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Renewable Energy Green Innovation, Fossil Energy Consumption and Air Pollution--- Spatial Empirical analysis based on China

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Abstract: The rapid development of China's economy has led to a rapid increase in energy production and use. Among them, the excessive consumption of coal in fossil energy consumption is the leading cause of air pollution in China. This paper incorporates renewable energy innovation, fossil energy consumption and air pollution into a unified analysis framework, and uses spatial measurement models to investigate the spatial effects of renewable energy green innovation and fossil energy consumption on air pollution in China, and decomposes the total impact into direct and indirect effects. influences. The empirical results show that China's air pollution, renewable energy green innovation and fossil energy consumption are extremely uneven in geographical space, generally showing the characteristics of high in the east and low in the west, and showing a strong spatial aggregation phenomenon. Fossil energy consumption will lead to increased air pollution, and the replacement of fossil fuels with clean and renewable energy is an important means of controlling pollution emissions. The direct and indirect effects of renewable energy green innovation on air pollution are significantly negative, indicating that renewable energy green innovation not only suppresses local air pollution, but also suppresses air pollution in neighboring areas. The consumption of fossil energy will significantly increase the local air pollution, and the impact on the SO₂ and Dust&Smoke pollution in the adjacent area is not very obvious. It is recommended to strengthen investment in renewable energy green innovation, reduce the proportion of traditional fossil energy consumption, and pay attention to the spatial connection and spillover of renewable energy green innovation.

Key words: renewable energy; energy consumption; air pollution; spatial dubin model ; spatial analysis

1. introduction

In the 21st century, with the rapid economic development, China's energy consumption has increased rapidly year by year. Because of the large increase in energy consumption, the problem of air pollution has become more serious. According to a report by the International Energy Agency (2016), up to 99% of SO₂ and NO_x emissions and up to 85% of PM_{2.5} emissions are attributed to energy production and use[1], it is as shown in Fig1.

SO₂, NO_x, Dust&Smoke in China's air pollutants mainly come from the burning of fossil fuels, because coal is the most important energy source in China's fossil energy consumption.

The important reason for China's air pollution is the burning of coal as a fuel [2]. Because coal combustion will produce a lot of SO₂, NO_x, Dust & Smoke, which will increase the concentration of air pollutants, and studies have shown that the increase in the concentration of air pollutants will significantly reduce the health of residents [3]. Both short-term and long-term income elasticity show that sulfur oxide emissions have a significant positive impact on health expenditure [4]. And previous studies have found that air pollution has a strong spatial spillover effect, and air pollution in geographically close cities or regions has strong mutual effects [5][6][7][8].

Therefore, to reduce air pollution, it is necessary to reduce the proportion of coal consumption in fossil energy consumption, so as to reduce the SO₂, NO_x, Dust & Smoke emissions during energy consumption. At this stage, to reduce the proportion of coal consumption, replacing fossil fuel combustion with clean renewable energy is generally considered to be the best solution [9]. Therefore, the proportion of renewable energy consumption must be increased to replace part of the fossil energy consumption. But the problem is that the price, stability, and technological maturity of renewable energy at this stage are worse than fossil energy. Obviously, this has hindered the consumption of renewable energy. Therefore, to increase the consumption of renewable energy on the consumer side To account for the proportion, we must increase renewable energy innovation research and development, so that the price, stability, technological maturity of renewable energy and fossil energy are comparable. Only in this way will the proportion of renewable energy consumption be increased, and the proportion of coal consumption will be reduced accordingly.

However, existing research focuses on the impact of energy consumption and economic and social factors on air pollutant emissions. Few studies have focused on the impact of renewable energy green innovation and fossil energy consumption on air pollution. It also ignores the spatial effects of air pollution, renewable energy green innovation, and fossil energy consumption.

In order to fill this gap, this paper fully considers the spatial effect and uses a spatial econometric model to investigate the spatiotemporal evolution characteristics, spatial correlations, and spatial aggregation effects of air pollution in my country. And pay attention to the impact of renewable energy green innovation, fossil energy consumption on air pollution emissions.

The rest of the study is organized as follows: Section 2 is a literature review of relevant studies and the contributions made by this study. Section 3 introduces the variables, models, data sources and methods of this study. Section 4 is the results and discussion of space exploration analysis. Section 5 is the empirical results of the space panel model. Conclusions and policy recommendations are provided in Section 6.

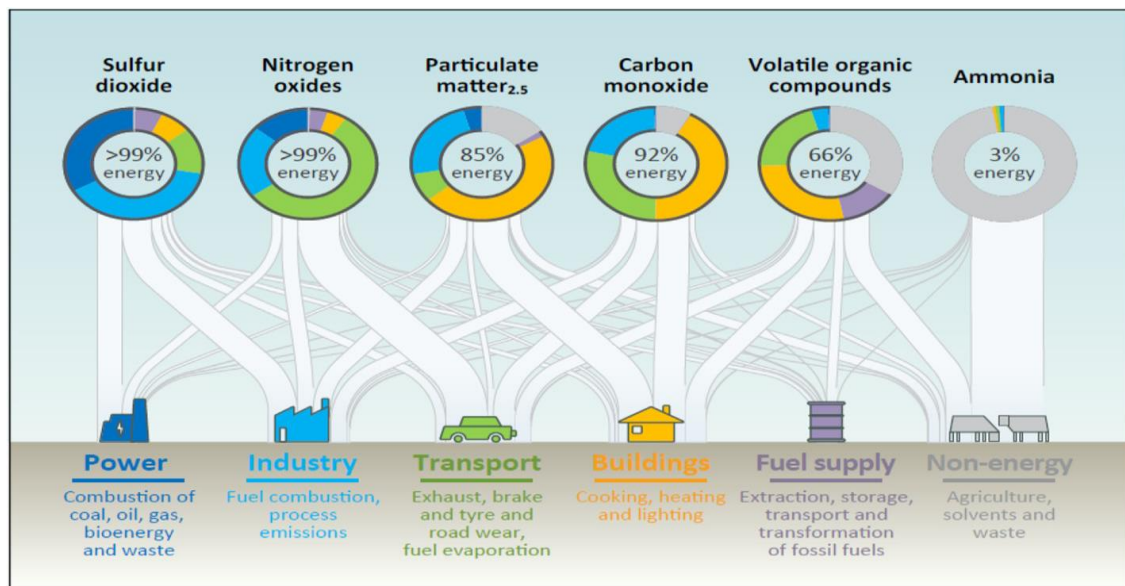


Fig. 1. Selected primary air pollutants and their sources, 2015. Source: International Energy Agency (2016): 26.

2. Literature review

In recent years, with the rapid increase of energy consumption in China, the problem of air pollution caused by energy consumption has also intensified, which has led many scholars to pay attention to the problem of air pollution. Brunt, H et al (2016) found that air pollution, poverty and health issues are inseparable. If the local air pollution problems and solutions are considered in the context of broader health determinants, greater health benefits can be achieved (Reduce health risks and inequality) [10]. Dong K. et al (2019) found that respirable suspended particles (PM₁₀) are a typical component of particulate matter, which can lead to increased morbidity and mortality of respiratory and cardiovascular diseases[11]. The findings of Signoretta et al (2019) show that the perception of major air pollution problems and worse mental wellbeing go hand in hand only in partial and established environmental States[12]. Gu, H et al (2019) nested household registration data of the 2014 China Floating Population Dynamics Survey with urban feature data and pollution data, and found that an increase in air pollution concentration significantly reduced residents' health. Men and urban residents are more sensitive to air pollution and are more adversely affected[13].

In these studies, scholars have paid more attention to the direct factors of air pollution. Wang, X.-C. et al (2019) found that energy production and consumption caused air pollution, with 75% of global greenhouse gas emissions, 66 % Of NO_x emissions and most PM emissions come from the energy sector[14]. Yuan, J. et al (2017) found that due to the large-scale utilization of high-carbon carbide energy, a large amount of critical air pollutants (CAPs) and greenhouse gases (GHG) were emitted, resulting in increasing global climate change and local air pollution problems[15]. Zhang, S. et al (2015) found that the cement

industry is China's second largest energy-consuming industry and a major emitter of carbon dioxide and air pollutants. The cement industry accounts for 7% of China's total energy consumption and 15% of CO₂, 21% of PM, 4% of SO₂, 10% of NO_x[16].

However, few scholars are currently concerned about the indirect factors of air pollution, especially the impact of renewable energy on air pollution. Boudri, J. et al (2002) studied the potential of using renewable energy in China and India and their cost-effectiveness in reducing air pollution in Asia, and found that increasing the use of renewable energy can reduce sulfur dioxide by 17-35% in China Emissions control costs can be reduced by more than two thirds in India[17].Zhu, Y (2019) found that technological innovations in renewable energy are conducive to reducing the concentration of nitrogen oxides (NO_x) and respirable suspended particles (PM₁₀)[18]. Xie, Y. et al (2018) concluded from scenario analysis that renewable energy has been more effective than taxis in reducing carbon dioxide and air pollutant emissions[19].The results of Alvarez et al (2017) confirmed the positive impact of the energy innovation process on air pollution, and pointed out that renewable energy contributes to improving air quality [20].

Although the above studies occasionally involve the temporal and spatial distribution of pollution, few studies have studied the spatial correlation and spatial spillover effects of air pollution, green innovation in renewable energy, and fossil energy consumption. Space models are rarely used to study the impact of renewable energy green innovation and fossil energy consumption on air pollution. Only a limited number of studies have involved this aspect. For example, Xie Q et al (2019) found that PM_{2.5} pollutants have strong spatial overflow characteristics [21].Zhao, D et al (2018) discussed the temporal trends and spatial differences of air pollution in five hot spots in china, as well as the impact of macro-influencing factors on four pollutants, and found that particulate matter exceeded standard in national-wide[22].Zeng, et al (2019) found that provincial-level renewable energy policies have a positive impact on the reduction of SO₂ and PM_{2.5}. A province's energy policy will affect pollutant emissions from neighboring provinces[23]. Li, L et al (2019) found that atmospheric pollution emissions have a significant agglomeration effect. The spatial aggregation pattern of atmospheric pollution emissions is similar to that of fossil energy consumption. The proportion of clean energy consumption and the allocation of energy labor factors have suppressed atmospheric pollution emissions[24].

In recent years, renewable energy technologies represented by solar power generation and photovoltaic power generation have been applied on a large scale. Does renewable energy green innovation really improve air pollution? To what extent has air pollution been improved? What is the relationship between renewable energy green innovation, fossil energy consumption, and air pollution? Very few scholars have done research. Based on the

previous research results, this article finds that there is room for the following: the traditional non-spatial econometric model needs to be expanded into a spatial econometric model for research. Spatial aggregation and spatial correlation effects of renewable energy green innovation, fossil energy consumption, and air pollution, and the effects of the former two on the latter.

