5 refers to particles less than 2.5 microns in diameter and also the culprit of fog and haze weather. In recent years, under the five development concepts of innovation, coordination, green, openness, and sharing, our governments at all levels have made great efforts in harnessing the haze. At the same time, we should also see that the formation of haze has a complex cause, so it is a long and arduous process to harness the haze. To achieve the strategic goal of building beautiful China and national sustainable development, we must actively adopt scientific methods to promote energy conservation and emission reduction, hard to orientate fog and haze pollution propaganda.

2. Literature Review

At present, scholars at home and abroad have studied the haze problem from different angles. Lancet points out that foreign literature will lead to the main driving factors of haze to generalize human factors and natural factors [1–4]. Natural factors include temperature, precipitation, wind speed, relative humidity, sunshine temperature, and time. Human factors include population agglomeration, such as urbanization, regional trade, and industrial development. Li et al. studied the regulatory costs related to the haze from the market perspective and found that the initial market expectation provides the corporate social responsibility report and the company's corporate pollution industry is not subject to overregulatory costs, but with the government's attention to produce greater expected regulatory costs [5]. Evanoski-Cole et al. studied the sources of regional haze and found that ammonium nitrate was the main contributor to haze events [6]. The domestic and foreign studies of haze control are mainly analyzed in different perspectives, such as Nurhidayah from the legal point of view that a good legal framework is very important for haze control [7]; Lee et al. [8] have studied the problem of cross-boundary haze regulation, and pollution and climate change are often affected by the state. The impact of participation in the strategy, the cross-border haze act passed by the government of Singapore, plays a leading role in environmental protection and ecosystem protection. Domestic scholars mainly study the haze problem from different fields of view, and Liu and Zhang from the political point of view point out that strengthening the construction of local government is an effective means to solve the increasingly serious fog and haze pollution. From the perspective of economic development [9], Zheng and Yang analyzed the causes of the fog weather and proposed the establishment of regional intergovernmental cooperation mechanism [10]. Li et al. analyzed the causes of the haze weather in Beijing, Tianjin, and Hebei Province from the energy structure angle and put forward the comprehensive control and haze treatment measures [11]. Ma and Zhang believe that China's transformation of coal-based energy consumption structure and optimization of the industrial structure is the key to haze control [12]. Jutze and Gruber believe that atmospheric pollution is cross-regional and stated joint measures should be taken to control and for monitoring pollution to find out the causes of pollution and reduce pollution sources [13]. Lee et al. [8] have studied cross-border smog and haze regulation. Pollution and climate change are often affected by national participatory strategies. The government's cross-border smog and haze act has a leading role in protecting the entire ecosystem. Maddison used spatial econometric methods to study the correlation between environmental pollution and prevention in Europe [14]. In 2014, general secretary Xi Jinping pointed out that the fog and haze pollution should be taken active measures from the aspects of industrial adjustment, joint control, and management according to law. Therefore, based on the dynamic evolution, space accumulation, and spatial linkage, this paper systematically studies the spatial pattern evolution, influence factors, and spatial spillover effects of haze in the province of China.

3. The Spatial Effect Test of Regional Haze in China

3.1. Space Effect and Space Test Theory. How to distinguish objectively whether there is a spatial effect of regional haze is the first problem to be solved in spatial econometric model analysis. In real life, completely independent observations are not universal. The traditional econometric model is based on the assumption that the observations are independent, and the observation samples are spatially independent. In the analysis of real economic behavior, spatial econometrics take into account the difference in spatial interaction between individuals, that is, the spatial effect, and the traditional econometric model has the independence and homogeneity in space [15]. Getis points out that there is a closer spatial relationship between the observed variables and the variable data far away from the observed data with spatial attributes [16]. The economic effects are mainly manifested in two kinds of spatial interaction: spatial dependence, also known as spatial correlation, and spatial heterogeneity.

4. Space Effect

Spatial correlation is also known as spatial dependence, which generally refers to the spatial autocorrelation between variables, and the spatial correlation is introduced into the traditional econometric model through the spatial lag factor of variables [17]. Spatial dependence also means that, in the course of sample observation, observations on a single space unit are related to observations in other space units and will be affected by other observations. Spatial dependence not only indicates that the observational values in space are lack of independence but also imply that the potential lies in the spatial correlation data structure, which means that the spatial correlation intensity and pattern pointed out by the first law of geography are determined by the spatial pattern and the spatial distance [18]. The spatial dependence of the substantive space reflects the spatial interaction of each unit [19–21]. The spatial element of this hypothesis is often inconsistent with the boundary of the research problem, which leads to the measurement error.

Spatial heterogeneity, also known as the spatial difference, refers to the lack of uniformity in the geographic space of the observation unit, the existence of not equilibrium, and the spatial structure difference between the main behavior [22–26]. Spatial heterogeneity reflects the instability of the spatial observation unit in economic practice, and the heterogeneity of geographical location and development stage in the economic and geographical structures will lead to greater spatial differences in economic and social development.

4.1. Space Effect Test. The test methods of spatial autocorrelation can be divided into two types: global spatial autocorrelation test and test spatial autocorrelation test. Moran's I, Geary's statistics, and joint count statistics are used in all domain autocorrelation tests. The global spatial autocorrelation indexes of Moran' I and Geary's are usually used to test the spatial effect of the whole domain, and the local spatial autocorrelation indexes mainly include Moran's index and local domain index and scatter plot.

4.2. Autocorrelation Test of Whole Space. The global spatial autocorrelation tests the overall distribution of certain phenomena to determine whether the phenomenon is clustered in a specific area. Local spatial autocorrelation tests local spatial clustering, which indicates the location of convergence and can detect spatial anomalies.

4.2.1. Moran's I Index. The definition of the index is as follows:

$$\text{Moran's } I = \frac{\left|\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)\right|}{\left|S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right|}, \tag{1}$$

where $S^2 = (1/n)\sum_{i=1}^{n}(Y_i - \overline{Y})^2$, $\overline{Y} = (1/n)\sum_{i=1}^{n} Y_i$, and Y_i represents the observational values of the I region (such as fog and haze) and N is the total number of regions (provincial), representing a binary adjacent space weight matrix, representing any of the elements in it, using the adjacent matrix (contiguity matrix) and the distance matrix (distance matrix), to define the mutual proximity of the space objects. Among them, the weights are set according to the adjacent distance:

$$W_{ij} = \begin{cases} 1, & \text{when regional } i \text{ and regional } j \text{ are adjacent,} \\ 0, & \text{when regional } i \text{ and regional } j \text{ are not adjacent,} \end{cases} \tag{2}$$

where $i = 1, 2, \ldots, N$; $j = 1, 2, \ldots, M$; and $m = n$ or $m \neq n$.

$$Z(d) = \frac{\text{Moran's } I - E(\text{Moran's } I)}{\sqrt{\text{VAR}(\text{Moran's } I)}}. \tag{3}$$

According to the distribution of geospatial data, calculate the expected value of normalized Moran's I:

$$E_{\text{n}}(\text{Moran's } I) = -\frac{1}{n-1}. \tag{4}$$

For normal distribution of spatial data, the variance formula is

$$\text{VAR}_{\text{n}}(\text{Moran's } I) = \frac{n^2 w_1 + n w_2 + 3w_0^2}{w_0^2(\text{Moran's } I)} - E_0^2(\text{Moran's } I). \tag{5}$$

The Z value of the test statistic can be calculated based on the above formula, and the significance of null hypothesis can be judged according to the Z value of the test statistic. If the significant level of 0.05 (or 0.1) is less than 0.05 (or 0.1), the absolute value of the test statistics obeying the normal distribution is greater than the critical value of 1.65 (or 1.96), indicating that the regional haze has a significant spatial dependence on the spatial distribution.

4.3. Autocorrelation Test of Local Space. Local spatial autocorrelation test is an important part of exploratory data analysis in spatial statistics, and it can judge spatial association patterns in different regions. The spatial autocorrelation of the whole domain describes the spatial autocorrelation model of the haze in China, but because of the difference between regions, the spatial structure of the local area is ignored and the spatial dependence of each region cannot be reflected. When the whole-domain spatial effect test proves that there is a global spatial correlation conclusion, we need to further use the local index and the Moran scatter plot to prove the possible local significant spatial correlation effect. According to Anselin's view, the local Moran's I index of the I observation unit is a special case of the local spatial association index LISA, which can be defined as the following expression form:

$$I_i = z \sum_{j}^{n} \omega_{ij} z_j. \tag{6}$$

Among them, the deviation between the observed value and the mean value is expressed. In order to explain the spatial weight matrix in a standardized form, it is conventionally assumed. Therefore, I_i represents the weighted average product of Z_i and observed unit observations around unit I. The correlation of the local space can be analyzed by the Moran exponent scatter graph. The Moran scatter plot can further distinguish the spatial connection form between the regional unit and the adjacent unit and identify the different units and the transition paths of the spatial distribution.

5. Accounting for China's Fog and Haze and the Result of Space Effect Test

The haze in 30 regions of China was calculated, and the spatial autocorrelation and local spatial autocorrelation tests were used to analyze the spatial effects of regional haze and whether there was a significant spatial cluster effect.

5.1. Accounting for China's Haze. As a new key research topic in the field of economic construction in China, the haze problem is also the biggest problem involved in the coordinated development of the world's relations. Therefore, how to accurately measure the haze is the key to the problem.