Therefore, the contribution of this study will be in the following aspects: First, the use of non-spatial and spatial measurement models to study the impact of renewable energy green innovation and fossil energy consumption on air pollution. Second, fully consider renewable energy green innovation, the spatial correlation of fossil energy consumption and space spillover effects, and quantify their impact on air pollution. Third, use visual methods to show the characteristics of the spatiotemporal evolution of renewable energy green innovation, fossil energy consumption, and air pollution. Fourth, expand the STIRPAT model to quantitatively study the impact of renewable energy green innovation, fossil energy consumption, environmental regulations, industrial structure, population, GDP and other factors on air pollution.

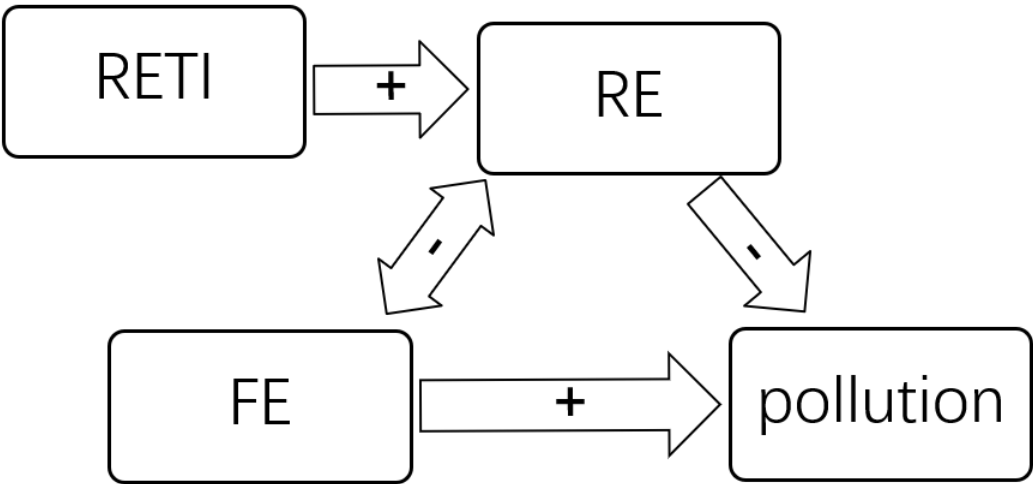


Fig2 the framework of the research

2. methodology

2.1 variables and data

3.1.1 explained variable:

(1) Air pollution: The most representative of air pollution is the amount of air pollutants. In previous studies, the concentration of PM2.5 was generally used as a proxy variable to measure the degree of air pollution, but PM2.5 cannot be used for a comprehensive evaluation on air pollution. Therefore, the main pollutant indicators for measuring air pollution in this paper are SO2, NOX, Dust&Smoke. And considering that each pollutant has

its own limitations, this article specifically reduces the dimensions of these indicators to find a comprehensive pollution amount, so as to make the objective and comprehensive evaluation of air pollution to the greatest extent possible.◦

This paper draws on the method of Liu et al (2015) for index dimensionality reduction. First, the factor analysis method is used to uniformly reduce the three environmental output indicators. After the barlett sphere test, the statistic value is 56.077, the significance probability is 0.000, and the KMO value is 0.748. Therefore, the original hypothesis of irrelevance between indicators is rejected, and the indicator is suitable for factor analysis. At the same time, the corresponding weight of each indicator is calculated by the variance contribution rate of the factor score matrix and the common factor. The weights of the indicators for sulfur dioxide, nitrogen oxides, and smoke (dust) are 24%, 49%, and 27%, respectively. Combined with the weights of the three types of pollution indicators, comprehensive pollution can be calculated[25].The formula is as follows:

$$CP_{it} = \sum_{i=1}^n w_{it} * X_{it}$$

Among them: w_{it} is the weight of each pollutant, X_{it} is the pollutant component.

3.1.2Explanatory variables:

3.1.2.1 Main explanatory variables

(1) Renewable energy green innovation (RETI): In this paper, the renewable energy patent is selected as a proxy variable for green innovation. Refer to Zhu, Y et al (2019) to select the IPC code shown in the following table[26].Patents have an impact on the corresponding technology from the date of application, so previous studies mostly counted the number of patents based on the patent application date. This article refers to the practice of Wang ban-ban et al (2019) and uses the application date of each patent Count the number of renewable green patents [27].

Table1 renewable energy IPC code

Energy	IPC codes
Wind	F03D
Solar	F03G6; F24J2; F26B3/28; H01L27/142; H01L31/042-058
Marine	E02B9/08; F03B13/10-26; F03G7/05
Biomass	C10L5/42-44; F02B43/08
Storage	H01M10/06-18; H01M10/24-32; H01M10/34; H01M10/36-40

- Hypothesis1-1 Renewable energy green innovation will reduce comprehensive air pollutant emissions.
- Hypothesis1-2 Renewable energy green innovation will reduce SO2 emissions.
- Hypothesis1-3 Renewable energy green innovation will reduce NOx emissions.
- Hypothesis1-4 Renewable energy green innovation will reduce Dust&Smoke emissions.

(2) Fossil Energy Consumption (FEC): China’s rapid development has led to a large amount of energy consumption, especially a significant increase in the consumption of fossil fuels. The main cause of pollution is the consumption of fossil fuels, while coal consumption accounts for more than 50% of China’s fossil energy consumption [28], Therefore, coal consumption and pollutant emissions are closely related, so this paper selects coal consumption to represent fossil energy consumption.

Hypothesis2-1 Fossil energy consumption (FEC) will increase integrated air pollutant emissions.

Hypothesis2-2 Fossil energy consumption (FEC) will increase SO2 emissions.

Hypothesis2-3 Fossil energy consumption (FEC) will increase NOx emissions.

Hypothesis2-4 Fossil energy consumption (FEC) will increase Dust&Smoke emissions.

3.1.2.2 Control variable

(1) Environmental regulation (ER) , There are many ways to measure the intensity of environmental regulation. Considering China's environmental pollution control policy, this article refers to the practice of Zhu Y et al (2019), and selects the number of environmental punishment cases as a proxy variable for the intensity of environmental regulation [29]. To a certain extent, environmental regulations will suppress pollutant emissions from micro-main bodies.

(2) Industrial Structure (IS): The proportion of the secondary industry is selected as the proxy variable. Hao et al (2016) empirical research shows that the correlation coefficient of the secondary industry's discharge of pollutants is positive[30]. Therefore, this article assumes that there is a positive correlation between industrial structure and air pollution.

(3) GDP: Because there is a gap between the nominal GDP and the actual GDP of each province and municipality, this article uses the GDP of each province and municipality as the benchmark in 2000 to calculate the GDP deflator of each province and municipality, thus calculating the constant price GDP of each province and municipality .

(4) Population (POP). There is a direct link between population size and pollutant emissions. The increase in population will significantly increase energy consumption and pollutant emissions.

3.1.3 Variable descriptive statistics

Table 2 Description of variables in models

Variables	Explanation	units
CP_{it}	Comprehensive pollution of i province in t year	104 ton
$SO2_{it}$	SO2 emission of i province in t year	104 ton
NOX_{it}	NOx emission of i province in t year	104 ton
DS_{it}	Dust and smoke emission of i province in t year	104 ton
$RETI_{it}$	Number of renewable energy patents	Item
FEC_{it}	Fossil energy consumption	104 ton
IS_{it}	The proportion of secondary industry	%
ER_{it}	environmental regulation	%
GDP_{it}	province gross domestic product	108yuan

POP_{it}

Province people

104 people

3.1.4 data resources

Air pollutant emission data and environmental regulation data come from China Environment Yearbook, energy consumption data come from China Energy Statistical Yearbook, GDP and population data come from China Statistical Yearbook, and patent data come from Smart Bud patent database. (<https://www.zhihuiya.com/>).

2.2 spatial autocorrelation test

2.2.1 global correlation index

Here, the global spatial correlation is calculated according to the global Moran index:

$$\text{Moran's } I^{\text{global}} = \frac{\sum_{i=1}^n \sum_{j \neq i}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sigma^2 \sum_{i=1}^n \sum_{j \neq i}^n w_{ij}} = \frac{\sum_{i=1}^n \sum_{j \neq i}^n w_{ij} (x_i - \frac{1}{n} \sum_{i=1}^n x_i)(x_j - \frac{1}{n} \sum_{i=1}^n x_i)}{\frac{1}{n} \sum_{i=1}^n (x_i - \frac{1}{n} \sum_{i=1}^n x_i)^2 \sum_{i=1}^n \sum_{j \neq i}^n w_{ij}} \quad (1)$$

Among them: x_i 、 x_j denote spatial regional units i and j , respectively, and $i \neq j$. w_{ij} represents the spatial weight matrix; \bar{x} represents the average of provinces and municipalities. σ^2 means variance; $(x_i - \bar{x})(x_j - \bar{x})$ means the similarity of spatial units i and j ; n means quantity.

2.2.2 local correlation index

However, the global correlation index cannot measure the local correlation, so the local Moran index needs to be quoted:

$$\text{Moran's } I_i^{\text{local}} = \frac{n(x_i - \bar{x}) \sum_{j=1}^n w_{ij} (x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (2)$$

(1)H-H: area units with high observations are surrounded by high-value areas.

(2)H-L: area units with high observations are surrounded by low-value areas

(3)L-L: area units with low observations are surrounded by low-value areas

(4)L-H: area units with low observations are surrounded by high-value areas

Whether it is global spatial autocorrelation and local spatial autocorrelation, the establishment of spatial weight matrix is very important. In this paper, the spatial adjacency weight matrix is selected.

The spatial adjacency weight matrix is a spatial weight matrix that reflects the spatial adjacency relationship. It can be set as that there is a significant mutual influence relationship between the areas that are adjacent to each other, and the interaction between the areas that are not adjacent is not significant. The spatial adjacency weight matrix can reflect the spatial role relationship of the development indicators between provinces and municipalities.