The primary task of haze treatment to improve air quality is to control PM2.5. Therefore, this paper uses the research data about haze at home and abroad, uses the international geoscience information network center of Columbia University and the PM 2.5 year concentration of aerosol optical thickness by satellite loading equipment, and refers to the monitoring number of the environmental Protection Bureau of China. According to the information, the reliability of China's haze is high.

5.2. Autocorrelation Test of Whole Space

5.2.1. Whole-Domain Moran's Test. In this paper, Moran's index is used to test the regional haze in China, to define the not normal distribution of the haze in a region. The statistical significance of the spatial autocorrelation of Moran's index can be calculated under the hypothesis of randomness. Table 1 describes the test results of the spatial autocorrelation test of haze in 30 provinces in China during 2000~2015. The results show that the statistical values of Moran's I in all provinces and haze in China have passed a significant level test in the year of 2000~2015, which provides strong spatial correlation evidence for regional haze in China. Moran's I index of each year has passed a significant test of 5% of the significant level, and the range of Moran's I index is between 0.3678 and 0.5044. It is proved that the haze level between the 30 provinces of China has a significant spatial autocorrelation spatial dependence, that is, the spatial correlation model, so the regional haze is not in the space distribution. During the whole sample period, the spatial distribution of haze in China showed a spatial cluster pattern as follows: relatively high regional fog and haze tended to be adjacent to other provinces with higher fog and haze levels, and relatively low haze levels tended to be adjacent to other provinces with lower fog and haze levels. This indicates that the level of provincial fog and haze is related in space, so it cannot be assumed as an independent observation value.

It can be seen that the spatial autocorrelation of regional haze is obviously changed with time. In 2001, the spatial dependence of haze in China is obviously enhanced, but the number of Moran's I in 2006 began to decline, the spatial correlation intensity of regional haze decreased and also the space of 2011. The relative intensity is relatively large, but it decreases rapidly, which indicates that the spatial dependence of the haze in the provinces of China has the change trend of the inverted "U" type which is first enhanced and then weakened. The spatial autocorrelation of regional haze shows that the haze level in a province is not only affected by haze in the region but also affected by the surrounding area. Therefore, it is necessary to consider the mechanism of spatial haze to study regional haze more accurately.

5.2.2. Analysis of Moran Scatter Plot. The spatial correlation between haze in different provinces is preliminarily calculated based on the global Moran's I statistics and null hypothesis test. The average Moran haze I of 30 provinces in China during 2000~2015 was 0.467452 (it can be seen in Figure 1), and it can be proved that there is a positive correlation between fog and haze in the neighboring provinces of China. But the whole-domain Moran's I has great limitations; for example, some provinces have positive correlation (spillover effect), and other provinces have negative correlation (reflux effect). After the two are counterbalanced, the whole-domain Moran's I may show that there is no correlation between the provinces. Therefore, this paper analyzes the haze of China's 30 provinces and regions in 2000, 2015, and 2000~2015 in three time periods by Moran dispersion.

Table 1: Haze pollution statistics of 30 provinces in China between 2000 and 2015.

Year	Moran's I	P
2000	0.3678	0.0020
2001	0.4286	0.0010
2002	0.4335	0.0010
2003	0.5115	0.0010
2004	0.4457	0.0010
2005	0.4614	0.0010
2006	0.5044	0.0010
2007	0.5015	0.0010
2008	0.4704	0.0010
2009	0.4423	0.0010
2010	0.4390	0.0010
2011	0.5021	0.0010
2012	0.4709	0.0010
2013	0.4942	0.0010
2014	0.4590	0.0010
2015	0.4767	0.0020
2000~2015 mean value	0.4675	0.0010

Note: space weight matrix selects rook first-order spatial weight matrix.

As can be seen in Figure 2, in the first quadrant of the province in 2000, Beijing, Shandong, Anhui, Hebei, Jiangsu, Henan, Tianjin, Shaanxi, Ningxia, Shanghai, and Hubei are the cluster models of high fog and haze level and high spatial lag. The provinces of the second quadrant are Shanxi and Inner Mongolia, which have low haze level and high altitude—the negative autocorrelation cluster model of interlag. The provinces of the third quadrant are as follows: Jiangxi, Sichuan, Liaoning, Hunan, Fujian, Guangxi, Guangzhou, Guizhou, Jilin, Heilongjiang, and Yunnan, showing low fog and haze level and low spatial lag negative autocorrelation cluster mode. The province of the fourth quadrant is Xinjiang, showing low haze level—the negative autocorrelation model of low spatial lag. The province across the quadrant of the first and second quadrants is Zhejiang. The provinces across the second and third quadrants are Hainan, Qinghai, and Chongqing. The provinces across the first and fourth quadrants are Gansu.

In Figure 3, the first quadrant of the province in 2015, Beijing, Tianjin, Shanghai, Shandong, Liaoning, Hubei, Jiangsu, Anhui, Hebei, and Henan showed a cluster model of high haze level and high spatial lag, and the provinces of the second quadrant are Zhejiang and Shanxi, showing low haze level and high spatial lag—the negative autocorrelation cluster model. The provinces of the third quadrant are Jiangxi, Heilongjiang, Shaanxi, Hunan, Ningxia, Gansu,

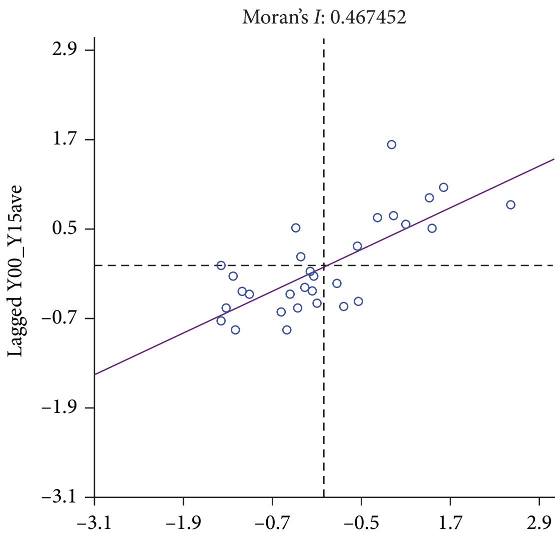

Figure 1: Moran's *I* scatter plot of China's carbon emissions from 2000 to 2015.

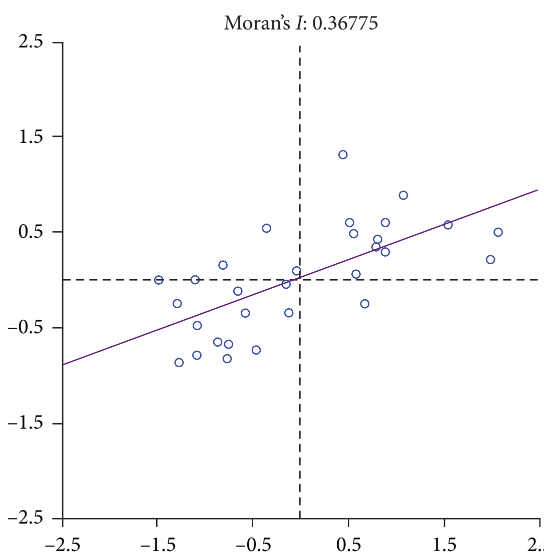

Figure 2: Moran's *I* scatter plot of China's haze in 2000.

Guangxi, Guangzhou, Guizhou, Chongqing, Fujian, Qinghai, and Sichuan, etc.—the negative autocorrelation cluster model of low fog and haze level and low spatial lag; they are low negative fog and haze level and low spatial lag negative autocorrelation mode. The provinces across the first and second quadrants are Inner Mongolia and Hainan.

In Figure 3, Beijing, Shandong, Tianjin, Jiangsu, Shanghai, Henan, Anhui, Hebei, and Hubei are located in the first quadrant of the province in 2000~2015, showing a cluster model of high fog and haze level and high spatial lag. The provincial region of the second quadrant is Zhejiang and Shanxi, which are shown as low haze level and high spatial lagging negative autocorrelation cluster model. The provinces of the third quadrant are Shaanxi, Jiangxi, Liaoning, Chongqing, Gansu, Guangzhou, Guangxi, Guizhou, Jilin, Qinghai, Fujian, Inner Mongolia, Sichuan, etc., are negative autocorrelation cluster models with low fog and haze level and low spatial lag. Xinjiang and Ningxia showed low negative correlation between low haze level and low spatial lag, and the provinces across the first and fourth quadrants were Hainan. According to the spatial Moran's scatter distribution in the four quadrants in 30 provinces of China in 2000 and 2015, the provincial distribution shows that the common feature is the positive spatial autocorrelation in the geographical space. The scatter plot of Moran's *I* in 2000 shows that 73.33% (22) provinces have similar spatial correlation, of which 36.67% (11) provinces are in the first quadrant (HH: high haze intensity and high spatial lag) and 36.67% (11) provinces are in the third quadrant (LL: low haze intensity and low spatial lag), and Moran's *I* in 2015. In the scatter plot, 80% (24) provinces have similar spatial correlation, of which 33.33% (10) provinces are in the first quadrant (HH: high haze intensity and high spatial lag) and 46.67% (14) provinces are in the third quadrant (LL: low fog haze intensity and low spatial lag). According to the results, it is further proved that there is a significant spatial correlation between provincial haze and even spatial dependence and the spatial autocorrelation is increasing.