Therefore, the spatial adjacency weight matrix of provinces and municipalities is introduced to make the spatial relationship of development indicators concrete.

$$W_{ij}^A = \begin{cases} 1, & \text{if province } i \text{ and } j \text{ is adjacent} \\ 0, & \text{if province } i \text{ and } j \text{ is not adjacent} \end{cases}$$

2.3 spatial econometric model

Based on the above regression model, we set a general provincial pollutant emission regression model:

The IPAT model is used to explore the complex social dynamics mechanisms generated by environmental problems. The original IPAT model was proposed by the famous American demographer Ehrlich & Holdren in 1971. The model believes that environmental pressure is the product of population, affluence, and technology[31]. When Dietz et al[32][33][34] are estimating the environmental impact of population, wealth and technology, the IPAT model is expressed in a random form, and a stochastic impacts by regression on population, affluence and technology (STIRPAT model) is proposed. The specific expression of the STIRPAT model is.:

$$I_{it} = aP_{it}^b A_{it}^c T_{it}^d e_{it} \quad (3)$$

Where a is a constant term, b , c , and d are exponential terms of P , A , and T , respectively, and e is an error term.

Take the logarithm of the left and right sides of the equation:

$$\ln I_{it} = \ln a + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \ln e_{it} \quad (4)$$

Applied to this article, you can get the following formula:

$$\ln Y_{it} = \lambda_0 + \lambda_1 \ln RETI_{it} + \lambda_2 \ln POP_{it} + \lambda_3 \ln GDP_{it} + e_{it} \quad (5)$$

However, the general regression model does not take into account the spatial influence between variables. The spatial economic model incorporates the spatial influence on the basis of the ordinary regression model[35]. The spatial lag model (SLM) can be expressed as:

$$y = \rho W y + X \beta + \varepsilon \quad (6)$$

Where y is the vector of the dependent variable; X represents a matrix of explanatory variables; W is the spatial weight matrix; $W y$ is the vector of the spatial lag dependent variable; ρ is the spatial regression coefficient, reflecting the spatial correlation of the dependent variable; β is a parameter vector, reflecting the influence of explanatory variables on the dependent variable; ε is a vector of disturbance terms.

By distinguishing the spatial correlation error ε and the spatial independent error μ , the spatial error model (SEM) can be expressed as [36]:

$$\begin{cases} y = X \beta + \varepsilon \\ \varepsilon = \lambda W \varepsilon + \mu \end{cases} \quad (7)$$

Where λ is the spatial autocorrelation coefficient on the error term, which reflects the influence of the residual in the nearby area on the residual; μ is the interference term of a vector. The values of other variables and parameters are the same as the SLM formula. In

addition, in order to estimate the spatial spillover effect of pollutants in provinces and municipalities, this study examines the direct and indirect effects of explanatory variables.

Due to the mutual influence of air pollution, innovation factors and energy factors between regions. Therefore, when measuring their impact from a spatial perspective, the spatial measurement model is generally used. In order not to lose the generality, this article uses the spatial dubin model (SDM), which is the spatial lag model (SLM) and the spatial error model (The general form of SEM), the expression is.:

$$y_{it} = \delta \sum_{j=1}^n W_{ij} y_{it} + c + x_{it} \beta + \sum_{j=1}^n W_{ij} x_{it} \theta + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

Among them, y_{it} is the explanatory variable, x_{it} is the explanatory variable, c is the constant term, δ is the spatial autoregressive coefficient, β and θ are the coefficients to be estimated, ε is the residual term. $x_{it} \beta$ is the influence of regional independent variable on dependent variable, $\delta \sum_{j=1}^n W_{ij} y_{it}$ is a space lag item, represents the dependent variable composed of the observation values of the explanatory variables of each spatial unit ($i = 1, \dots, n$) at time t ($t = 1, \dots, T$). ε_{it} is an independent and identically distributed random error term; μ_i and λ_t represent the spatial and temporal effects, respectively. This paper constructs a spatial variable W -dependent variable to characterize the spatial spillover effects of pollutant emissions, renewable energy green innovation, and fossil energy consumption. W is expressed as a spatial weight, which is used to calculate the degree of correlation and mutual influence between various spatial elements.

2.4 Direct and indirect spatial influence

In the spatial econometric model, the independent variables usually have an indirect effect on the dependent variables in the surrounding non-local areas (spatial spillovers). We estimated the direct, indirect, and total spatial effects based on the estimated spatial regression coefficients [37] [38]. Further quantify the spatial spillover effects of renewable energy green innovation, energy consumption and other socio-economic indicators on air pollution. Determine the direct and indirect spatial effects according to the determined spatial correlation coefficient ρ , as shown in the formula below:

$$Y_t = (X_t \beta + WX \theta + \varepsilon + \tau_n \alpha_t)(I - \rho W)^{-1} \quad (9)$$

Where X represents the explanatory variable, τ_n represents the constant vector, α is the parameter of the intercept term.

The matrix of the partial derivative differential equation of the explained variable to the K th independent variable is:

$$\left[\frac{\partial y}{\partial X_{ik}} \dots \frac{\partial y}{\partial X_{Nk}} \right] = \begin{bmatrix} \frac{\partial y_1}{\partial X_{ik}} & \dots & \frac{\partial y_1}{\partial X_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_n}{\partial X_{ik}} & \dots & \frac{\partial y_n}{\partial X_{Nk}} \end{bmatrix} =$$

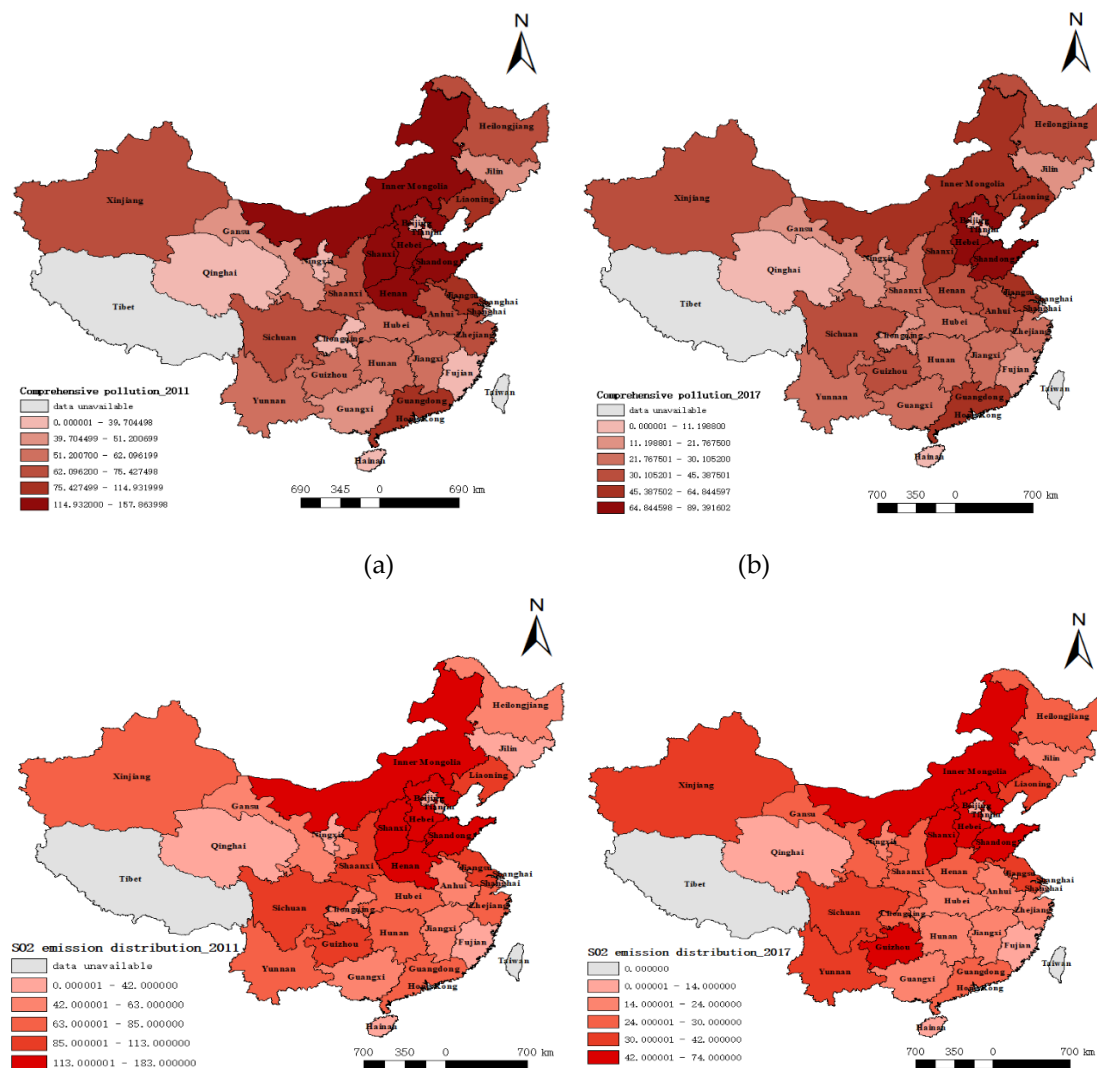
$$(I - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdots & w_{1n}\theta_k \\ w_{21}\theta_k & \beta_k & \cdots & w_{2n}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\theta_k & w_{n2}\theta_k & \cdots & \beta_k \end{bmatrix} \quad (10)$$