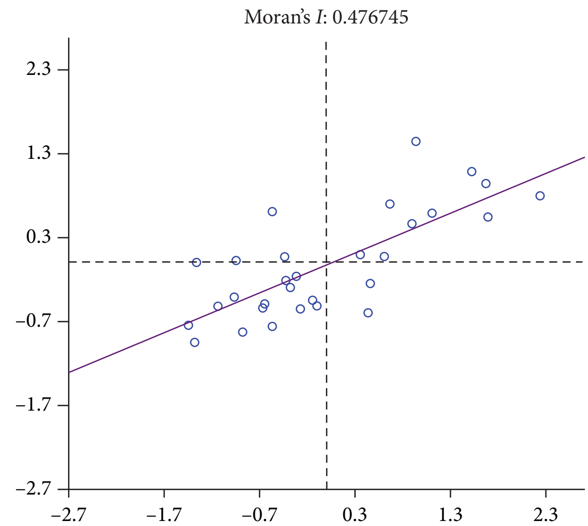

Figure 3: Moran's *I* scatter plot of China's haze in 2015.

5.3. Spatiotemporal Dynamic Analysis. The spatial and temporal evolution of Moran's *I* scatter diagram in China is further analyzed based on Rey's space-time transitions. There are four types of spatiotemporal transition measures: type I, type II, type III, and type 0. Type I transition represents only the transition of the provincial unit itself. The type II transitions represent only the transitions of provincial units adjacent to the provincial regions, such as HH, HL, HL, HH, belonging and type III. Type III is also divided into two types: type III A and type III B, in which the type III A transitions represent the same transition direction in the provincial unit and its adjacent province. For example, in HH-HH, HL-HL, LH-LH, and LL-LL, type III B transitions represent the same inverse of the transition direction of the provincial unit itself and its adjacent provinces, such as HH, LL, and HL, and there are no transitions in the provincial and adjacent provinces. In this paper, the results of provincial haze detection in China in 2000 and 2015 are shown in Table 2.

The detection of high and low value haze in 30 provinces of China in 2000 and 2015 showed obvious spatial imbalance and spatial continuity characteristics. According to Table 2, comparing the transition types of the Moran' *I* scatter point of haze levels in 30 provinces of China in 2000 and 2015, it can be seen that, during the period of 2000~2015, the main transition mode is to maintain the same level of type III in the province and its adjacent provinces, and the 21 provinces belong to the transition type III A transition (the transition path is HH to HH and HL to HL). The 3 provinces Shaanxi, Ningxia, and Liaoning are typical regions of type III B transition. The transition paths are HH to LL and LL to HH, respectively. It shows that the fog and haze level in the 80% of province shows the space stability relatively, and the haze level spatiotemporal transition is relatively less than that of the three types, belonging to type I. The province has the typical Jilin region (the transition path is LL to HL), and the two quadrants of Zhejiang, Hainan, Qinghai, Chongqing, Gansu, and Inner Mongolia belong to the atypical transition region at the same time. According to the evidence, there is no significant displacement in the spatial cluster structure detected in the whole period, and it can be judged that the regional fog haze level has a serious path dependence on the spatial geographic distribution and has the characteristics of significant agglomeration and low liquidity.

5.4. Local Spatial Autocorrelation Test. Local spatial correlation test is needed in order to further study the spatial dependence of regional haze specific areas. The Moran scatter plot does not obtain the specific level of the local saliency level of the provincial haze. The map and the significance of the regional agglomeration can show the spatial correlation and the significance of the local area more intuitively and can also provide evidence for the convergence of the haze. Therefore, it is necessary to calculate the local statistical values of the local spatial autocorrelation and the local statistical values of the local space. The level of significance, therefore, of Local Indicators of Spatial Association (LISA) is needed to analyze the provincial haze. In order to distinguish the pattern of haze cluster in local space in 2000~2015 years, the study focused on the index of the local spatial cluster with a high significant level and was analyzed three periods in 2000, 2015, and 2000~2015, respectively.

Figures 4–6 are local spatial autocorrelation of LISA maps of China's provincial haze level in 2000, 2015, and 2000~2015, respectively. The haze level of local spatial autocorrelation of LISA province is identified with different colors, corresponding to the provincial domain of the Moran scatter plot, and the white region indicates no significant test of the autocorrelation of the local space; the light green region indicates the 5% local spatial autocorrelation explicit test; and the dark green region indicates 1% of the local passed through the spatial autocorrelation significance test. Figures 5, 7, and 8 are the local spatial autocorrelation LISA cluster maps of the fog and haze levels in China's 30 provinces in 2000, 2015, and 2000~2015, respectively. The red region indicates that the province of high fog and haze is surrounded by other provinces with higher fog and haze levels, which belong to the high haze cluster area; the blue region represents the province of low fog and haze. The region is surrounded by a lower haze level in a lower haze cluster province; the gray area indicates that the province of low fog is surrounded by a province with high fog and haze level, a haze of space outgoing provinces, and the pink area is surrounded by a province of low fog and haze, which belongs to the haze space. Outlying provinces are white areas representing regions with little spatial effect.

According to Figures 4 and 7, we can see that the haze of four provinces in Guizhou, Guangxi, Guangdong, and Hunan of China in 2000 passed the significant level test of 1%. The haze of 6 provinces Yunnan, Fujian, Zhejiang, Jiangxi, Heilongjiang, and Jilin had passed the 5% significant level test; the two provinces Heilongjiang and Jilin were located in the H-H high type. The 8 provinces of Yunnan, Guizhou, Hunan, Jiangxi, Fujian, Guangxi, Guangdong, and Zhejiang are located in the L-L low value agglomeration region. The H-H high type value agglomeration area and the L-L low type concentration zone all represent the positive correlation between the fog and haze concentration in the neighboring provinces, and the other provinces are in no special characteristics and regional spatial outliers.

According to Figures 5 and 9, we can see that the haze in provinces Yunnan, Hunan, Guizhou, and Guangxi of China in 2015 passed 1% significant level tests, and the haze of 5 provinces Heilongjiang, Jilin, Jiangxi, Fujian, and Guangzhou had passed 5% significant level tests; Heilongjiang and Jilin were located in the H-H high value agglomeration area; Yunnan, the expensive state, Hunan, Jiangxi, Fujian, Guangxi, and Guangzhou provinces are located in the low value agglomeration area of L-L, and Hainan is located in the regional spatial outlier area.

According to Figures 6 and 8, we can see that the haze in provinces Yunnan, Hunan, Guangxi, and Guizhou of China passed the 1% significant level test, and the haze in 5 provinces of Guangdong, Jiangxi, Fujian, Heilongjiang, and Jilin had passed 5% significant level tests; Heilongjiang and Jilin were located in the H-H high value concentration zone; Yunnan, Guizhou, Hunan, Jiangxi, Fujian, Guangxi, and Guangzhou provinces are located in the L-L low value cluster area; the other provinces have no special characteristics and regional spatial outliers. Based on the comprehensive analysis of the regional LISA cluster map and the LISA saliency map (as shown in Figures 4–9), it can be seen that the haze in China has formed two different spatial agglomeration areas: first, Heilongjiang and Jilin, which is the center of high fog and haze level of the spatial cluster area composed of the surrounding provinces, and the second, Hunan and Jiangxi, which is the center of the haze space cluster area with its surrounding provinces.

6. Spatial Econometric Model of Regional Haze in China

There are spatial autocorrelation in regional haze in China according to the previous evidence. If we use traditional

Table 2: Moran scatter transition of China's haze level between 2000 and 2015.

Quadrant	Year	
	2000	2015
The first quadrant (HH)	Beijing, Tianjin, Shanghai, Shandong, Hubei, Jiangsu, Anhui, Hebei, Henan, Shanxi, Ningxia	Beijing, Tianjin, Shanghai, Shandong, Liaoning, Hubei, Jiangsu, Anhui, Hebei, Henan
The second quadrant (LH)	Shanxi, Inner Mongolia	Zhejiang, Shanxi
Third quadrant (LL)	Jiangxi, Sichuan, Liaoning, Hunan, Fujian, Guangxi, Guangzhou, Guizhou, Jilin, Heilongjiang, Yunnan	Jiangxi, Heilongjiang, Shanxi, Hunan, Ningxia, Gansu, Guangxi, Guangzhou, Guizhou, Chongqing, Fujian, Qinghai, Sichuan, Yunnan
Fourth quadrant (HL)	Xinjiang	Xinjiang, Jilin
Cross-quadrant province	Zhejiang, Hainan, Qinghai, Chongqing, Gansu	Inner Mongolia, Hainan

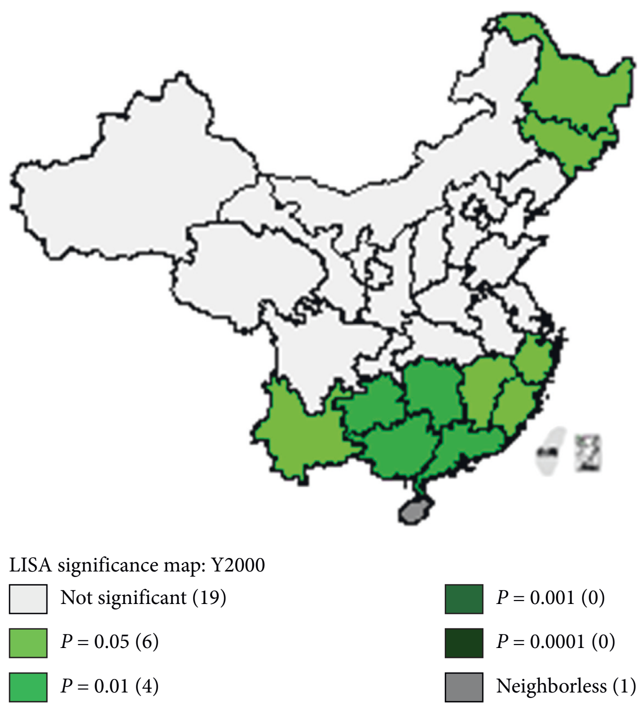

Figure 4: LISA significance map based on the first-order matrix of haze pollution in 2000.