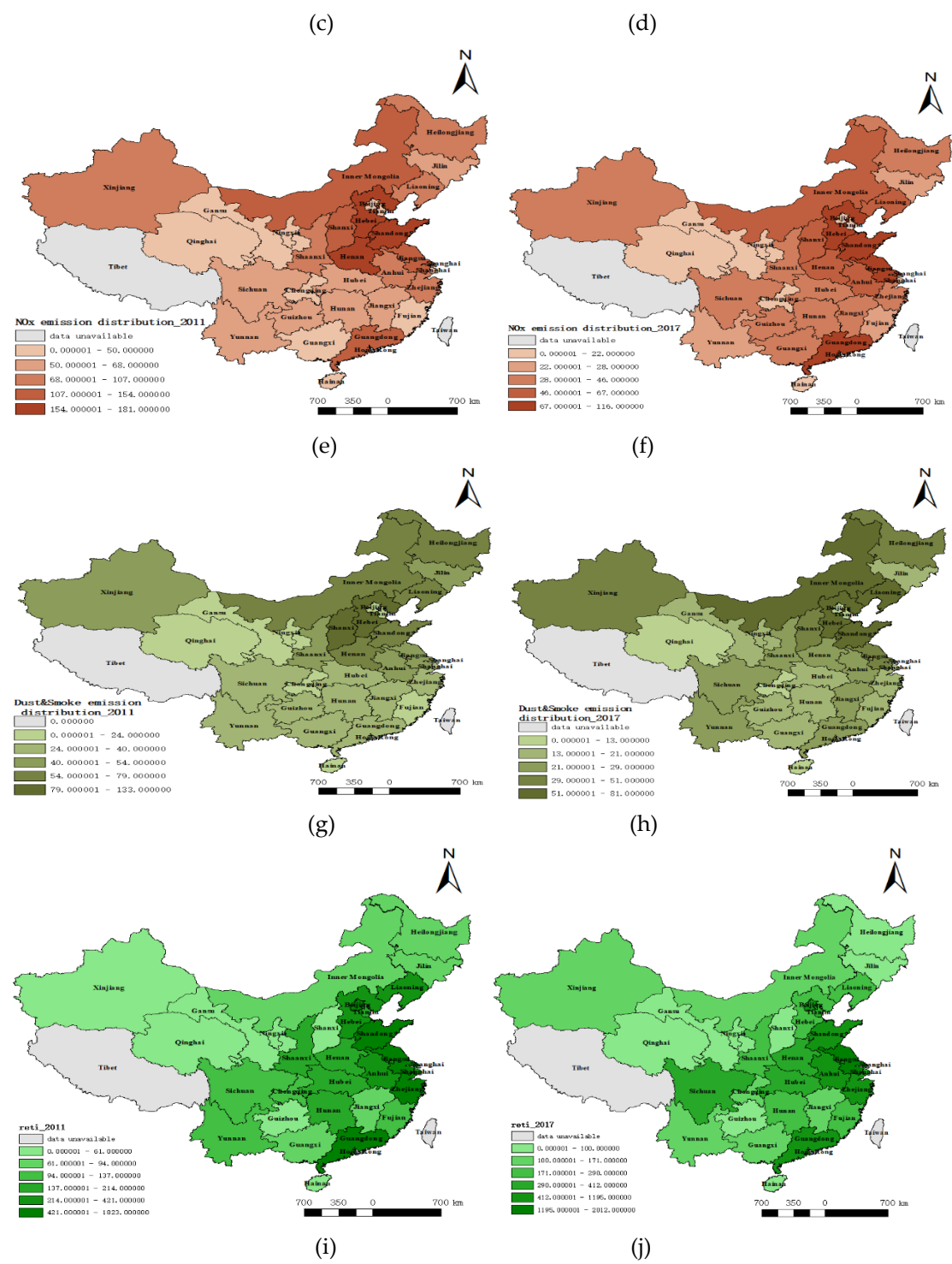
In the above formula (10), the average value of the sum of the values of the matrix elements on the right is defined as the direct effect, and the average value of the sum of all the row and column elements of the non-diagonal elements is the indirect effect, reflecting the influence of other regional independent variables on the regional dependent variable.

3. Exploratory Spatial Analysis Results and discussion

3.1 Spatio-temporal distribution characteristics of pollutant emissions, RETI, fossil energy consumption

In order to visualize the spatial and temporal distribution characteristics, we used Arcgis to display the comprehensive pollution emissions, SO₂, NO_x, Dust&Smoke, renewable energy green innovation, fossil energy consumption and other variables in 26 provinces and 4 municipalities in China in 2011 and 2017 Spatiotemporal distribution characteristics.





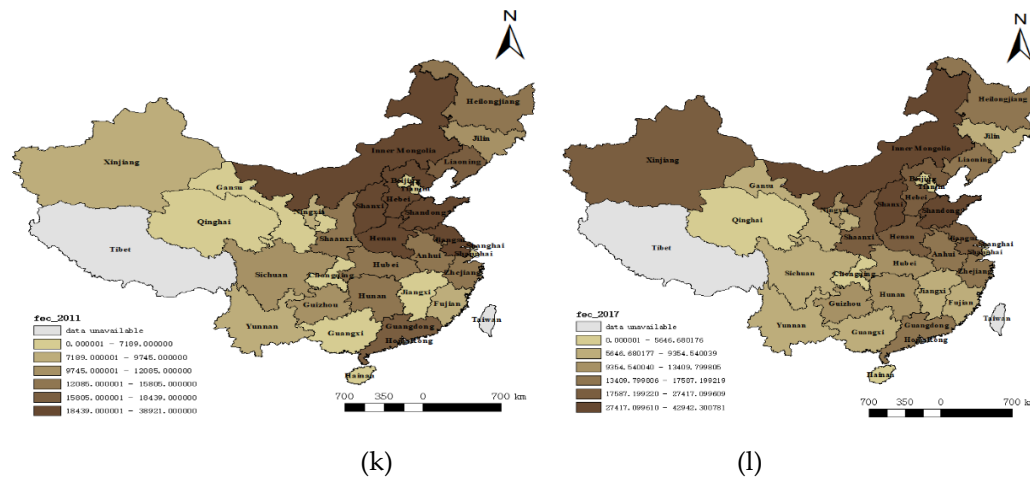


Fig3. Spatial distribution of China's pollution, renewable energy innovations and fossil energy consumption

From Fig 3 (a) and (b), we can find that the overall distribution of air pollutant emissions in China is high in the east and low in the west, and high in the north and low in the south. The peaks of comprehensive pollutant emissions are located in Inner Mongolia, Shanxi, Hebei, Shandong, Liaoning in the northeast, Henan in the middle, and Guangdong in the south. Although the overall comprehensive pollutant discharge in the whole country showed a large decline over time, the peak of comprehensive pollutant discharge in northeastern provinces is still much higher than that in southwestern provinces. This finding is consistent with Zhao et al (2018) [39].

Fig3 (c) and (d), (e) and (f), (g) and (h) show the spatial distribution of SO₂, NO_x, Dust & Smoke respectively, from which we can see that their geographical distribution is akin. Peak emissions are distributed in Shandong, Hebei, Inner Mongolia, Liaoning, Jiangsu, and Guangdong in the southeast.

From Fig 3 (i) and (j), we can find that Liaoning, Beijing, Shandong, Jiangsu, Shanghai, Zhejiang, and Guangdong in the eastern and southern coastal areas of China have advantages in renewable energy green innovation far beyond the central and western provinces. And this advantage has gradually expanded with the evolution of time. Although the central and western provinces have also made great progress in renewable energy technology year by year, it is far less than the southeast coastal area. It is clear that the southeast coastal area has formed a green innovation highland.

From Fig 3 (k) and (l), we can find that the provinces with the most fossil fuel consumption in my country in 2011 are the northeastern provinces Inner Mongolia, Hebei, Shanxi, Shandong, Jiangsu, Henan in the middle, and Guangdong in the south. But with the evolution of time, the central area of fossil fuel combustion gradually moved northward. And it can be found that the peak areas of fossil fuel combustion and the peak areas of pollutant emissions are highly coincident.

3.2 Global spatial correlation analysis

As shown in Table 3, it is the global Moran index of pollutant emissions, renewable energy green innovation, and fossil energy consumption in 26 provinces and 4 municipalities in China. It can be seen from them that they all have a very significant spatial correlation. However, with the evolution of time, the spatial correlation of environmental pollution has gradually weakened, and its significance has also decreased. It may be that the pollution control measures of the provincial government are working. On the one hand, the discharge of pollutants is reduced, and on the other hand, the spatial diffusion of pollutants between provinces is controlled. However, the overall correlation and significance of renewable energy green innovation and fossil energy consumption among provinces are still very high.

Table3 The Moran’s I statistics of China’s pollution ,reti and fossil energy consumption

	2011	2012	2013	2014	2015	2016	2017
cp	0.3386***	0.3285***	0.3153***	0.2501**	0.2719**	0.2425**	0.1980**
	3.337109	3.242872	3.125831	2.34488	2.527662	2.538885	2.119734
so2	0.2397**	0.2288**	0.1641*	0.2152**	0.2253**	0.1460*	0.1242
	2.454958	2.360465	1.63636	2.234856	2.330737	1.666974	1.424221
d&s	0.3589***	0.3351***	0.3131***	0.3863***	0.4104***	0.3136***	0.2230**
	3.645495	3.374994	3.194374	3.860736	4.095359	3.341564	2.354572
Nox	0.3444***	0.2565**	0.3265***	0.3248***	0.3321***	0.2351**	0.2467**
	3.379879	2.390973	3.222591	3.208654	3.277173	2.440664	2.572206
Reti	0.3100***	0.3170***	0.3243***	0.2979***	0.3426***	0.3258***	0.3090***
	3.302344	3.622955	3.61426	3.326746	3.390146	3.578343	3.445492
Fes	0.3655***	0.3496***	0.3679***	0.3564***	0.3486***	0.3277***	0.3278***
	3.598077	3.468931	3.621565	3.533754	3.467786	3.272563	3.288949

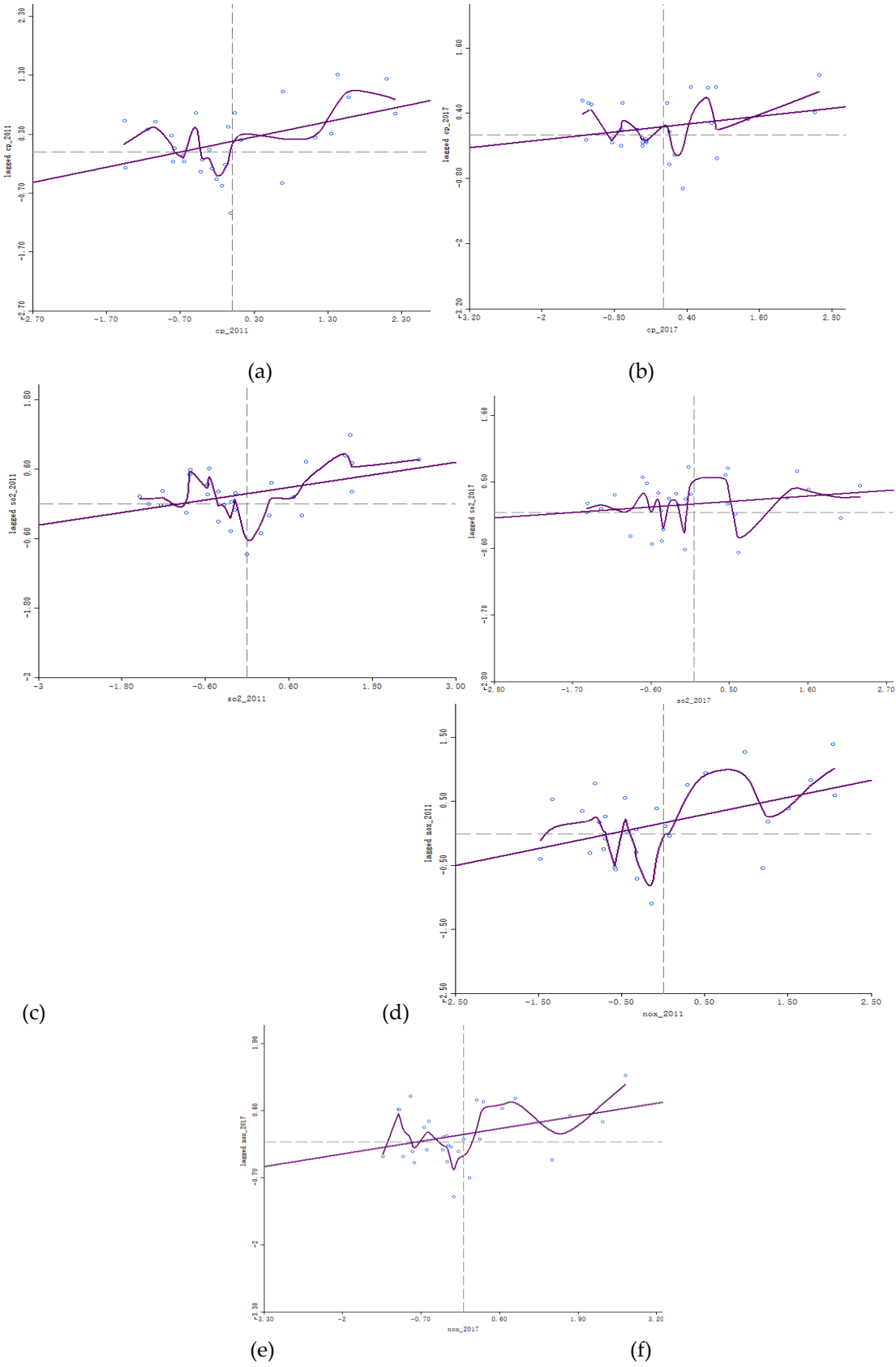
Notes: z-statistics in parenthesis. *, **, and *** indicate that p values is less than 0.1, 0.05, and 0.01 levels, respectively.

3.3 Local spatial correlation analysis (Local Indicators of Spatial Association (LISA) analysis results)

Although we have calculated the global Moran index for air pollution, renewable energy green innovation and fossil energy consumption, it cannot detect the local spatial correlation, so we drew Moran's I scatter plots for 2011 and 2017, as shown in Fig 4 .

According to Fig 4 (a) and (b), in 2011, the total air pollutant emissions in the first and third quadrants were 20 sample points (66.7%), and this number was 19 (63.3%) in 2017. Fig 4(c) and (d) show that in 2011, 14 sample points (46.7%) of SO2 emissions were located in the first and third quadrants, while in 2017 this Fig dropped to 12 sample points (40%). Fig 4 (e) and (f) show that the NOx data is 18 sample points (60%) in 2011, and 19 (63.3%) in 2017.Dust&Smoke's data is 24 in 2011 (80%) and 20 in 2017 (66.7%). As for green innovation in renewable energy, the sample points in the first and third quadrants remained at 22 (73.3%) in 2011 and 2017. The fossil energy consumption data in 2011 was 19 (63.3%), and in 2017 the

data was 21 (70%).



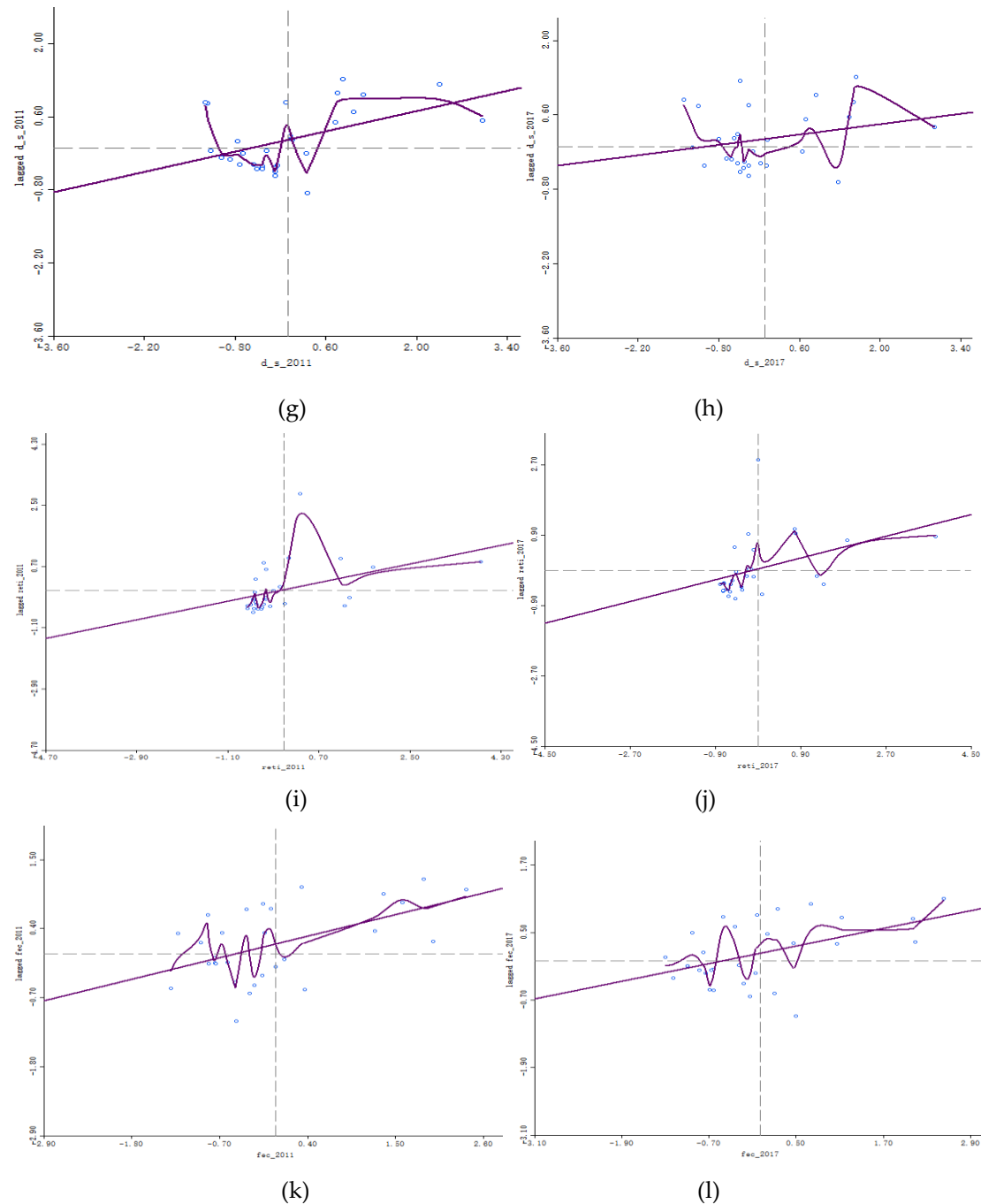
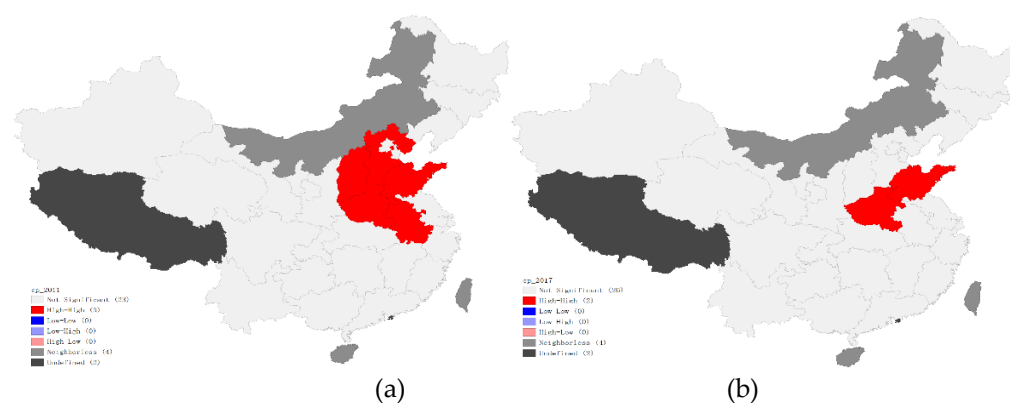


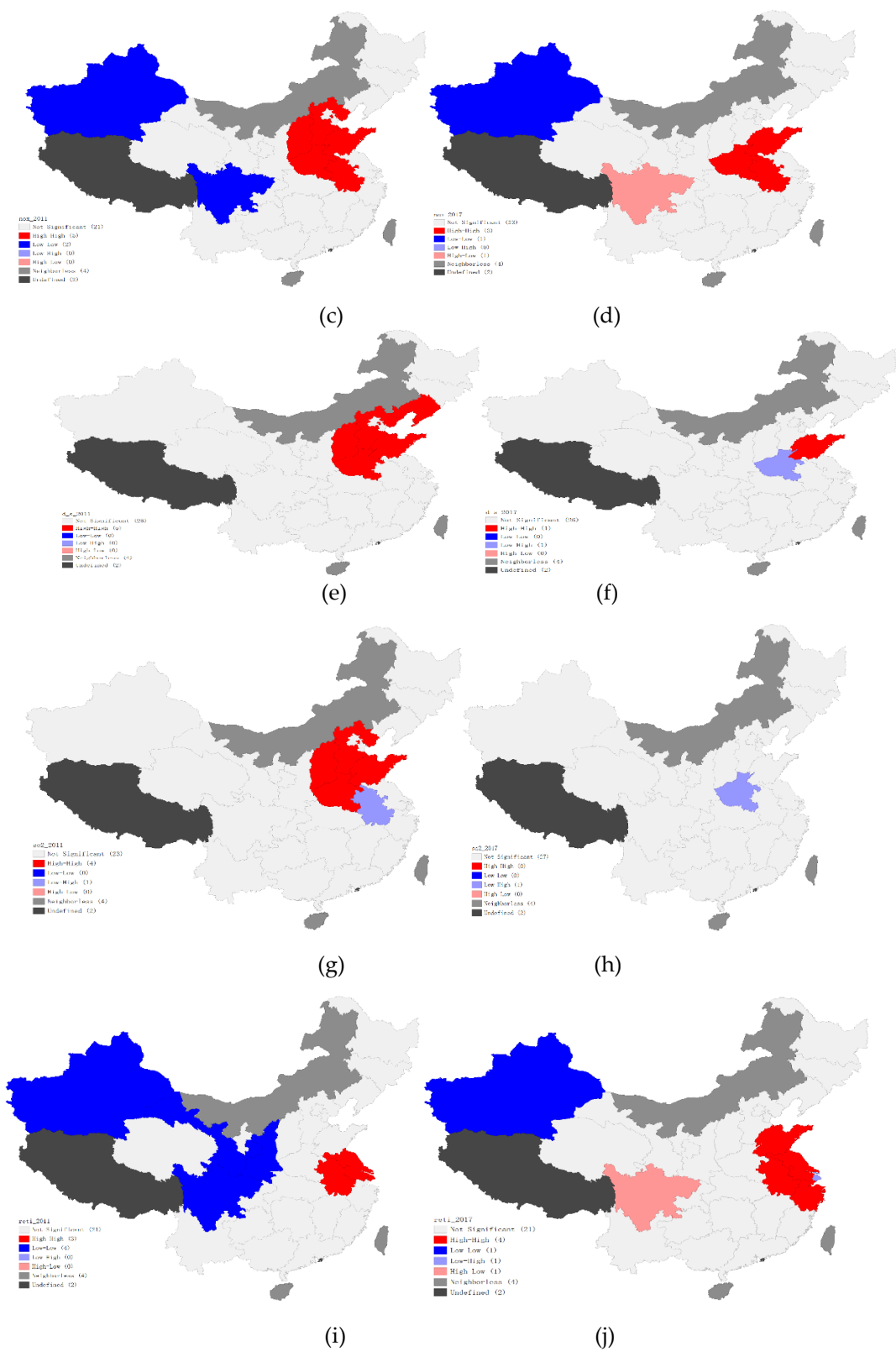
Fig 4. The Moran's I plot of pollution, renewable energy innovation and fossil energy consumption