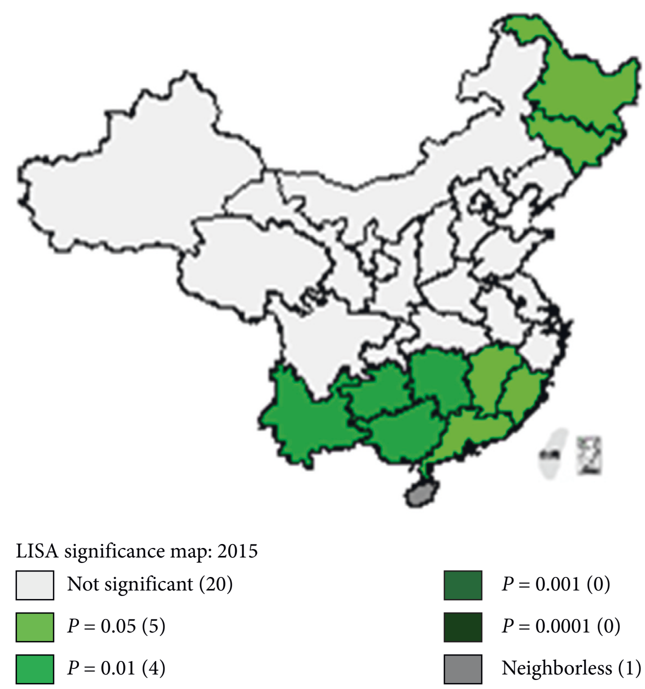

Figure 5: LISA significance map based on the first-order matrix of carbon emissions in 2015.

econometric methods to study the difference of regional fog and haze, it is necessary to use the spatial econometric model to consider the spatial effect of regional haze. First of all, the specific form of the spatial econometric model and the method of test estimation are introduced. In 1979, the Holland economist Paelinck proposed the concept of the spatial econometrics model, and the spatial econometrics developed rapidly. Cliff and Ord [27] put forward the corresponding parameter estimation and test technology for the spatial autoregressive model, and the scholars of Anselin and other scholars have combed the theory of spatial econometrics. Through the continuous efforts of experts and scholars, spatial econometrics has gradually developed and developed and has formed a systematic theoretical framework of spatial econometrics, which has been widely recognized in the application of economic status. As a branch of econometrics, spatial econometrics mainly takes into account the correlation among individuals and considers the heterogeneity of an individual and has better estimation properties and application prospects. At present, the spatial econometrics model has been widely applied in the multidisciplinary field of society, and it is also one of the hotspots in spatial econometrics.

The spatial econometric model is used to study the spatial effect of economic phenomena into the econometric model. According to the different embodiments of "spatial dependence," the spatial econometric model is divided into two types: spatial lag model (SLM) and spatial error model (SEM) type. The spatial econometric model helps to improve the oversimplified time-series model and provides a more practical and flexible model for the spatial impact factors, especially the inter-regional spatial impact factors in China. As the existing research panel data model is dominated by a fixed effect, the spatial lag model, spatial error model, generalized space model, and geoweighted regression model are mainly introduced.

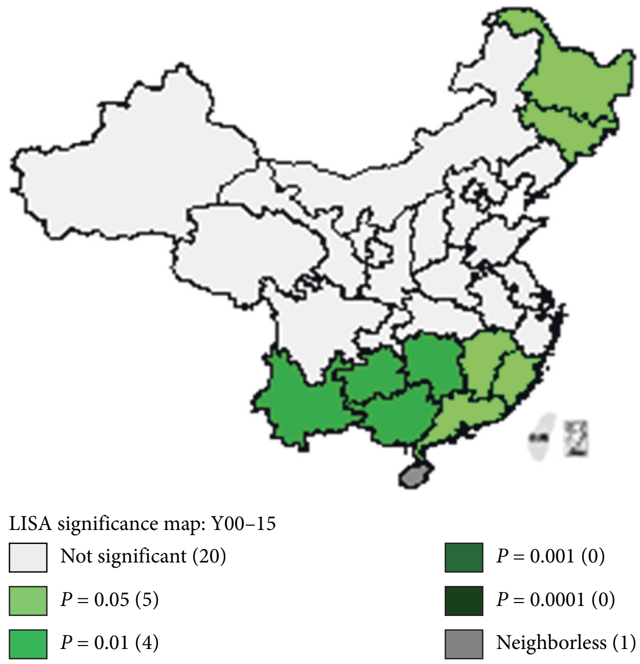

Figure 6: LISA significant map based on the first-order matrix of carbon emissions in 2000~2015.

Figure 7: LISA cluster map based on the first-order matrix of carbon emissions in 2000.

6.1. The Principle of Spatial Econometric Model. Anselin presents the general form of the spatial linear model. The spatial linear model derives a specific model through the difference of the parameters of the model, and the specific expression is shown as follows:

$$\begin{aligned} Y &= \rho W^1 y + X\beta + \varepsilon, \\ \varepsilon &= \lambda W^2 \varepsilon + u, \\ u &\sim N\left(0, \sigma^2 I_n\right), \end{aligned} \tag{7}$$

where Y represents the dependent variable, X represents the exogenous explanatory variable matrix of $N \times k$, ρ represents the spatial autoregressive coefficient, λ represents the spatial error coefficient of the dependent variable of $n * 1$, W^1 and W^2 represent the space weighted matrix of $n * n$, and u represents the random error vector of the normal distribution. When it is zero, the corresponding model is a spatial lag model. When it is $\sigma^2 I_n$, the model is a spatial error model.

The spatial lag model (SLM) mainly studies the economic behavior of an economic unit affected by the economic behavior spillover of adjacent units and is a regression model of the spatial lag factor in the model. The expression of the spatial lag model is as follows:

$$\begin{aligned} Y &= \rho W_y + X\beta + u, \\ u &\sim N\left(0, \sigma^2 I_n\right), \end{aligned} \tag{8}$$

where Y represents the dependent variable; X represents the exogenous variable of $N \times k$; and W_y is a spatial lag factor, which is a spatial regression coefficient, reflecting the spatial dependence of the observation value of the sample, that is, the direction and degree of the influence of the observed value W_y on the observed value Y in the region, and can show whether the dependent variable has diffusion in a region. That is the spillover effect; W is the spatial weight matrix of $n * n$ order, and u represents the random error term vector.

The influence of an independent variable X on the dependent variable Y is reflected by an parameter. Spatial lag variable W_y is an endogenous variable, which indicates the effect of spatial distance on regional haze. Regional haze is affected by economic environment and cost related to space distance and has strong regional characteristics. Because the spatial lag model is similar to the autoregressive model in time series, the spatial lag model is also called spatial autoregressive model (SAR).

The spatial error model (SEM) disturbance shows the spatial correlation. The spatial error model is needed when the inter-regional interaction is different because the relative position is different. The expression of the spatial error model is as follows:

$$\begin{aligned} Y &= X\beta + \varepsilon, \\ \varepsilon &= \lambda W \varepsilon + \mu, \\ u &\sim N\left(0, \sigma^2 I_n\right), \end{aligned} \tag{9}$$

where the random error term vector is expressed and the random error vector of the normal distribution is expressed by the spatial error coefficient of the cross section of the $n * 1$ order because of the variable vector.

The parameter in the spatial error model indicates the influence of an independent variable on the dependent variable Y. Parameter L is used to measure the spatial dependence of the observed values of the samples, that is, the

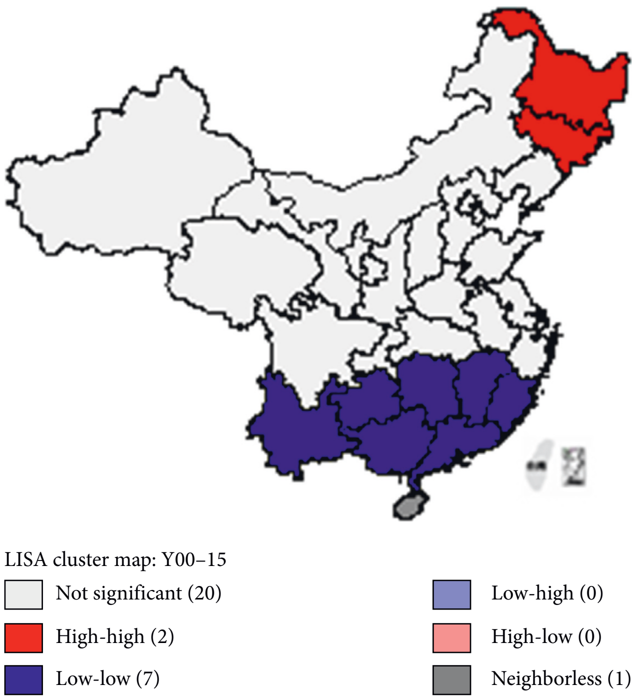

FIGURE 8: LISA cluster map based on the first-order matrix of carbon emissions in 2000~2015.