In addition, the corresponding LISA (Local Indicator of Spatial Autocorrelation) maps of 26 provinces and 4 municipalities in China also provide visual evidence of spatial clustering of air pollutants, green innovation in renewable energy, and fossil energy consumption (see Fig 5). Fig 5 (a) and (b), (c) and (d), (e) and (f), (g) and (h) show that in 2011, Shandong, Hebei, Shanxi and Henan in the northeastern provinces, are in the HH accumulation mode of pollutant emission. However, this kind of pollution aggregation phenomenon has been significantly alleviated by 2017, and the provinces in H-H aggregation mode in 2017 have significantly reduced.

Through Figs 5 (i) and (j), we find that the spatial aggregation of renewable energy green innovation is very significant. Xinjiang, Gansu, Sichuan, and Shaanxi are in L-L clusters, forming a green innovation depression for renewable energy. This innovation depression gradually increased from 2011 to 2017. In contrast, the innovation highland in the H-H model expanded from Jiangsu and Anhui in 2011 to Jiangsu, Anhui, Zhejiang, and Shandong provinces in 2017. However, we can find that renewable energy green innovation has not fully flowed, and several economically developed provinces in the east have invested a lot of money in renewable energy green innovation. However, the innovation achievements have largely served the province's micro-subjects, without fully exerting the spillover effect. Huang et al (2012) found that the national science and technology plan is the main aspect of China's renewable energy green innovation, and the research and development funds for renewable energy green innovation are mainly from the country's three major science and technology plans. Most national projects are funded by universities or research institutions. Undertaken. The motivation and opportunity for the private sector to fully participate in re-technology innovation seem insufficient[40].

From Fig 5 (k) and (l), it can be found that Hebei, Shanxi, Henan, Shandong, and Anhui are in the HH accumulation mode of fossil energy consumption, and this highland of fossil energy consumption gradually moves northward. The center is located in Shanxi, Shandong and Hebei. Fossil energy consumption has a strong spatial correlation, probably because the energy consumption model and the economic development model are closely related. Li Li et al (2019) believe that because a region's economic policies are often easily imitated and tracked by surrounding regions; this demonstration The effect produces a spatial spillover effect. If the economic development model brings better returns and economic benefits, the surrounding areas will learn and imitate⁴¹. And Lin et al (2019) found that with the increase of coal-based energy consumption structure, RETI's effect on suppressing CO₂ emissions weakened [42].





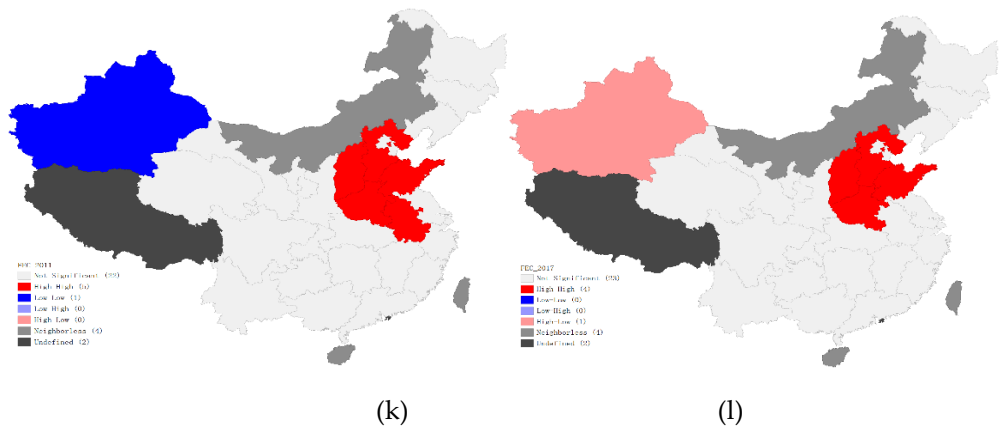


Fig 5 LISA map of comprehensive pollution, renewable energy technology innovation, fossil energy consumption

Based on the above analysis, we can find that China's air pollution, renewable energy green innovation and fossil energy consumption are extremely uneven in geographical space. In general, it shows the characteristics of high in the east and low in the west, and shows a strong spatial aggregation phenomenon. Therefore, spatial factors cannot be ignored in analyzing the role of renewable energy green innovation and fossil energy consumption in air pollution in China. Next, we will use spatial measurement models to analyze.

5. Spatial Panel Estimate Results and discussion

5.1 Analysis of non-spatial panel model results

First, in order to compare with the spatial panel model, we first use the non-spatial panel model to analyze, the results are shown in Table 4. Renewable energy green innovation, environmental regulation and comprehensive air pollution, NOx, SO2, Dust&Smoke show a significant negative correlation, which is significant at the 1% level, thus confirming Hypothesis1-1,1-2,1-3,1-4 This is consistent with the findings of Alvarez et al[43].On the other hand, fossil energy consumption is positively correlated with SO2, Dust & Smoke, and is significant at the 10% level. This finding supports Hypothesis 2-2, 2-4. However, fossil energy consumption has a negative correlation with comprehensive pollutant emissions and NOx emissions, which may be related to the progress of clean coal combustion technology and the increase of coal combustion exhaust emission standards. Mingchen Xu et al (2019) verified through experiments that adopting fuel-rich/lean technology can further reduce NOx emissions [44].But do they still exist spatially? We need to further verify through the spatial Dubin model.

Table 4 Estimation results of non-spatial panel models with spatial fixed effects

	lncp	lnnox	lnso2	lnds
lnreti	-0.1625*** (0.0447)	-0.1056** (0.0415)	-0.2224** (0.0684)	-0.2993*** (0.0726)

Infec	-0.0370 (0.0829)	-0.1030 (0.0769)	0.2434* (0.1270)	0.2355* (0.1347)
lnpop	1.6969 (1.1027)	0.7971 (1.0229)	2.6985 (1.6881)	4.6511** (1.7911)
lnis	1.2855*** (0.1733)	1.2633*** (0.1608)	1.6842*** (0.2653)	0.8334** (0.2815)
lnrer	-0.1247*** (0.0218)	-0.0948*** (0.0203)	-0.1893*** (0.0334)	-0.1253*** (0.0355)
lngdp	2.0521** (0.7251)	0.5965 (0.6726)	4.0354*** (1.1100)	2.8432** (1.1777)
(lngdp)2	-0.1370*** (0.0375)	-0.0630* (0.0348)	-0.2577*** (0.0574)	-0.1601** (0.0609)
_cons	-14.0485 (8.6659)	0.6090 (8.0388)	-31.6856** (13.2663)	-46.1835** (14.0754)
N	210	210	210	210
R-sq	0.745	0.769	0.728	0.334

Note: Standard errors in parentheses. ** p<0.10 ** p<0.05 *** p<0.001

5.2 Spatial Durbin model

We construct a spatial Durbin model and use the spatial adjacency matrix for regression. The results are shown in Table 5, where the Wald and LR test results are both significant at the 1% level, indicating that the spatial Durbin model cannot be replaced by SEM and SLM. Judging from the results of the SDM model, there is a negative correlation between renewable energy green innovation and emissions of comprehensive pollutants, NO_x, and SO₂, which supports Hypothesis 1-1, 1-2, 1-3. The fossil energy consumption is negatively correlated with the emissions of comprehensive pollutants, NO_x, SO₂, Dust&Smoke, especially the negative correlation between SO₂ and Dust&Smoke emissions at 1% level, which confirms our Hypothesis1-1, 1-2, 1-3, 1-4. The coefficients of lnGDP and (lnGDP)2 under different air pollutants are positive and negative, respectively, but they do not pass the significance level test, so they do not support EKC hypothesis. Under 4 explanatory variables (composite pollution, NO_x, SO₂, dust&smoke), the coefficients of ρ are 0.6408 ($t=0.0564$, $p=0.000$), 0.5248 ($t=0.0680$, $p=0.000$), 0.6043 ($t=0.0592$, $p=0.000$), 0.6320 ($t=0.0543$, $p=0.000$), which shows that there is a significant provincial space spillover effect of air pollution in China. In addition, we use partial differential methods to study the direct, indirect and total impact of renewable energy green innovation and fossil energy consumption on air pollution in China (see table 6).

Table 5 results of spatial Durbin model

	lncp	lnnox	lnso2	lnsd
Main				
lnreti	-0.0258 (0.0263)	-0.0439 (0.0288)	-0.0401 (0.0431)	0.0130 (0.0421)
lnfec	0.0313	0.0050	0.4982***	0.4350***

	(0.0569)	(0.0655)	(0.0754)	(0.0750)
lnpop	0.6722***	0.6427***	0.3229**	0.7107***
	(0.1882)	(0.1882)	(0.1587)	(0.2092)
lnis	0.3281**	0.2756*	0.5179**	0.3524*
	(0.1296)	(0.1416)	(0.1696)	(0.1905)
lnrer	-0.0537***	-0.0490***	-0.0673**	-0.0088
	(0.0125)	(0.0138)	(0.0215)	(0.0202)
lngdp	0.9549**	0.2234	0.7882	0.3224
	(0.4424)	(0.4684)	(0.5982)	(0.6165)
(lngdp)2	-0.0471**	-0.0030	-0.0375	-0.0369
	(0.0223)	(0.0238)	(0.0307)	(0.0320)
_cons	-6.4776*	-4.2013	-14.0928**	-2.6661
	(3.4906)	(3.6056)	(4.6683)	(4.7041)
Wx				
lnreti	-0.1090**	-0.0371	-0.0795	-0.3228***
	(0.0480)	(0.0507)	(0.0752)	(0.0761)
lnfec	0.0988	0.1038	-0.3217**	-0.2858**
	(0.0937)	(0.1012)	(0.1188)	(0.1247)
lnpop	-0.6155**	-0.5392**	-0.0940	-0.7550**
	(0.2660)	(0.2676)	(0.2454)	(0.2959)
lnis	0.3541*	0.8603***	0.2420	0.0286
	(0.2053)	(0.2408)	(0.2822)	(0.2666)
lnrer	-0.0106	-0.0084	-0.0578	-0.0923**
	(0.0236)	(0.0253)	(0.0404)	(0.0368)
lngdp	0.6716	1.0241	2.3489**	0.4698
	(0.6865)	(0.7194)	(0.9698)	(0.9943)
(lngdp)2	-0.0360	-0.0617*	-0.1337**	0.0164
	(0.0349)	(0.0367)	(0.0495)	(0.0500)
q	0.6408***	0.5248***	0.6043***	0.6320***
	(0.0564)	(0.0680)	(0.0592)	(0.0543)
LR-lag	28.83***	38.44***	35.60***	52.37***
LR-error	44.43***	56.55***	39.14***	34.72***
wald-lag	32.84***	42.43***	60.52***	59.05***
wald-error	30.29***	34.94***	34.23***	28.62***

Note: Standard errors in parentheses. ** p<0.10 ** p<0.05 *** p<0.001 "cppg,so2pg, noxpg,dspg are emissions unit currency

5.3 Direct action, indirect action and total action

Space spillover effects include direct and indirect effects. Table 6 shows the direct, indirect and total effects of renewable energy green innovation and fossil energy consumption on comprehensive pollutants, SO₂, NO_x, Dust&Smoke emissions. The direct and indirect effects of renewable energy green innovation on integrated air pollution, NO_x, SO₂, Dust&Smoke are negative. This result supports Hypothesis 1-1, 1-2, 1-3, 1-4. Among them, the indirect impact coefficients of reti on comprehensive air pollution and Dust&Smoke are: -0.3079 (t value is 0.1130, p value is 0.000), -0.7686 (t value is 0.1664, p value is 0.05), which shows the green innovation of renewable energy Not only does it suppress local air pollution, it also suppresses air pollution in neighboring provinces.

The direct impact of fossil energy consumption on comprehensive air pollution, NO_x, SO₂, Dust & Smoke is positive, because at this stage coal is the main body of China's current energy consumption, accounting for 64.0% of China's total energy consumption in 2015, coal is China's economic growth Foundation[45].When fossil energy consumption increases, NO_x, SO₂, Dust & Smoke emissions will increase accordingly, this finding is consistent with Zhu et al (2017) [46]、 Dong &Liang et al (2014) [47].However, the indirect impact of fossil energy consumption only on comprehensive pollution and NO_x is positive, indicating that fossil energy consumption will significantly increase local air pollution, while the impact on SO₂ and dust&smoke pollution in nearby areas is not very obvious. This may be due to the coordinated management of coal combustion waste gas emissions by government departments in different regions, which makes the diffusion effect of coal combustion emissions of SO₂ and dust&smoke on the adjacent areas weaker.

In terms of social and economic factors, the direct and indirect effects of industrial structure on air pollution emissions are positive, which is the same as the findings of Zheng Y et al (2020). According to his research results, reducing the proportion of secondary industry output in GDP can significantly reduce NO_x pollution and S02 pollution, and the industrial structure can change the impact of economic development on atmospheric pollution [48].The increase in population size also has a positive correlation with air pollution, which is consistent with the empirical results of Li and K et al (2019). Their empirical results show that both population size and urbanization rate have a significant positive effect on air pollution. However, this effect is spatially heterogeneous. The impact of population size on air pollution in the eastern region is much smaller than that in the central and western regions [49].Environmental regulations have a negative impact on the emission of pollutants in various provinces, especially the control effects of NO_x and SO₂ are more significant.

Table 6 Estimate results of direct effects, indirect effects and total effects

	lncp	lnnox	lnso2	lns
LR_Direct				
lnreti	-0.0531* (0.0300)	-0.0520* (0.0309)	-0.0586 (0.0467)	-0.0560 (0.0461)
lnfec	0.0582 (0.0590)	0.0208 (0.0641)	0.4919*** (0.0746)	0.4301*** (0.0798)
lnpop	0.6462*** (0.1811)	0.6270*** (0.1755)	0.3592** (0.1488)	0.6614*** (0.2000)
lnis	0.4631*** (0.1351)	0.4437** (0.1397)	0.6371*** (0.1832)	0.4137** (0.2013)
lnrer	-0.0645*** (0.0141)	-0.0550*** (0.0143)	-0.0885*** (0.0237)	-0.0315 (0.0226)
lngdp	1.2637** (0.4962)	0.4199 (0.4936)	1.3969** (0.6635)	0.4875 (0.6954)

(lngdp)2	-0.0637** (0.0258)	-0.0146 (0.0258)	-0.0719** (0.0347)	-0.0400 (0.0368)
LR_Indirect				
lnreti	-0.3079** (0.1130)	-0.1075 (0.0928)	-0.2227 (0.1611)	-0.7686*** (0.1664)
lnfec	0.3183 (0.2389)	0.2151 (0.1857)	-0.0372 (0.2544)	-0.0201 (0.3043)
lnpop	-0.5079 (0.5199)	-0.4269 (0.3953)	0.2040 (0.4495)	-0.7953 (0.5858)
lnis	1.4485** (0.4614)	1.9555*** (0.3751)	1.2891** (0.6277)	0.6552 (0.6728)
lnrer	-0.1183** (0.0568)	-0.0697 (0.0468)	-0.2332** (0.0904)	-0.2490** (0.0918)
lngdp	3.3012* (1.7082)	2.2426 (1.3902)	6.6331** (2.2782)	1.6962 (2.5653)
(lngdp)2	-0.1697** (0.0859)	-0.1236* (0.0700)	-0.3671** (0.1154)	-0.0176 (0.1295)
LR_Total				
lnreti	-0.3610** (0.1292)	-0.1595 (0.1057)	-0.2813 (0.1817)	-0.8246*** (0.1880)
lnfec	0.3765 (0.2665)	0.2359 (0.2070)	0.4548 (0.2818)	0.4101 (0.3460)
lnpop	0.1383 (0.5753)	0.2001 (0.4238)	0.5632 (0.4806)	-0.1340 (0.6411)
lnis	1.9115*** (0.5200)	2.3992*** (0.4223)	1.9262** (0.7281)	1.0688 (0.7721)
lnrer	-0.1828** (0.0657)	-0.1247** (0.0545)	-0.3217** (0.1046)	-0.2806** (0.1059)
lngdp	4.5650** (2.0213)	2.6625 (1.6614)	8.0300** (2.6918)	2.1837 (2.9974)
(lngdp)2	-0.2334** (0.1024)	-0.1382 (0.0846)	-0.4390** (0.1373)	-0.0575 (0.1526)

Note: Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.001

6. Conclusion and policy implication

The air pollution problem in China is complex and comprehensive, and involves many factors. The distribution of air pollution is spatially related, and air pollution also has a strong spatial spillover effect. Renewable energy green innovation and fossil energy consumption have a profound impact on air pollution in space. The discussion mainly reached the following conclusions:

(1) The spatial distribution of China's air pollution is high in the east and low in the west, high in the north and low in the south. The peak emissions of NO_x, SO₂, Dust & Smoke are distributed in the northeastern provinces of Shandong, Hebei, Inner Mongolia, Liaoning, Jiangsu and Guangdong in the south. In addition, China's air pollution has a strong spatial concentration effect, and Shandong, Hebei, Shanxi, and Henan are in the H-H highland where pollution is emitted.

(2) Renewable energy green innovation and fossil energy consumption also have a strong spatial relationship, and this relationship has been strengthened year by year. Renewable energy green innovation highlands and depressions are becoming more and more prominent. Xinjiang, Gansu, Sichuan, and Shaanxi are in the L-L cluster of renewable energy green innovation, which constitutes a depression for renewable energy green innovation. This innovation depression gradually increased from 2011 to 2017. On the contrary, the innovation highland in the H-H aggregation mode of renewable energy green innovation expanded from Jiangsu and Anhui in 2011 to Jiangsu, Anhui, Zhejiang and Shandong in 2017. Fossil energy consumption also shows a high degree of aggregation. Hebei, Shanxi, Henan, Shandong, and Anhui are in the HH accumulation mode of high fossil energy consumption, and this highland of fossil energy consumption gradually moves northward. By 2017, the center of the HH accumulation mode Located in Shanxi, Shandong and Hebei.

(3) Renewable energy green innovation and environmental regulations have a significant inhibitory effect on air pollution (SO₂, NO_x, Dust & Smoke). The consumption of fossil energy, the increase in the proportion of secondary industries in the industrial structure, and the increase in the size of the population will all lead to increased air pollution.

Based on the above analysis, the following suggestions are made to mitigate air pollution:

(1) According to the spatial overflow characteristics of pollutant discharge, it is recommended to establish a mechanism for regional cooperative governance, especially in areas with high pollution concentration. Neighboring provinces should work together to control pollution, and establish environmental governance exchanges and cooperation between regions. When formulating environmental policies, strengthen coordination and communication between regions, and fully consider the environmental impact of air pollution in one province on surrounding provinces.

(2) It is recommended to strengthen the space diffusion of renewable energy green innovation, to allow scientific and technological innovation factors to fully flow, so that renewable energy green innovation in one province can fully serve the surrounding provinces. The government should encourage the flow of regional innovation factors to allow the full flow of technological innovation, and the state should build a platform for provinces with backward innovation to easily introduce advanced energy technologies. Renewable energy green innovation is widely used, will make renewable energy technology more applied, thereby increasing the proportion of renewable energy consumption, to achieve the purpose of effectively reducing air pollutant emissions. Increase investment in research and development of renewable energy technologies, the development of renewable energy green innovation in one province will reduce pollutant emissions from neighboring provinces.