FIGURE 9: LISA cluster map based on the first-order matrix of carbon emissions in 2015.

direction and extent of the observed value y of the observed value Y in the adjacent area. The spatial dependence of the perturbation error term is used to measure the influence of the adjacent region on the observation value of the region caused by the error impact of the dependent variable.

Spatial autocorrelation (SAC) includes spatial lag condition and spatial error structure:

$$\begin{aligned} Y_t &= \rho W_{1y} + X\beta + \mu, \\ u &= \lambda W_2 u + \varepsilon, \\ u_t &\sim N\left(0, \sigma_\varepsilon^2 I_n\right), \end{aligned} \tag{10}$$

where $t = 1, 2, 3, \ldots, T$; Y_t is $y_{1t}, y_{2t}, \ldots, Y_{nt}$, which represents the dependent variable of N section data at t time point; X_t is $x_{1t}, x_{2t}, \ldots, X_{nt}$, which represents the explanatory variable of the N section data at t time point; u is $U_1, U_2, \ldots, U_N$, which represents the individual effect of regression equation; u_t is $u_{1t}, u_{2t}, \ldots, U_{nt}$, indicating the random error term obeying normal distribution; and W is a spatial weight matrix, and the parameter beta represents the regression coefficient of the explanatory variable X_t. As a parameter that needs to be estimated, the dependent variable Y_t of a region is affected by the influence of the dependent variable Y_t on the adjacent region. The geographical weighted regression (GWR) considers the global regression model's formula:

$$Y_t = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i. \tag{11}$$

The geographically weighted regression model (GWR) allows local parameter estimation. The extended model is as follows:

$$Y_t = \beta_0 (u_i, v_i) + \sum_k \beta_k (u_i, v_i) x_{ik} + \varepsilon_i, \tag{12}$$

where (u_i, u_i) is the spatial coordinates of the I sample points and K (u_i, v_i) is the value of continuous K (u, u) at I point. When K (u_u, v_i) remains unchanged in space, the model is a global regression model.

6.2. Estimation and Selection of Spatial Econometric Models. According to the endogenous characteristics of the variables of the spatial econometric model, the spatial econometric model is estimated by the traditional least square estimation. The estimated values of the coefficients are biased or invalid, so the least squares estimate is no longer applicable: LM (maximum likelihood estimation), GMM (generalized moment estimation), IV (tool variable estimation), GLS (generalized least squares estimator), and Bayesian method (Bayes method). The following is a brief introduction to the maximum likelihood estimation method recommended by Anselin to study the spatial econometric model.

The principle and process of the maximum likelihood estimation for spatial lag model is as follows: first of all, we carry out ordinary least squares regression for the model, calculate the residual of the least squares regression, respectively, and get the parameter ρ value by maximizing the centralized logarithmic likelihood function:

$$L_c = -\left(\frac{n}{2}\right) \ln \left[\left(\frac{1}{n}\right) \left(e_0 - \hat{\rho} e_L\right)' \left(e_0 - \hat{\rho} e_L\right)\right] + \ln |I - \hat{\rho} W|. \tag{13}$$

The remaining parameter estimates are calculated, and the maximum likelihood function is

$$\log L = -\left(\frac{N}{2}\right)\ln(2\pi) - \left(\frac{N}{2}\right)\ln\hat{\sigma}_{\varepsilon}^{2} + \ln|I - \hat{\rho}W| - \left(\frac{1}{2}\hat{\sigma}_{\varepsilon}^{2}\right)(y - \hat{\rho}Wy - \beta X)' \cdot (y - \hat{\rho}Wy - \beta X)'(y - \hat{\rho}Wy - \beta X). \quad (14)$$

The estimation process of the maximum likelihood estimation of the spatial error model is also an ordinary least square estimate of the model, and the unbiased estimation value of the beta is obtained. The residual error of the ordinary least squares estimate is calculated, and the estimation value of the parameter is obtained by the logarithmic maximum likelihood function:

$$L_c = -\left(\frac{n}{2}\right)\ln\left[\left(\frac{1}{n}\right)\left(e_0 - \hat{\lambda}e_L\right)'\left(e_0 - \hat{\lambda}e_L\right)\right] + \ln|I - \hat{\lambda}W|. \quad (15)$$

The iterative iteration method proposed by Anselin is used to deal with the maximization condition:

$$\log\ L_c = -\left(\frac{N}{2}\right)\ln(2\pi) - \left(\frac{N}{2}\right)\ln\hat{\lambda}\sigma_{\varepsilon}^{2} - \left(\frac{1}{2}\hat{\lambda}\sigma_{\varepsilon}^{2}\right)e'(I - \hat{\lambda}W)'(I - \hat{\lambda}W)e. \quad (16)$$

In general, a certain hypothesis condition is first set. Finally, the maximum condition of the logarithmic likelihood function is derived to determine the estimated value of the model parameter.

Through a series of spatial effect tests, such as Moran's I test, maximum likelihood LM-lag test, and maximum likelihood LM-error test, the spatial lag model, and spatial error model are tested, and the spatial correlation exists between the regions. These statistical methods can also be used to diagnose the estimated results of spatial econometric models. In addition to the use of the goodness-of-fit R^2 test, other common criteria are natural logarithmic likelihood ($\log L$), Akaike information criterion (AIC), likelihood ratio (LR), Schwartz criterion (Schwartz), etc. When the AIC and SC values are smaller and the logarithmic likelihood value increases, the fitting effect of the model is better. These indexes can be used to compare the classical linear regression model, spatial lag model, and spatial error model of OLS estimation. When the natural logarithm of the likelihood is maximum, the model is best.

The main practice of the existing research is to use the fixed effect panel data econometric model to estimate and then use the likelihood ratio (LR) test. When the likelihood ratio test statistic is more than 0.05, the fixed effect model is selected, or the Hausman test is used to estimate the likelihood ratio, when the Hausman test is used. When the significance level of the test statistic is less than 0.05, the random effect model is chosen as the fixed effect model.

Without considering the spatial correlation constraints, the general least squares regression method is used to carry on the correlation test at the same time, according to the selection of the LM-lag and LM-error significance judgment model. If any one of LM-lag and LM-error is significant, select the model with significant experience; if both LM-lag and LM-error are not significant, the ordinary least squares regression is used to analyze. If LM-lag and LM-error are both significant, the Robust LM-lag and Robust LM-error are judged, and the significance of the Robust LM-lag and LM-error is compared. St LM-lag is more significant than the Robust LM-error, then the spatial lag model is selected; otherwise, the spatial error model is selected.

The main test statistics are as follows: the commonly used R^2 judgment method of goodness-of-fit degree, likelihood ratio, natural logarithmic likelihood function value, red pool information criterion (AKaike information criterion, AIC), and Schwartz criterion (SC). When the logarithmic likelihood function $\log L$ is larger, the smaller the Akaike information criterion and the Schwartz criterion value, the better the model fitting effect is. Considering the goodness-of-fit R^2 and logarithmic likelihood function $\log L$ of the model, the fitting degree of the model is higher when the value of both is larger.

6.3. The Construction of the Spatial Econometric Model of Haze. In 1970s, Professor of Stanford and a commoner Ehrlich of the United States established the IPAT formula for assessing environmental pressure and studied the mechanism of the effects of population, economic growth, and technological progress on haze. The extended stochastic environmental impact assessment model (Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT)), a revision and extension of the IPAT model, can overcome the shortage of the hypothesis of the IPAT model.

In this paper, the STIRPAT model is used to construct a haze change model to estimate the influence factors on the elastic coefficient of haze and to test the spillover effect in the process of haze change. The IPAT model is an important way to analyze environmental factors:

$$I = P \times A \times T, \quad (17)$$

where I represents the environmental load, P represents the population, A represents GDP per capita, and T represents the environmental load of unit GDP. In 1994, York and other scholars proposed the STIRPAT model on the basis of the IPAT model, which is an extended stochastic model to evaluate the environmental impact through the three independent variables of population, property, and technology and the relationship between the dependent variables:

$$I = a \times P^b \times A^c \times T^d \times e. \quad (18)$$

When a, b, c, and d are all 1, the STIRPAT model is reduced to the IPAT model. a is the constant of the model, and b, c, and d are all exponential terms. e is the error term. The STIRPAT model is used to build a quantitative model for the relationship between haze and influencing factors:

$$I = a \times P^b \times A^c \times T^d \times S^e \times F^f \times E^g \times \mathrm{EX}^h \times U^k \times \mathrm{FD}^l + \varepsilon, \quad (19)$$

where I, P, A, T, S, F, E, EX, U, and FD, respectively, represent haze, population, economic growth, technological progress, industrial structure, financial development, energy price, international trade, urbanization rate, and fiscal decentralization.

Taking the logarithm of the haze function (formula (19)) on both sides, it becomes an empirical analysis model:

$$\begin{aligned}\ln I_i = {} & \ln a + b\ln P_i + c\ln A_i + d\ln T_i \\ & + e\ln S_i + f\ln F_i + g\ln E_i + h\ln \mathrm{EX}_i \\ & + k\ln U_i + l\ln \mathrm{FD}_i + \varepsilon_i,\end{aligned} \tag{20}$$

where a is a constant, b represents the elastic coefficient of population growth to haze in the I region, c represents the elastic coefficient of economic growth, d represents the elastic coefficient of technological progress, e indicates the elastic coefficient of the industrial structure, F indicates the elastic coefficient of financial development, G represents the elastic coefficient of energy price, H represents the bomb of international trade, sex coefficient K indicates the elasticity coefficient of urbanization rate, l represents the elastic coefficient of fiscal decentralization, and I indicates a random term.