(3) Reducing the consumption of fossil energy in one province can effectively reduce air

pollution in neighboring provinces, and replacing traditional fossil energy with more renewable energy can effectively reduce air pollution. For the regions with high coal fossil energy consumption and high energy consumption intensity in the northwest, the government should rationally control the proportion of industries with high energy consumption and high pollution while appropriately upgrading the industrial structure, appropriately increase environmental regulations, and promote the introduction of advanced energy production technologies.

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- [1] International Energy Agency, 2016. Energy and Air Pollution: World Energy Outlook Special Report. Paris. Retrieved from. <https://www.iea.org/publications/freepublications/publication/WorldEnergyOutlookSpecialReport2016EnergyandAirPollution.pdf>
 - [2] Ren, F., & Xia, L. (2017). Analysis of China’s Primary Energy Structure and Emissions Reduction Targets by 2030 Based on Multiobjective Programming. *Mathematical Problems in Engineering*, 2017, 1–8.
 - [3] Gu, H., Cao, Y., Elahi, E., & Jha, S. K. (2019). Human health damages related to air pollution in China. *Environmental Science and Pollution Research*.
 - [4] Khoshnevis Yazdi, S.K., Khanalizadeh, B., 2017. Air pollution, economic growth and health care expenditure. *Econ. Res.-Ekonomika Istrazivanja* 30 (1), 1181-1190
 - [5] Xu, B., Lin, B., 2016. Regional differences of pollution emissions in China: contributing factors and mitigation strategies. *J. Clean. Prod.* 112, 1454-1463.
 - [6] 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, 323e333.
 - [7] Hao, Y., Liu, Y., 2016. The influential factors of urban PM2.5 concentrations in China: a spatial econometric analysis. *J. Clean. Prod.* 112, 1443e1453.
 - [8] Zhang, X., Shi, M., Li, Y., Pang, R., Xiang, N., 2018. Correlating PM2.5 concentrations with air pollutant emissions: a longitudinal study of the Beijing-Tianjin-Hebei region. *J. Clean. Prod.* 179, 103-113.
 - [9] Dong N, Prentice IC et al (2017) Leaf nitrogen from first principles: field evidence for adaptive variation with climate, *Biogeosciences*, 14:481–495.
 - [10] Brunt, H., Barnes, J., Jones, S. J., Longhurst, J. W. S., Scally, G., & Hayes, E. (2016). Air pollution, deprivation and health: understanding relationships to add value to local air quality management policy and practice in Wales, UK. *Journal of Public Health*.

-
- [11] Dong, K., Hochman, G., Kong, X., Sun, R., & Wang, Z. (2019). Spatial econometric analysis of China's PM10 pollution and its influential factors: evidence from the provincial level. *Ecological Indicators*, 96, 317–328
- [12] Signoretta, P. E., Buffel, V., & Bracke, P. (2019). Mental wellbeing, air pollution and the ecological state. *Health & Place*, 57, 82–91.
- [13] Gu, H., Cao, Y., Elahi, E., & Jha, S. K. (2019). Human health damages related to air pollution in China. *Environmental Science and Pollution Research*.
- [14] Wang, X.-C., Klemeš, J. J., Dong, X., Fan, W., Xu, Z., Wang, Y., & Varbanov, P. S. (2019). Air pollution terrain nexus: A review considering energy generation and consumption. *Renewable and Sustainable Energy Reviews*, 105, 71–85.
- [15] Yuan, J., Ou, X., & Wang, G. (2017). Establishing a Framework to Evaluate the Effect of Energy Countermeasures Tackling Climate Change and Air Pollution: The Example of China. *Sustainability*, 9(9), 1555.
- [16] Zhang, S., Worrell, E., & Crijns-Graus, W. (2015). Mapping and modeling multiple benefits of energy efficiency and emission mitigation in China's cement industry at the provincial level. *Applied Energy*, 155, 35–58.
- [17] Boudri, J. C., Hordijk, L., Kroeze, C., Amann, M., Cofala, J., Bertok, I., ... Srivastava, L. (2002). The Potential Contribution Of Renewable Energy In Air Pollution Abatement In China And India. *Energy Policy*, 30(5), 409–424.
- [18] Zhu, Y., Wang, Z., Yang, J., & Zhu, L. (2019). Does Renewable Energy Technological Innovation Control China's Air Pollution? A Spatial Analysis. *Journal Of Cleaner Production*, 119515.
- [19] Xie, Y., Dai, H., & Dong, H. (2018). Impacts of SO₂ taxations and renewable energy development on CO₂, NO_x and SO₂ emissions in Jing-Jin-Ji region. *Journal of Cleaner Production*, 171, 1386–1395.
- [20] Alvarez-Herranz, A., Balsalobre-Lorente, D., Shahbaz, M., & Cantos, J. M. (2017). Energy Innovation And Renewable Energy Consumption In The Correction Of Air Pollution Levels. *Energy Policy*, 105, 386–397.
- [21] Xie, Q., Xu, X., & Liu, X. (2019). Is there an EKC between economic growth and smog pollution in China? New evidence from semiparametric spatial autoregressive models. *Journal of Cleaner Production*.
- [22] Zhao, D., Chen, H., Li, X., & Ma, X. (2018). Air pollution and its influential factors in china's hot spots. *Journal Of Cleaner Production*, 185, 619–627.
- [23] 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.
- [24] Li, L., Hong, X., & Wang, J. (2019). Evaluating The Impact Of Clean Energy Consumption And Factor Allocation On China'S Air Pollution: A Spatial Econometric Approach. *Energy*, 116842.
- [25] Liu Xin, Li Shumin. Empirical Analysis of Energy Efficiency of Chinese Province Based on Unexpected Output SBM Model [J]. *Mathematical Practice and Understanding*, 2015,45 (02): 35-43.
- [26] Zhu, Y et al., Does renewable energy technological innovation control China's air pollution? A spatial analysis, *Journal of Cleaner Production*, <https://doi.org/10.1016/j.jclepro.2019.119515>.
- [27] Wang ban-ban, Zhao cheng. Green technology innovation in China: patent statistics and influencing factors [J]. *Industrial technology economy*, 2019,38(07):53-66.
- [28] GOSG. Strategic Action Plan for Energy Development (2014-2020). 2014. p. 2014-2020.
- [29] Zhu, Y., Wang, Z., Yang, J., & Zhu, L. (2019). Does renewable energy technological innovation control China's air pollution? A spatial analysis. *Journal of Cleaner Production*, 119515.
- [30] Hao, Y., Liu, Y., Weng, J.-H., & Gao, Y. (2016). Does the Environmental Kuznets Curve for coal consumption in China exist? New evidence from spatial econometric analysis. *Energy*, 114, 1214–1223.
- [31] Ehrlich P R, Holdren J P. Impact Of Population Growth [J] *Science*, 1971, 171(3977): 1212-1217
- [32] Dietz T, Rosa E A. Rethinking The Environmental Impacts Of Population, Affluence And Technology [J]. *Human Ecology Review*, 1994, 12: 277-300
- [33] Rosa E A, York R, Dietz T. Tracking The Anthropogenic Drivers Of Ecological Impacts [J]. *Ambio: A Journal Of The Human Environment*, 2004, 33(8): 509-512

-
- [34] Dietz T, Rosa E A. Effects Of Populatifon And Affluence On Co2 Emissions [J]. Proceedings Of The National Academy Of ScienFEC The United States Of America, 1997, 94(1): 175-179
- [35] Hao, Y., Liu, Y., Weng, J.-H., & Gao, Y. (2016). Does the Environmental Kuznets Curve for coal consumption in China exist? New evidence from spatial econometric analysis. *Energy*, 114, 1214–1223.
- [36] Zhang, R., Du, Q., Geng, J., Liu, B., & Huang, Y. (2015). An improved spatial error model for the mass appraisal of commercial real estate based on spatial analysis: Shenzhen as a case study. *Habitat International*, 46, 196–205.
- [37] Elhorst J.P. (2014) Spatial Panel Data Models. In: Spatial Econometrics. SpringerBriefs in Regional Science. Springer, Berlin, Heidelberg
- [38] Pace, R.K., LeSage, J.P. A sampling approach to estimate the log determinant used in spatial likelihood problems. *J Geogr Syst* 11, 209–225 (2009). <https://doi.org/10.1007/s10109-009-0087-7>
- [39] Zhao, D., Chen, H., Li, X., & Ma, X. (2018). Air pollution and its influential factors in China's hot spots. *Journal of Cleaner Production*, 185, 619–627.
- [40] Huang, C., Su, J., Zhao, X., Sui, J., Ru, P., Zhang, H., & Wang, X. (2012). Government funded renewable energy innovation in China. *Energy Policy*, 51, 121–127. doi:10.1016/j.enpol.2011.08.069
- 41 Li, L., Hong, X., & Wang, J. (2019). Evaluating the Impact of Clean Energy Consumption and Factor Allocation on China's Air Pollution: A Spatial Econometric Approach. *Energy*, 116842.
- [42] Lin, B., & Zhu, J. (2019). The role of renewable energy technological innovation on climate change: Empirical evidence from China. *Science of The Total Environment*.
- [43] Alvarez-Herranz, A., Balsalobre-Lorente, D., Shahbaz, M., & Cantos, J. M. (2017). Energy innovation and renewable energy consumption in the correction of air pollution levels. *Energy Policy*, 105, 386–397.
- [44] Mingchen Xu, Yaojie Tu, Guang Zeng, Qingxiang Wang, Anqi Zhou, Wenming Yang. Numerical study of further NOx emission reduction for coal MILD combustion by combining fuel-rich/lean technology[J]. *International Journal of Energy Research*, 2019, 43(14).
- [45] Tang, X., Jin, Y., McLellan, B. C., Wang, J., & Li, S. (2018). China's coal consumption declining—Impermanent or permanent? *ResourFEC, Conservation and Recycling*, 129, 307–313.
- [46] Zhu L, Gan Q, Liu Y, Yan Z. The impact of foreign direct investment on SO2 emissions in the Beijing-Tianjin-Hebei region: A spatial econometric analysis. *J Clean Prod* 2017;166:189-196.
- [47] Dong L, Liang H. Spatial analysis on China's regional air pollutants and CO2 emissions: emission pattern and regional disparity. *Atmos Environ* 2014;92:280-291
- [48] Zheng, Y., Peng, J., Xiao, J., Su, P., Li, S., Industrial Structure Transformation and Provincial Heterogeneity Characteristics Evolution of Air Pollution: Evidence of a Threshold Effect from China, *Atmospheric Pollution Research*, <https://doi.org/10.1016/j.apr.2019.12.011>.
- [49] Li, K., Fang, L., & He, L. (2019). How population and energy price affect China's environmental pollution? *Energy Policy*, 129, 386–396. doi:10.1016/j.enpol.2019.02.020