Based on the STIRPAT model established in this paper, we construct the provincial haze space panel data model in China and estimate the elastic coefficient and the spatial spillover effect of the haze influence factors in the province. The econometric model of haze standard panel data without considering the spatial effects is

$$\begin{aligned}\ln I_{it} = {} & b\ln P_{it} + c\ln A_{it} + d\ln T_{it} + e\ln S_{it} + f\ln F_{it} \\ & + g\ln E_{it} + h\ln \mathrm{EX}_{it} + k\ln U_{it} + l\ln \mathrm{FD}_{it} \\ & + \mu_{it} + \upsilon_{it} + \varepsilon_{it},\end{aligned} \tag{21}$$

where I represents the cross section of the province ($i = 1, 2, \ldots, N$); T represents the period ($t = 1, 2, \ldots, T$); I_{it} is an interpreted variable, representing a $N \times 1$ vector composed of I region and t period fog, explaining variables P_{it}, A_{it}, T_{it}, U_{it}, S_{it}, E_{it}, EX_{it}, population, economic growth, technological progress, industrial structure, financial development, energy prices, international trade, urbanization rate, and fiscal decentralization observations. The matrix $b, c, d, e, f, g, h, k,$ and l are the constant regression parameters of the constant. The epsilon is an independent and identically distributed random error term, and for I and t to satisfy the zero mean and the same variance, the space effect is expressed as the time effect [], so that the model 21 is a spatial and time double effect panel model; when model 21 is not mixed with it, it is represented as a mixed panel model; when it is removed, the spatial effect panel model is represented; and when it is removed, the time effect panel model is used.

The standard panel econometric model ignores the problem of bias in parameter estimation of spatial effects. Therefore, the provincial fog haze function of the spatial effect is included in this paper. The spatial lag panel data econometric model (SLPDM) are needed when the fog haze in the region is determined by the fog and haze observations in its neighboring regions and the observed group of local characteristics:

$$\begin{aligned}\ln I_{it} = {} & \rho\sum_{j=1}^{N}\omega_{ij}\ln I_{jt} + b\ln P_{it} + c\ln A_{it} + d\ln T_{it} \\ & + e\ln S_{it} + f\ln F_{it} + g\ln E_{it} + h\ln \mathrm{EX}_{it} \\ & + k\ln U_{it} + l\ln \mathrm{FD}_{it} + \mu_{it} + \upsilon_{it} + \varepsilon_{it},\end{aligned} \tag{22}$$

where ρ is the spatial lag (autoregression) coefficient and W_{ij} are the elements of the space weight matrix W. The weight matrix is processed by row standard, and the sum of the elements of each row is 1. For the setting of W, we use an adjacency matrix to set the weight matrix W.

If the region haze is interpreted by the explanatory variable, it is determined by the observed group of local features and the important variables that are neglected in space (the error term), which is the spatial error panel data econometric model (SEPDM):

$$\begin{aligned}\ln I_{it} = {} & +b\ln P_{it} + c\ln A_{it} \\ & + d\ln T_{it} + e\ln S_{it} + f\ln F_{it} \\ & + g\ln E_{it} + h\ln \mathrm{EX}_{it} \\ & + k\ln U_{it} + l\ln \mathrm{FD}_{it} + \phi_{it}, \\ \phi_{it} = {} & \lambda\sum_{j=1}^{N}\omega_{ij}\phi_{jt}\rho + \varepsilon_{it},\end{aligned} \tag{23}$$

where x is represents the error term of spatial autocorrelation and is the coefficient of the spatial error (autocorrelation). In addition to the spatial spillover effect of haze in adjacent areas, if the influence factors in the space adjacent to the haze of the province are also affected, it is necessary to use the spatial Dobbin panel data econometric model (SDPDM):

$$\begin{aligned}\ln I_{it} = {} & \rho\sum_{j=1}^{N}\omega_{ij}\ln I_{jt} + b\ln P_{it} + c\ln A_{it} + d\ln T_{it} \\ & + e\ln S_{it} + f\ln F_{it} + g\ln E_{it} + h\ln \mathrm{EX}_{it} \\ & + k\ln U_{it} + l\ln \mathrm{FD}_{it} + \alpha\sum_{j=1}^{N}w_{ij}\ln P_{ji} \\ & + \beta\sum_{j=1}^{N}w_{ij}\ln A_{ji} + \chi\sum_{j=1}^{N}w_{ij}\ln T_{ji} \\ & + \delta\sum_{j=1}^{N}w_{ij}\ln S_{ji} + \xi\sum_{j=1}^{N}w_{ij}\ln F_{ji} \\ & + \zeta\sum_{j=1}^{N}w_{ij}\ln E_{ji} + \eta\sum_{j=1}^{N}w_{ij}\ln \mathrm{EX}_{ji} \\ & + \varpi\sum_{j=1}^{N}w_{ij}\ln E_{ji} + \psi\sum_{j=1}^{N}w_{ij}\ln \mathrm{EX}_{ji} + \mu_{it} + \upsilon_{it} + \varepsilon_{it},\end{aligned} \tag{24}$$

where $W\ln P$, $W\ln A$, $W\ln T$, $W\ln S$, $W\ln F$, $W\ln E$, $W\ln \mathrm{EX}$, $W\ln U$, and $W\ln \mathrm{FD}$ are the spatial lag variables in the neighboring provincial population, economic growth, technological progress, industrial structure, financial development, energy prices, international trade, urbanization rate, and fiscal decentralization. The constant regression parameters are estimated.

7. Empirical Analysis of the Influence Factors of Regional Haze in China

The spatial econometric model of 30 provinces in China, Tibet, Taiwan, Hong kong, and Macao is selected to establish the spatial econometric model. Because the haze management is involved in the whole economic system, the influence mechanism of the haze in the areas of economy, technology, finance, and policy is studied. Taking the fog and haze levels in each province as an explanatory variable (I), the factors affect the nine different horizons: population (P), economic development level (A), technological progress level (T), industrial structure (S), financial development (F), energy price policy (E), international trade (EX), and urbanization rate (U). In order to make it easier to compare and analyze the econometric model of the explanatory variable (FD), the traditional panel econometric model regression analysis and the spatial panel econometric model regression analysis are carried out at the same time.

8. Spatial Econometric Models and Results

First, the general panel model is used for regression. Hausman test was used to decide whether to establish random effect model or fixed effect model and then set up a general panel data model. According to the results of the study in Table 3, we can see that the Hausman test value of the panel data model is 20.8925. Through the significant test of 0.05%, the original hypothesis of establishing the random effect model is rejected. Therefore, the fixed effect model should be used.

Secondly, the effect of space spillover is tested. The least squares regression was performed by MATLAB software, and LM-lag, LM-error, Robust LM-lag, and Robust LM-error were tested simultaneously. According to the results of Table 4, we can see that the spatial lag panel model has passed the 5% significant level test, but the spatial error panel model does not pass the 5% significant level test, the LM and Robust test values of the spatial lag panel model are 124.9192 and 42.9130, the LM and Robust test values of the spatial error panel model are 7.4859 and 3.6542, and it is more reasonable to adopt the spatial lag panel model. In order to avoid the effect of heteroscedasticity in the sample, the generalized least squares estimation method was used to analyze the panel data model (Table 5).

According to the Wald and LR test, the spatial panel model can be transformed into the spatial lag model and spatial error model. The test results show that Wald_spatial_lag and LR_spatial_lag are 28.2250 and 22.5580, respectively, and the adjoint probability values are $8.6461e-004$ and 0.0073; Wald_spatial_error and LR_spatial_error are 46.0096 and 20.3784, respectively, and the adjoint probability values are $5.9975e-007$ and 0.0157, respectively. The SDPDM is better than the SEPDM).

Table 3: Hausman estimates of ordinary panel of the model.

Test summary	Chi-square statistic	Chi-square d.f.	Probablility
Cross section random	48.7724	9	0.0000

Table 4: Spatial correlation of the model test.

	Test method	Statistical value	P value
Spatial correlation test	LM test: no spatial lag	136.6296	0.000
	Robust LM test: no spatial lag	51.0239	0.000
	LM test: no spatial error	119.6694	0.000
	Robust LM test: no spatial error	34.9637	0.000

Finally, we compare and analyze the estimation results of the three models of the common panel data model, the spatial lag panel data model, and the spatial error panel data model. According to the previous results, the three models, such as the ordinary panel data model, the spatial lag panel data model, and the spatial error panel data model, should be estimated with the fixed effect model, and the data used in this study are processed logarithmically, which can avoid the existence of the estimation process to a certain extent.

In this paper, the panel data model is selected to greatly increase the sample size; at the same time, the sample's degree of freedom is improved, the multiple collinearity of the explanatory variables is reduced, and the error is reduced. At the same time, the estimation results of the spatial lag panel data model, the spatial error panel data model, the fixed effect, the time fixed effect, and the individual time double fixed effect are compared and analyzed.

According to Table 6, the spatial error model of haze in provinces of China and the model of the space Durbin model and the test results show that the logarithmic likelihood values of the spatial fixed effect model SEPDM model IV and the SDPDM model VIII are 559.2720 and 570.5510, respectively, and the corresponding goodness-of-fit coefficients are 0.9728 and 0.9736, respectively. All of them are relatively high. According to the actual situation in China, the economic meaning of the model is obvious. Therefore, this paper chooses SEPDM model IV and SDPDM model VIII to empirically study the elastic coefficient and its spatial spillover effects of various haze factors in China.

8.1. Estimation and Analysis of Coefficient of Spatial Lag Panel Data Model Results. The estimation results of SEPDM model IV in Table 6 show that the technological progress, industrial structure, and energy price elasticity coefficient are positive, and the industrial structure has a significant positive effect on the growth of haze, but the technological progress and the energy price have not passed the significant test. Under the conditions of other factors, the increase of 1% of the industrial structure can lead to the growth of haze in China by 0.1574%. It may be related to the current industrial structure in China. Population, economic

Table 5: Standard panel estimation results of provincial carbon emissions.

Variables	No fixed effects	Fixed effects	Random effects	Spatial fixed effects	Time period fixed effects
C	1.2246 (0.4409)	8.1067 (0.0000)	4.0870 (0.0002)	5.1783 (0.0001)	5.2015 (0.0000)
$\ln P$	−0.2102 (0.0036)	−0.2197 (0.0482)	−0.0248 (0.1212)	−0.2285 (0.0395)	−0.0344 (0.6717)
$\ln A$	0.1859 (0.0161)	−0.2501 (0.0009)	0.1151 (0.0089)	0.1086 (0.0113)	−0.0915 (0.1727)
$\ln T$	0.0212 (0.6532)	0.0136 (0.4885)	0.0107 (0.5893)	0.0089 (0.6408)	0.0203 (0.2971)
$\ln S$	0.3387 (0.0007)	0.0544 (0.4597)	−0.0557 (0.4108)	−0.079 (0.2494)	0.0319 (0.6472)
$\ln F$	0.0137 (0.8834)	−0.0120 (0.6070)	0.0092 (0.6923)	0.0124 (0.5841)	−0.0059 (0.7996)
$\ln E$	0.2807 (0.3411)	−0.0474 (0.8133)	0.0276 (0.8743)	0.0150 (0.9286)	−0.0604 (0.7630)
ln EX	−0.1533 (0.2076)	−0.1675 (0.0004)	−0.1359 (0.0052)	−0.1373 (0.0034)	−0.1494 (0.0016)
$\ln U$	0.0768 (0.0015)	−0.0264 (0.1279)	−0.0028 (0.8703)	−0.0094 (0.5796)	−0.0124 (0.4663)
ln FD	0.0432 (0.5408)	−0.0184 (0.5232)	−0.0277 (0.3475)	−0.0343 (0.2313)	−0.0126 (0.6611)
R^2	0.2251	0.9527	0.0385	0.9429	0.5758
R^2adj	0.2102	0.9468	0.0201	0.9380	0.5535
$\log L$	−212.0153	458.9933			
DW	0.1296	1.3009	0.0957	0.9156	0.0535

growth, financial development, international trade, and urbanization rate have negative effects on haze, economic growth, and urbanization. The rate has passed a significant level test. Economic growth per 1% increase will make China's haze growth decline by 0.2475%, which is consistent with the characteristics of haze in China.

8.2. Estimation and Analysis of Coefficient of Spatial Data Model of Durbin Panel Results. The spatial fixed effect SDPDM model VIII in Table 6 shows that population, economic growth, technological progress, financial development, international trade, and urbanization rate coefficient are negative; that is, the growth of haze has a negative effect. Under the conditions of other factors, the growth of economic growth is 1%, which can lead to the haze drop in China as low as 0.2185%; the urbanization rate increased by 1%, resulting in the haze reduction of 0.1014% in China; the upgrading of the industrial structure in adjacent areas could reduce the spatial spillover effect of 0.3511% of the fog and haze; and the effect of energy price on the fog haze in adjacent areas was verified by a significant test, resulting in 0.6211% space spillover effect, and the haze had a significant spatial overflow effect. Therefore, combining the influence of the haze to the elastic coefficient, we can see that the haze problem caused by the industrial structure in our country needs to be solved, and the spatial mechanism of haze influence factors should be considered.

8.3. Spillover Effect and Analysis of Spatial Lag Panel Data Model and Spatial Durbin Panel Data Model Results. The regression results of Table 6 also show that ρ (0.7386) of the spatial lag effect SEPDM model IV and the value of ρ (0.6670) of the fixed effect SDPDM model VIII have passed the significant level test. It can be seen that the haze growth of the provincial region will all lead to the neighboring provinces in the case of considering and without considering the adjacent lag effect of the explanatory variable space. Fog and haze change. Therefore, it can be proved that when analyzing regional haze growth, the traditional panel data model without considering spatial effects is biased. At the same time, the spatial lag factor of the industrial structure is significantly negative, which indicates that there is a significant spatial spillover effect in the industrial structure of the province and the 0.5% significant test, which shows the effect of the inter-regional industrial transfer on the haze. Energy prices have significantly reduced the growth of haze in neighboring provinces. It can be concluded that there are obvious spatial spillovers in the haze-influencing factors and haze growth in the neighboring provinces. It is proved that there is an interaction between the explanatory variables in the provincial haze model and interaction between the explanatory variables. In the process of haze growth in the provincial region of China, the different haze influence factors in one province can lead to the rise or decline of fog and haze growth in the neighboring provinces. The influence factors in the province and the influence factors in the neighboring provinces have little difference, which drives the change of the haze in the province of China, and this space spillover effect is in the low carbon region of China. Economic transformation is of great significance, so we should strengthen the regional linkage governance of haze in the time and space.

China's economic development is in the period of rapid economic development. China's economic growth generally plays a higher role in haze control. The promotion of technological progress on haze control should attract the attention of the government and relevant departments. Energy price has no significant effect on haze control. To improve the effect of energy price on haze control, we need to consider the applicable environment of policy. We can achieve the goal of haze management, accelerate trade transformation, and combine other factors to achieve haze management combining the factors of the industrial structure upgrade and low-carbon international trade. At the same time, we should realize that the effect of haze factors on haze is different. We should formulate corresponding regional targets and measures to reduce haze and achieve the haze control of the whole national according to the actual development situation of each province and the different relationship between haze and different factors.

Table 6: Spatial econometric model estimation results of provincial carbon emissions.

Variables	Spatial lag panel model				Space Durbin panel mode			
	No fixed effects I	Spatial fixed effects II	Time period fixed effects III	Spatial and time period fixed effects IV	No fixed effects V	Spatial fixed effects VI	Time period fixed effects VII	Spatial and time period fixed effects VIII
C	3.0373 (0.0219)				1.9219 (0.2208)			
$\ln P$	−0.2257 (0.0002)	−0.0705 (0.416)	−0.2753 (0.0002)	−0.0613 (0.4609)	0.0547 (0.4333)	−0.0122 (0.9158)	−0.0105 (0.8864)	−0.2411 (0.0284)
$\ln A$	0.3199 (0.0000)	0.0821 (0.0007)	0.3549 (0.0001)	−0.2475 (0.0000)	−0.1502 (0.0742)	0.0261 (0.5498)	−0.0446 (0.6249)	−0.2185 (0.0001)
$\ln T$	−0.0393 (0.2935)	−0.0237 (0.0633)	−0.0021 (0.9581)	0.0056 (0.7020)	0.0226 (0.5142)	−0.0050 (0.7664)	0.0333 (0.3516)	−0.0004 (0.9795)
$\ln S$	−0.3024 (0.0017)	0.0252 (0.6158)	−0.2485 (0.0034)	0.1574 (0.0043)	0.0080 (0.9327)	0.0651 (0.2374)	0.0511 (0.6051)	0.0509 (0.3853)
$\ln F$	−0.0391 (0.4693)	−0.0083 (0.6192)	−0.0166 (0.7806)	−0.0259 (0.1396)	−0.0056 (0.9082)	−0.0060 (0.7332)	0.0192 (0.7098)	−0.0311 (0.0656)
$\ln E$	0.1600 (0.5123)	0.0092 (0.8877)	0.5818 (0.3458)	0.0810 (0.5897)	0.3388 (0.3057)	0.2894 (0.0427)	1.0324 (0.0506)	0.1534 (0.2933)
$\ln \mathrm{EX}$	0.1140 (0.0000)	0.0039 (0.7396)	0.0807 (0.0037)	−0.0251 (0.0534)	0.0977 (0.0000)	−0.0002 (0.9903)	0.0607 (0.0159)	−0.0149 (0.2521)
$\ln U$	−0.2804 (0.0057)	−0.0183 (0.6097)	−0.3214 (0.0027)	−0.0729 (0.0399)	−0.0906 (0.3493)	−0.0292 (0.4252)	−0.1258 (0.2033)	−0.1014 (0.0034)
$\ln \mathrm{FD}$	−0.1803 (0.0000)	−0.0062 (0.7807)	−0.2107 (0.0021)	0.0025 (0.9088)	0.0156 (0.7936)	0.0084 (0.7135)	−0.0280 (0.6541)	0.0202 (0.3369)
$W \ln P$					−0.2484 (0.0267)	−0.2705 (0.2204)	−0.4874 (0.0003)	−0.2918 (0.1773)
$W \ln A$					0.2771 (0.0222)	0.1380 (0.0077)	0.3835 (0.0076)	−0.0398 (0.4662)
$W \ln T$					−0.0743 (0.2081)	−0.0512 (0.0228)	0.0447 (0.5630)	0.0002 (0.9946)
$W \ln S$					−0.1689 (0.3149)	−0.2445 (0.0174)	−0.1633 (0.3760)	−0.3511 (0.0041)
$W \ln F$					0.0313 (0.7124)	0.0200 (0.4797)	0.0155 (0.8795)	0.0150 (0.6232)
$W \ln E$					−0.2346 (0.4018)	−0.3034 (0.0520)	0.0710 (0.8262)	−0.6211 (0.0037)
$W \ln \mathrm{EX}$					0.0425 (0.2265)	0.0295 (0.1239)	−0.1251 (0.0096)	0.0087 (0.7194)
$W \ln U$					0.0281 (0.8831)	−0.0085 (0.9217)	−0.2658 (0.2190)	0.0130 (0.8768)
$W \ln \mathrm{FD}$					0.2015 (0.1001)	−0.0553 (0.2788)	0.1667 (0.2294)	−0.0840 (0.0988)
P	0.3730 (0.0000)	0.8000 (0.0000)	0.3540 (0.0000)	0.7386 (0.0000)	0.7430 (0.0000)	0.7870 (0.0000)	0.7010 (0.0000)	0.6670 (0.0000)
$\log L$	−134.3397	513.1850	−207.8311	559.2720	−80.4815	522.7228	−736.1596	570.5510
R^2	0.4579	0.9694	0.4673	0.9728	0.6219	0.9703	0.6237	0.9736

9. Discussion

It is highlighted that haze was influenced by different influencing factors which need to be systematically monitored and managed to control the provincial area. In this research, the spatial agglomeration and path dependence of haze are analyzed considering the spatial effect. The results of the spatial panel data econometric model are of great significance to future regional haze control planning policies. This paper introduces the basic theory of spatial dependence and spatial heterogeneity of spatial effects in geoeconomics and further introduces the methods of testing and estimating spatial dependence and testing methods of global and local spatial autocorrelation. Spatial correlation tests were conducted on haze data from 30 provinces in China during 2000~2015.

The value Moran's I of annual and 16-year average of China between 2000 and 2015 are significantly positive. It indicate that there is a significant positive autocorrelation spatial correlation model in China's regional haze, and this degree of association is changing year by year, so the policy of haze related should be considered. In order to control haze, we should implement different strategic measures according to the different characteristics of the region and, at the same time, realize regional linkage mechanism to get out of the haze prevention dilemma.

The Moran's I scatter plot further proves that there is a significant spatial dependence in the haze level in the province of China, which is positive correlation. Most provinces have similar cluster characteristics with adjacent regions, and the provinces with higher fog and haze level are surrounded by high fog and haze levels. The spatial and temporal transition analysis of the Moran's I scatter point shows that the haze level in China has a serious path dependence in spatial geographic distribution, which has obvious characteristics of agglomeration and low mobility, and it is quite difficult for each province to get rid of its own cluster. By the LISA test, the local spatial autocorrelation test results show that the haze in China has formed the spatial agglomeration area of haze in the regional spatial distribution: the high fog and haze area in Heilongjiang Province and Jilin Province is in the center and the surrounding area with Yunnan, Guizhou, Hunan, Jiangxi, Fujian, and the haze area. Guangxi and Guangdong with Zhejiang as the center together with the surrounding areas constitute low haze level areas of the space cluster, according to China's haze space-time performance.

10. Conclusion

Until now, there is no systematic study on the spatial and temporal evolution characteristics and path dependence of haze combined with spatial effects. The problem of haze joint prevention and control is analyzed considering different regional influencing factors. Considering the spatial agglomeration characteristics of haze, according to the spatial and temporal evolution characteristics of haze, haze control is achieved by combining the characteristics of regional population, economic development, technological progress, industrial structure, financial development, energy prices, international trade, urbanization rate, and fiscal decentralization. Accelerating regional energy conservation and emission reduction, organic integration of economic development and technological progress, active regulation and control of green financial policies, and the process of urbanization must be taken into account in regional and surrounding regional environmental governance as the premise, and the fiscal policy is inclined to green sustainable development.

According to the conclusion of spatial correlation and spatial evolution of the spatial pattern of fog haze in China's provinces, considering the mechanism of the spatial effect, the related theories such as spatial lag economic model, spatial error economic model, and panel data spatial econometric model are introduced, from population, economic development, technological progress, industrial structure, financial development, energy prices, international trade, urbanization rate, and fiscal decentralization are selected as explanatory variables to analyze the impact factors of haze. It can be seen that different factors have different mechanisms of carbon emissions in different provinces and regions, and there are great differences among regions. According to the regional characteristics, different regions actively carry out energy saving and haze reduction and combine the spatial spillover effect of inter-regional haze control to achieve the overall haze cosssntrol.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

[1] The Lancet, "(Barely) living in smog: China and air pollution," *The Lancet*, vol. 383, no. 9920, p. 845, 2014.

[2] H. Liu, C. Fang, X. Zhang, Z. Wang, C. Bao, and F. Li, "The effect of natural and anthropogenic factors on haze pollution in Chinese cities: a spatial econometrics approach," *Journal of Cleaner Production*, vol. 165, pp. 323–333, 2017.

[3] N. L. Seaman, "Future directions of meteorology related to air-quality research," *Environment International*, vol. 29, no. 2-3, pp. 245–252, 2003.

[4] H. L. Wang, L. P. Qiao, S. R. Lou et al., "Chemical composition of PM2.5 and meteorological impact among three years in

urban Shanghai, China," *Journal of Cleaner Production*, vol. 112, pp. 1302–1311, 2016.

[5] C. K. Li, J.-H. Luo, and N. S. Soderstrom, "Market response to expected regulatory costs related to haze," *Journal of Accounting and Public Policy*, vol. 36, no. 3, pp. 201–219, 2017.

[6] A. R. Evanoski-Cole, K. A. Gebhart, B. C. Sive et al., "Composition and sources of winter haze in the Bakken oil and gas extraction region," *Atmospheric Environment*, vol. 156, pp. 77–87, 2017.

[7] L. Nurhidayah, "Legislation, regulations, and policies in Indonesia relevant to addressing land/forest fires and transboundary haze pollution: a critical evaluation," *Asia Pacific Journal of Environmental Law*, vol. 16, p. 215, 2013.

[8] J. S. H. Lee, Z. Jaafar, A. K. J. Tan et al., "Toward clearer skies: challenges in regulating transboundary haze in Southeast Asia," *Environmental Science & Policy*, vol. 55, pp. 87–95, 2016.

[9] H. Liu and X. Zhang, "Research on the construction of the government haze governance performance evaluation index system," *Environmental Protection*, vol. 2, pp. 58–61, 2015.

[10] G. Zheng and L. Yang, "Solutions of fog and haze weather from the perspective of economic development," *Ecological Economy*, vol. 31, no. 9, pp. 34–38, 2015.

[11] Z. Li, G. Huang, D. Li et al., "The cause analysis of beijing haze weather formation from energy consumption structure and prevention and control measures," *Petroleum & Petrochemical Today*, vol. 1, no. 6, pp. 11–16, 2013.

[12] L. Ma and X. Zhang, "The spatial of China's pollution and the impact from economic change and energy structure," *China Industrial Economics*, vol. 4, pp. 19–31, 2014.

[13] G. A. Jutze and C.W Gruber, "Establishment of an intercommunity air pollution control," *Oxford Economic Papers*, vol. 59, no. 4, pp. 726–743, 2007.

[14] D. Maddison, "Modelling sulphur emissions in Europe: a spatial econometric approach," *Journal of the Air Pollution Control Association*, vol. 12, no. 4, pp. 192–194, 1962.

[15] L. Anselin, "Local indicators of spatial association-LISA," *Geographical Analysis*, vol. 27, no. 2, pp. 93–115, 1995.

[16] S. J. Rey, "Spatial empirics for economic growth and convergence," *Geographical Analysis*, vol. 33, no. 3, pp. 195–214, 2011.

[17] J. Paelinck and L. Klassen, *Spatial Econometrics*, Saxon House, Farnborough, UK, 1979.

[18] T. Shen, D. Feng, and T. Sun, *Spatial Econometrics*, Peking University, Beijing, China, 2011.

[19] S. Huang, *Study on The Regional Promotion Mechanism of China's Low-Carbon Economy*, Southwestern University of Finance and Economics, Chendu, China, 2012.

[20] IPCC 2006, *IPCC Guidelines for National Greenhouse Gas Inventories*, IGES, Kanagawa, Japan, 2006.

[21] H. L. Wang, L. P. Qiao, S. R. Lou et al., *A Spatial Econometric Study of Regional R&D, Knowledge Spillovers and Innovation in China*, People's Publishing House, Beijing, China, 2007.

[22] Z. Wu and S. Jia, "The influencing factor analysis and trend forecasting of Beijing energy carbon emission based on STIRPAT and GM(1,1) model's," *Chinese Journal of Management Science*, vol. 20, no. 11, pp. 803–809, 2014.

[23] P. R. Ehrlich and A. H. Ehrlich, *Population, Resources, Environment: Issues in Human Ecology*, Freeman, San Francisco, CA, USA, 1970.

[24] R. York, E. A. Rosa, and T. Dietz, "A rift in modernity? Assessing the anthropogenic sources of global climate change with the STIRPAT model," *International Journal of Sociology and Social Policy*, vol. 23, no. 10, pp. 31–51, 2003.

[25] R. York, E. A. Rosa, and T. Dietz, "STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts," *Ecological Economics*, vol. 46, no. 3, pp. 351–365, 2003.

[26] Y. Wu, "Spatial panel econometric analysis of tourism economic growth and its spillover effects," *Tourism Tribune*, vol. 29, no. 2, pp. 16–24, 2014.

[27] A. Cliff and J. K. Ord, *Spatial Processes: Models and Applications*, Pion, London, UK, 1981.